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Integration of Hydraulic and Thermal Sensors with Machine Learning For Enhanced Leak Detection and Localization in District Heating Systems

Mohammed ali JALLAL[1], Mathieu VALLEE[1], Nicolas LAMAISON[1]
[1]Univ. Grenoble Alpes, CEA, Liten, Campus Ines, 73375, Le Bourget du Lac, France
mohammed-ali.jallal@cea.fr; Mathieu.VALLEE@cea.fr; nicolas.lamaison@cea.fr

Abstract **-** Accurate leak localization within district heating networks (DHNs) is a significant challenge due to the complex hydraulic dynamics that govern these systems. Traditional methods for leak detection, such as manual inspections and thermal imaging, are often inefficient for real-time applications. Recent advancements in artificial intelligence (AI), particularly artificial neural networks (ANNs), offer promising solutions by analysing pressure and temperature variations in DHN pipelines to identify leak locations. This paper explores the potential of AI-driven techniques for improving leak localization accuracy within DHNs. Using synthetic data generated with a Modelica-based simulation of DHN conditions in Grenoble, France, the study evaluates the impact of pressure and temperature sensors installed in DHN. The model was developed and trained using multi-class classification techniques, with the dataset balanced via Random Under Sampling (RUS) to address class imbalances. Feature selection was performed using Random Forest to identify the most critical input features, which were then used in the ANN for leak localization. The results demonstrate the effectiveness of pressure sensors, particularly in the return lines, for enhancing leak localization precision, while temperature sensors, though less directly indicative of leaks, also contribute valuable insights. The study concludes that AI-based approaches, coupled with strategically placed sensors, can significantly improve the accuracy and efficiency of leak localization in DHNs, contributing to more effective predictive maintenance and reduced system downtime.

Keywords**:** District heating networks; Leak detection and localization; Artificial intelligence; Sensor placement.

1. Introduction

District heating networks (DHNs) cover extensive urban areas, presenting a significant challenge in leak localization, which is critical for ensuring efficient operation and minimizing maintenance costs. While leak detection has been extensively studied [1], [2], accurately pinpointing the exact location of leaks remains a complex issue due to the intricate hydraulic dynamics inherent in DHNs. Traditional methods, such as manual inspections or thermal imaging [3], are often costly and time-intensive, limiting their practicality for real-time detection. However, the integration of digital technologies and artificial intelligence (AI)-driven analytics offers a promising alternative, enabling real-time leak localization and improving both operational efficiency and service reliability.

Recent advancements in artificial intelligence, particularly artificial neural networks (ANNs), have shown considerable promise in various applications, including fault detection [4], anomaly identification [5], and time series forecasting within energy systems [6]–[8]. By analysing pressure and temperature variations in DHN pipelines, where leaks are more likely to occur due to thermal stress and pressure fluctuations, AI models can accurately infer the location of leaks. The strategic placement of sensors in these return lines is critical for optimizing the performance of AI-based localization techniques.

This paper investigates the potential of AI-driven approaches to enhance the accuracy of leak localization within DHNs, utilizing data from pressure and temperature sensors. The ANN model is trained using synthetic data generated with an in-house CEA library based on Modelica, simulating real climatic conditions in Grenoble, France, during the years 2019 and 2020. To improve model performance and interpretability, feature selection is performed using a Random Forest (RF) algorithm to identify the most relevant sensor inputs for leak localization. This study assesses the effectiveness of AI techniques in refining leak localization, contributing to more efficient maintenance strategies and reduced system downtime.

2. Related works

Various methodologies have been explored for leak detection and localization in DHNs, ranging from traditional physics-based models to advanced AI-driven approaches. Among these, AI-based techniques have shown significant promise due to their ability to analyse large datasets and recognize complex patterns.

Xue et al. (2020) applied the XGBoost algorithm to detect leakage faults based on flowmeter and pressure sensor data variations [9]. Losi et al. (2024) developed a data-driven diagnostic method using the NARX model to monitor DHNs in real time, demonstrating fault detection through time-series data analysis [10]. Zhou et al. (2024) combined ANNs with principal component analysis to diagnose multiple faults, including leaks and blockages [11]. However, these studies focus primarily on leak detection, leaving a gap in the accurate localization of leaks.

Beyond purely AI-based methods, hybrid approaches integrating AI with physical modeling have gained traction. Losi et al. (2023) further refined this approach by incorporating NARX with physics-based diagnostics, improving both detection and localization capabilities [12]. Yang et al. (2024) compared physical model-based and data-driven leak localization techniques, utilizing hydraulic simulations to enhance precision [13]. Additionally, Perpar and Rek (2021) investigated the use of soil temperature gradients for leak detection, showing that thermal anomalies are effective indicators of pipeline faults [14]. Thermal imaging remains a valuable tool for leak detection and localization, though it is not suitable for real-time applications. Vollmer et al. (2023) introduced an automated analysis program to reduce false alarms in airborne thermographic assessments [3], while Protić et al. (2024) demonstrated the effectiveness of UAV-mounted thermal cameras for identifying heat losses and localizing leaks in DHNs [15].

