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Application of Artificial Intelligence Algorithms for Estimation Daily Peak Load of the District Heating System in Ulaanbaatar

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Abstract - The heating system of Ulaanbaatar, has been in operation for more than 60 years; therefore, optimizing system operation, implementing data-driven system planning and improvement, and supporting informed decision-making have become priority objectives. This study investigates the forecasting of daily peak loads in the district heating system (DHS) of Ulaanbaatar, Mongolia, which is recognized as the coldest capital city worldwide. A comprehensive dataset comprising more than 80,000 hours of historical heat load and ambient temperature data collected between 2018 and 2024 was used to develop an artificial intelligence (AI) model based on a feed-forward back-propagation neural network. The model incorporates outdoor air temperature and historical load values from the previous day and the corresponding day of the preceding week as input variables. The results show that the AI-based approach achieves higher predictive accuracy than conventional regression models, with a correlation coefficient of 0.953 and a coefficient of determination R^2 of 0.925, compared with 0.91 for the regression-based method. These findings indicate that the proposed model is suitable for supporting operational planning and load management in district heating systems operating under extreme climatic conditions.

Key words - Artificial intelligence, peak load, statistical comparison, heat supply system.

Хиймэл Оюун Ухааны Алгоритм Ашиглан Дулаан Хангамжийн Системийн Хоногийн Оргил Ачааллыг Таацлах Судалгаа

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Хураангуй – Улаанбаатар хотын дулаан хангамжийн систем нь 60 гаруй жилийн түүхтэй бөгөөд системийн горим ажиллагааг оновчтой болгох, өгөгдөл дээр суурилсан системийн төлөвлөлт, сайжруулалтыг хийх, шийдвэр гаргалтанд ашиглах шаардлага нэн тэргүүнд тулгарч байна. Энэхүү судалгаанд Монгол Улсын нийслэл Улаанбаатар хотын дулаан хангамжийн системийн (DHS) өдрийн оргил ачааллыг урьдчилан таамаглах асуудлыг авч үзэв. Улаанбаатар хот нь дэлхийн хамгийн хүйтэн нийслэл хэмээн хүлээн зөвшөөрөгдсөн бөгөөд 2018–2024 оны хооронд цуглуулсан 80,000 гаруй цагийн дулааны ачаалал болон орчны агаарын температурын түүхэн мэдээлэлд үндэслэн хиймэл оюун ухааны (AI) загварыг боловсруулсан. Тус загвар нь feed-forward back-propagation мэдрэлийн сүлжээнд суурилсан бөгөөд оролтын хувьсагчаар гадна агаарын температур, өмнөх өдрийн болон өмнөх долоо хоногийн ижил өдрийн дулааны ачааллын утгуудыг ашигласан. Судалгааны үр дүнгээс харахад AI-д суурилсан арга нь уламжлалт регрессийн загвартай харьцуулахад илүү өндөр нарийвчлалтай байгааг харуулсан бөгөөд хамаарлын коэффициент 0.953, коэффициент R^2 = 0.925 байсан бол регрессийн аргын хувьд 0.91 байна. Эдгээр үр дүн нь санал болгож буй загвар нь эрс тэс уур амьсгалтай бүс нутагт үйл ажиллагаа явуулж буй дулаан хангамжийн системийн ашиглалтын төлөвлөлт, ачааллын удирдлагыг дэмжихэд тохиромжтойг харуулж байна.

Түлхүүр үг - хиймэл оюун ухаан, статистик харьцуулалт, дулаан хангамжийн систем

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I. INTRODUCTION

As of 2025, the actual heat supply in Ulaanbaatar is approximately 49.2% below the installed capacity and connected demand, indicating a high requirement for accurate heat load forecasting and operational adjustment.

The first-generation district heating system (DHS) which employs steam as the medium and concrete as the pipeline was developed in the United States in the 1880s. From the 1930s through the 1970s, the second generation DHS used 100 °C hot water as the carrier [1]. Nowadays, most DHSs are classified as the third generation, which are characterized by underground insulated pipelines and lower supply temperatures (below 100 °C) [2].

The heat supply system of Ulaanbaatar is classified as belonging to the second-generation of district heating system development [3]. Due to the large operational costs involved, efficient operation of the producing units in a district heating system is desirable [4].

The heat supply system of Ulaanbaatar is a comprehensive and cen-tralized network that has been in continuous operation for over 65 years. It currently delivers thermal energy to approximately 13,900 buildings via 10 primary distribution networks, supplied by four major combined heat and power (CHP) plants [5]. Accurate heat load forecast is important to operate CHP efficiently [6].

District heating (DH) load forecasting for buildings and cities is essential for DH production planning and demand-side management [7].

A previous study estimates that the heat load of the district heating system in Ulaanbaatar will reach 5006 Gcal/h by the year 2040 [8]. Accurate forecasting and planning of thermal energy consumption are essential for ensuring the reliable operation of heat source generators. Such planning supports the effective response to rapidly increasing energy demand and enables the rational selection and deployment of new generation sources [9].

In temperate and cold climates DH provides a more cost-effective and sustainable solution for supplying heat to buildings in urban areas [10].

Table 1. Daily Load Factor of Ulaanbaatar DHS by Week in January 2025.

Hour	Mon	Tues	Wed	Thur	Fri	Sat	Sun
1:00	1.000	0.990	1.000	1.000	0.996	0.992	0.982
2:00	0.997	0.987	0.995	0.997	0.991	0.990	0.979
3:00	0.988	0.979	0.988	0.990	0.983	0.985	0.972
4:00	0.981	0.975	0.983	0.982	0.984	0.980	0.966
5:00	0.973	0.968	0.977	0.975	0.975	0.973	0.959
6:00	0.973	0.965	0.974	0.975	0.972	0.970	0.957
7:00	0.966	0.966	0.974	0.975	0.973	0.968	0.955
8:00	0.966	0.967	0.973	0.966	0.974	0.967	0.955
9:00	0.968	0.969	0.973	0.975	0.975	0.971	0.954
10:00	0.967	0.970	0.974	0.977	0.976	0.971	0.949
11:00	0.975	0.980	0.977	0.986	0.984	0.979	0.962
12:00	0.977	0.980	0.983	0.971	0.987	0.984	0.968
13:00	0.984	0.983	0.986	0.991	0.992	0.992	0.977
14:00	0.986	0.984	0.987	0.994	0.993	0.996	0.982
15:00	0.984	0.984	0.988	0.995	0.993	0.998	0.971
16:00	0.988	0.984	0.988	0.995	0.994	0.996	0.987
17:00	0.986	0.985	0.986	0.992	0.994	0.996	0.987
18:00	0.986	0.984	0.987	0.990	0.994	0.995	0.987
19:00	0.962	0.982	0.986	0.990	0.995	0.993	0.988
20:00	0.987	0.984	0.985	0.992	0.995	0.994	0.989
21:00	0.991	0.991	0.993	0.991	0.999	0.998	1.000
22:00	0.992	0.991	0.994	0.996	1.000	0.999	0.997
23:00	0.992	0.994	0.994	0.992	0.996	0.998	0.997
24:00	0.996	1.000	0.993	1.000	0.994	1.000	1.000

Table 1 summarizes the peak load characteristics of Ulaanbaatar heat supply system during night hours and morning hours. The data indicate potential for energy savings through enhanced control and automation of the heating system. Additionally, transitioning to a fully consumption-based tariff structure could further optimize system performance and encourage more efficient energy.

With advances in computational power and the growing ability to record, collect, and utilize big data, artificial intelligence algorithms have become increasingly prevalent in various applications [9].

AI refers to computer software technologies designed to simulate human cognitive functions, enabling machines to perform tasks that typically require human intelligence [11].

In recent years, artificial intelligence has emerged as a core technology in the energy industry, enhancing system efficiency, reducing operational costs, minimizing human intervention, and promoting sustainable development.

In this work, a daily peak load forecasting model for the DHS was developed using an artificial intelligence algorithm, incorporating outdoor air temperature and historical load data from previous days as input variables. The forecasting results were compared to predictions obtained from traditional statistical methods based on regression analysis.

Table 2. Daily Load Factor of Ulaanbaatar DHS by Week in January 2025.

Hour	January	February	March	April	May	June	July	August	September	October	November	December
1	1.00	1.00	1.00	1.00	0.96	0.86	0.88	0.88	0.93	0.99	1.00	1.00
2	0.99	1.00	1.00	0.99	0.95	0.84	0.86	0.87	0.93	0.99	1.00	0.99
3	0.99	0.99	0.98	0.98	0.95	0.83	0.86	0.86	0.92	0.98	0.98	0.99
4	0.98	0.98	0.98	0.98	0.94	0.83	0.85	0.85	0.91	0.97	0.98	0.98
5	0.97	0.97	0.97	0.97	0.93	0.83	0.86	0.86	0.91	0.96	0.97	0.97
6	0.97	0.97	0.97	0.98	0.95	0.90	0.91	0.90	0.91	0.96	0.97	0.97
7	0.97	0.97	0.97	0.98	0.96	0.94	0.95	0.94	0.92	0.96	0.97	0.97
8	0.97	0.98	0.97	0.99	0.96	0.95	0.96	0.95	0.92	0.96	0.96	0.97
9	0.97	0.97	0.97	0.98	0.95	0.94	0.95	0.94	0.92	0.96	0.96	0.97
10	0.97	0.97	0.97	0.98	0.95	0.94	0.95	0.90	0.92	0.96	0.96	0.97
11	0.98	0.98	0.97	0.98	0.95	0.92	0.94	0.87	0.92	0.97	0.97	0.98
12	0.98	0.97	0.97	0.98	0.95	0.92	0.93	0.86	0.93	0.97	0.97	0.98
13	0.99	0.98	0.97	0.98	0.95	0.92	0.93	0.87	0.94	0.98	0.98	0.99
14	0.99	0.98	0.97	0.98	0.95	0.92	0.92	0.86	0.95	0.98	0.98	0.99
15	0.99	0.99	0.97	0.98	0.95	0.93	0.93	0.87	0.95	0.98	0.98	0.99
16	0.99	0.98	0.98	0.98	0.96	0.94	0.93	0.91	0.96	0.98	0.98	0.99
17	0.99	0.93	0.98	0.98	0.96	0.96	0.95	0.90	0.98	0.98	0.98	0.99
18	0.99	0.98	0.98	0.98	0.97	0.97	0.96	0.91	0.98	0.98	0.98	0.99
19	0.99	0.98	0.98	0.99	0.98	0.98	0.97	0.92	0.99	0.98	0.98	0.99
20	0.99	0.98	0.98	0.99	0.98	1.00	0.98	0.94	0.99	0.98	0.94	0.99
21	1.00	0.99	0.99	1.00	0.99	1.00	0.99	0.98	1.00	0.99	1.00	1.00
22	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

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23	1.00	0.99	0.99	1.00	0.99	0.98	1.00	1.00	1.00	1.00	1.00	1.00
24	1.00	0.99	0.99	0.99	0.96	0.92	0.94	0.94	0.98	1.00	0.99	1.00

As shown in Table 2, the period of peak load during winter months extends from 16:00 to 24:00 hours, while in the spring and autumn months it occurs between 20:00 and 23:00 hours. In the summer months, heavy congestion persists from 19:00 to 23:00 hours.

The daily load profiles exhibit significant variation between winter and summer seasons. Furthermore, weekday loads differ notably from weekend loads, with distinct differences observed even between individual weekdays such as Monday and Friday. Additionally, substantial differences exist between daytime and nighttime loads, underscoring the strong influence of time on heat demand [10]. In Fig. 1 illustrates hourly heat load of Ulaanbaatar city DHS in january 2025.

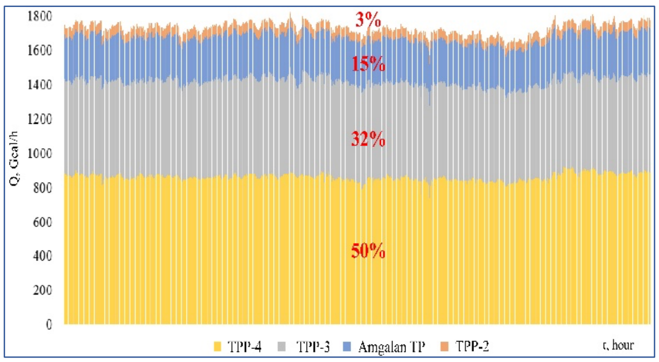

Fig. 1. Hourly heat load of Ulaanbaatar city DHS in January 2025.

Fig. 2 presents the annual load profile of the DHS in Ulaanbaatar, expressed as a percentage of the daily peak load.

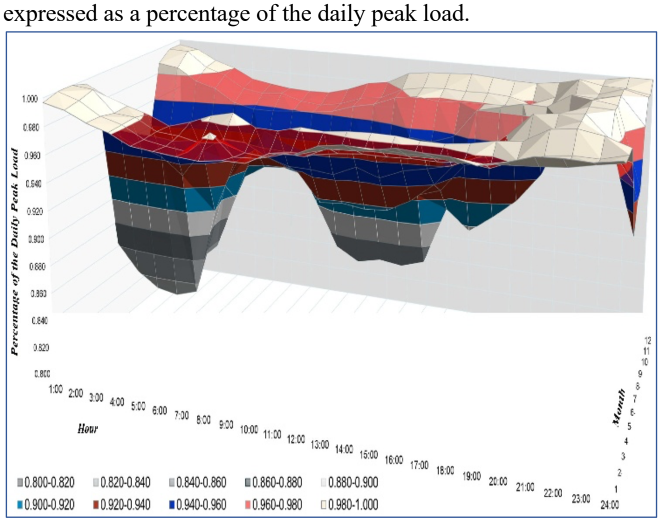

Fig. 2. The annual load profile of Ulaanbaatar DHS expressed as a percentage of the annual peak load.

II. METHODOLOGY

Thermal energy consumption is primarily driven by heating, hot water, ventilation, and domestic needs, resulting in a unique daily load profile for each of the 365 days in a year.

As shown in Table 1, the daily load patterns vary throughout the week and do not repeat consistently. Notably, heat load tends to be lower on weekdays and increases toward the end of the week. Therefore, it is essential to analyze the relationship between the DHS load and the outdoor air temperature, which fluctuates according to seasonal and weather conditions.

To assess the impact of outdoor air temperature on the thermal energy consumption of Ulaanbaatar DHS, the correlation coefficient was calculated between daily load and daily average temperature from 2018 to 2024.

As shown in Table 3, the result -0.937, indicates a strong inverse correlation between temperature and heat load.

Given the strong inverse linear relationship between the DHSs daily peak load and the average outdoor air temperature, a single-factor regression model can be developed to predict the peak load based solely on the mean outdoor air temperature.

In heat load forecasting, regression models are commonly employed, incorporating variables such as historical heat load performance, weather parameters, day of the week, and consumer categories.

Table 3. Correlation Coefficient Between Daily Peak Load and Average Outdoor Air Temperature (2018–2024).

Date	Correlation coefficient
2018	-0.927
2019	-0.936
2020	-0.947
2021	-0.929
2022	-0.949
2023	-0.928
2024	-0.949
Average	-0.937

Heating load prediction plays an important role in supporting the operation of a residential district energy station [13].

Approaches for modeling the heat load in DHS can generally be distinguished between physics-based (leveraging physics and behavioral models) and data-driven (leveraging AI models) [14].

Data-driven models, especially regression-based supervised learning techniques, have gained prominence in heat demand prediction within DHSs [15].

Heating load prediction algorithms for DHSs have become an important research area in recent years because these algorithms can improve the effectiveness of energy-saving strategies. [16]

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An AI algorithm is a computational method capable of automatically improving its performance by learning from data. With a sufficiently large dataset in this case, over 80,000 hours of recorded data these algorithms can generate highly accurate predictions.

In modern engineering practice, specialized software is widely used for scientific, technical, and economic calculations. Examples include Mathcad, MATLAB, Maple Flow, Python, and SMath, among others. These tools offer significant advantages such as time savings, the ability to solve complex differential equations, and improved calculation accuracy [12].

In this study, the training and optimization of the artificial intelligence algorithm were conducted using the Python programming language and IBM SPSS software.

In the early stages of heat load prediction research, statistical analysis techniques were primarily used, leveraging statistical and mathematical expertise to construct prediction models [17].

The AI algorithm utilized input variables including the previous day's load performance, the load from the same day one week prior, the average temperatures of those days, and the difference in ambient temperature on the forecasted day. The output of the model is the predicted daily peak load. The overall model framework is illustrated in Fig. 3.

Neural networks are a fundamental technology within AI and machine learning, modeled mathematically after the functioning of neurons in the human brain [11]. They are designed for data processing, feature extraction, prediction, and decision-making tasks.

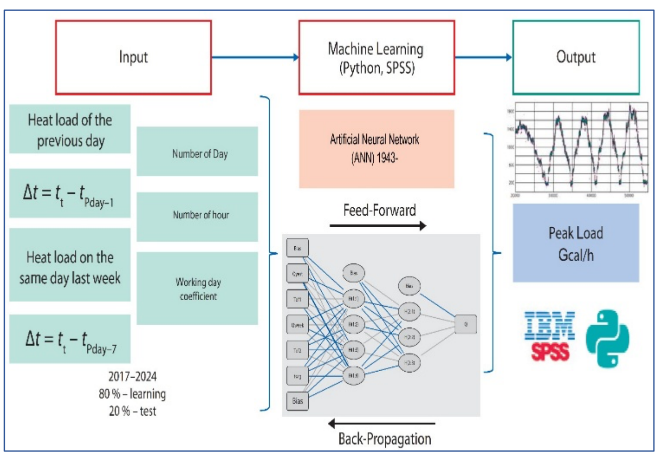

Fig. 3. Machine learning model.

A. Neural Network Architecture

The architecture consists of an input layer, two hidden layers, and an output layer. A two-layer architecture was chosen to provide sufficient depth for capturing thermal inertia in the district heating network without the computational risk of vanishing gradients found in deeper models. The configuration is detailed as follows:

Input Layer: Comprises 4 neurons corresponding to the selected features (Outdoor temperature, previous day load, and same-day-last-week load, working day coefficient).

Hidden Layers: To capture the non-linear complexities of the Ulaanbaatar heating network, two hidden layers were implemented.

Hidden Layer 1: 12 neurons with a ReLU (Rectified Linear Unit) activation function.

Hidden Layer 2: 8 neurons to further refine the feature extraction.

Output Layer: 1 neuron representing the predicted Daily Peak Load (Gcal/h).

B. Training Parameters and Optimization

To ensure the model converges efficiently and avoids overfitting, the following training parameters were set:

- **Optimizer:** Adaptive Moment Estimation optimizer was used, as it is robust for noisy datasets like urban heat loads.
- **Loss Function:** Mean Squared Error (MSE) was selected as the primary loss function to penalize larger forecasting deviations.
- **Data Split:** The dataset (2018–2024) was partitioned using an 80/10/10 split: 80% for training the weights, 10% for validation to tune hyperparameters, and 10% for the final independent testing to verify the results shown in Figure 3.
- **Software Implementation:** Data preprocessing and correlation matrices were generated in IBM SPSS v27. The neural network training and the comparative visualization were executed in Python 3.9.

The proposed model employs a feed-forward back-propagation neural network with two hidden layers. The network architecture was implemented and optimized using Python in combination with IBM SPSS.

III. RESULTS AND DISCUSSION

Table 4 shows that, when the neural network was developed using IBM SPSS software and trained with the artificial intelligence algorithm, the predicted heat load is most strongly correlated with and influenced by the heat load of the previous day and that of seven days prior.

Table 4. Correlation Between Predicted Heat Load and Influencing Factors.

Specification	Test-1 %	Test-2 %	Average %
The previous day's performance	49.5	84.1	66.8
Temperature difference outside the previous day	1.1	3.4	2.3
Previous 7-Day Performance	48.5	6.6	27.6
Temperature difference outside the previous 7 days	0.8	5.4	3.1
Others	0.1	0.5	0.3
Total	100	100	100

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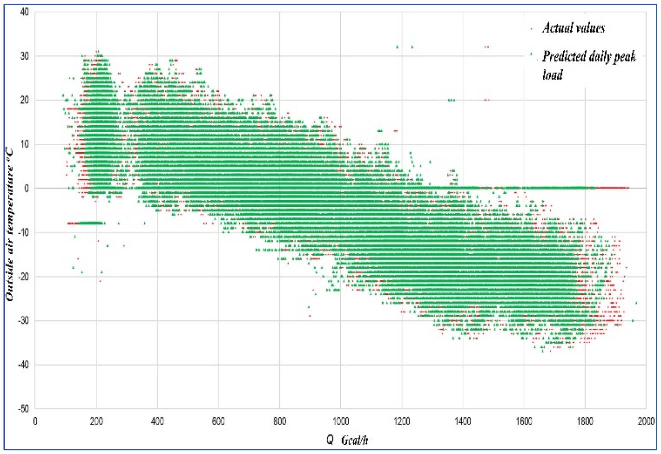

Fig. 4. The predicted daily peak load and actual values as a function of outdoor air temperature for selected days from the 2018–2024 dataset, generated using an AI-trained algorithm.

Fig. 4 illustrates the predicted peak load totals and actual values plotted against the outdoor air temperature for selected days from the 2018–2024 dataset, using an AI-trained algorithm.

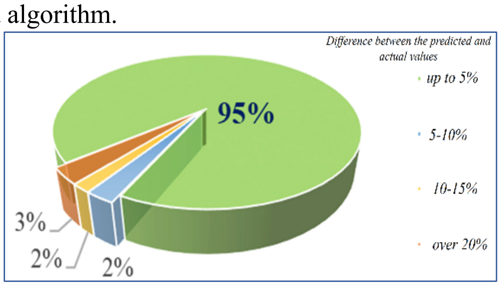

Fig. 5. Comparison of predicted peak load profiles and actual values using AI-trained algorithms.

Between 2018 and 2024, the artificial intelligence algorithm was trained using over 80,000 hours of data from Ulaanbaatar district heating system (DHS). The AI-generated predictions deviate by no more than ±5% from actual performance in 95% of cases.

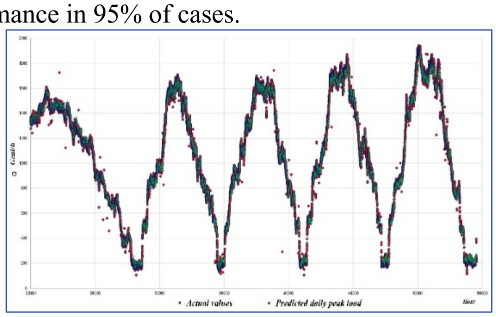

Fig. 6. Comparison of actual daily peak loads of the DHS (2018–2024) with predictions from the regression model and machine learning algorithm.

Using data from 2018 to 2024, the daily load for the years 2020–2024 was predicted by an AI-trained algorithm, as illustrated in Fig. 6.

Table 5 presents a statistical comparison between the predictions obtained from regression models and artificial intelligence algorithms. The regression model achieved a correlation coefficient of 0.91, while the artificial intelligence algorithm attained a higher correlation coefficient of 0.953, indicating superior accuracy.

Table 5. Comparison of Regression Model and Machine Learning Prediction Results.

Specification	Regression model	Machine learning
r_{xy}	0.91	0.953
R^2	0.83	0.925

IV. CONCLUSION

In the context of the increasing application of artificial intelligence algorithms in the energy sector, a methodology for heat consumption planning was developed and evaluated. The heat load characteristics of individual heating systems in Ulaanbaatar, one of the coldest capital cities worldwide, and potential energy-saving measures were identified.

The analysis shows that heat load predictions obtained using artificial intelligence algorithms exhibit a strong dependence on the measured load values of the previous day and the preceding seven days.

For daily peak load forecasting, the AI-based approach demonstrates higher predictive accuracy than conventional statistical methods, with approximately 95% of predictions derived from more than 80,000 hours of data falling within ±5% of the observed values.

This study demonstrates that neural network–based AI algorithms offer improved predictive capability for peak heat loads in extreme climates such as Ulaanbaatar when compared with traditional statistical methods. The obtained correlation coefficient of 0.953 indicates that such models are suitable for integration into real-time district heating system (DHS) operational management.

In heat supply systems, AI is regularly employed for energy demand forecasting, leak detection and network optimization, smart transmission and distribution network management, CO_2 emissions reduction, and the integration of renewable energy sources such as solar thermal systems, geothermal heat, biofuels, and waste heat recovery.

Despite the achieved accuracy, the black-box nature of the model remains a limitation, as it provides limited interpretability with respect to the underlying thermodynamic behavior of the network. In addition, the model performance depends on the availability and quality of historical data; consequently, prediction accuracy may deteriorate under anomalous weather conditions or during rapid urban expansion not represented in the training dataset.

Future work should therefore focus on hybrid modeling approaches that integrate physics-based constraints with AI techniques to enhance interpretability and robustness under extreme climatic variations.

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