Despite significant advancements, challenges persist in optimizing sensor placement and improving the accuracy of AI models for leak localization in DHNs. This study addresses these challenges by evaluating the impact of pressure sensors in the return pipelines and temperature sensors of DHNs, where leaks are most likely to occur. By leveraging artificial intelligence, specifically RF and ANNs, the proposed methodology aims to enhance leak localization precision and establish a data-driven framework for predictive maintenance within DHNs.

In this context, the study makes two primary contributions: First, it provides a comprehensive analysis of how pressure and temperature sensors in the return lines can enhance the accuracy of AI models for leak detection and localization. Second, it presents empirical results that demonstrate the effectiveness of this approach in improving the reliability and sustainability of DHNs. By utilizing data from these sensors, the study aims to develop more robust AI models that improve both leak detection accuracy and leak localization precision. Ultimately, this approach contributes to reducing operational costs and minimizing service disruptions.

2. Methodology

2.1. District Heating Network Model: Overview and Data Insights

A linear network model from the DistrictHeating library [16] is used to simulate DHN leak faults. The model consists of a thermal plant supplying heat to nC consumers placed linearly along the network, with equal spacing and no branches. The plant and the first consumer are co-located. Pipe diameters are designed for a nominal velocity of $2\ m/s$ and constant pressure gradient. The supply temperature $T_{N,suply}$ is determined by an expert law based on external temperature. The plant pump maintains a differential pressure ΔP so that the last consumer nC meets a setpoint ΔP_{sp}. Each consumer's demand $Q_{c,d}$ is derived from a global demand Q_{Nd} using normalized weights α_c, Eq. (1). The mass flow rate $\dot{m}_{cd}$ is calculated to meet local demand, considering heat and charge losses. Valve openings vo_c are adjusted to achieve the desired flow; if not possible, the valve remains fully open, and resulting temperatures and flow rates are computed.

$$\forall\, c \in [1, nC],\ \ Q_{c,d} = \alpha_c \cdot Q_{Nd} \tag{1}$$

For fault simulation, hydraulic leaks were introduced at the start of each pipe ($nC - 1$ locations) using valves connected to ambient air. The leak flow rate depends on local pressure and valve opening i_{leak} , which varies along the network. No additional fluid is injected into the network during leaks, assuming a compressor maintains pressure.

The studied DHN has a nominal demand of $6\ MW$, yearly demand of $28\ GWh$, and a $6.5\ km$ supply/return line with 10 equally spaced consumers. External temperature is constant at $15°C$, and pipes have $15\ cm$ insulation with

0.04 $W/m \cdot K$ conductivity. Substations are sized for 0.6 MW, with primary temperatures of $90/55°C$ and secondary temperatures of $70/50°C$.

Simulations were conducted over a four-week period using predefined boundary conditions, including the external temperature in Grenoble, France, thermal load, and supply temperature, for the years 2019 and 2020. Six time series representing the first 6 periods of a typical year were used. Leaks were simulated at nine locations on the return line with with random start times and intensities $i_{leak} \in [0.2,1]$. A total of 2268 simulations were performed, each recording 8065 instances of over 34 variables every 5 minutes. More details are presented in [1].

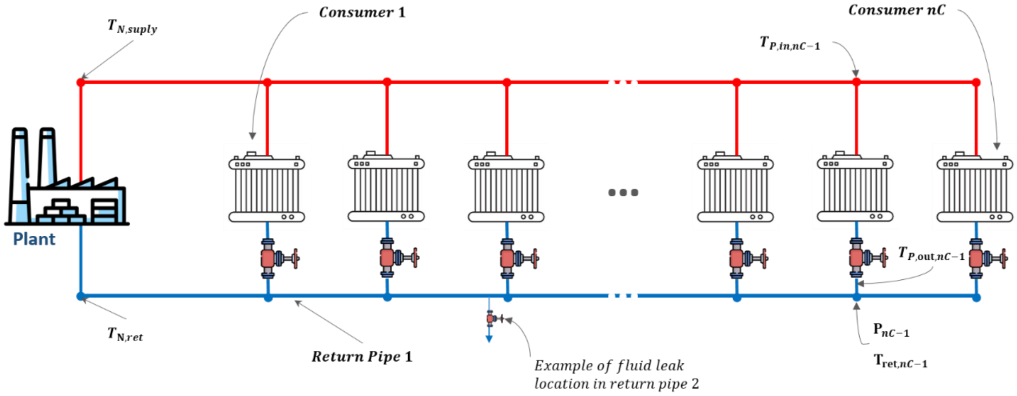


Fig. 1: Schematic diagram of the linear network model utilized for simulating hydraulic leaks.

2.2. AI model development

This section describes the methodology used in building, training, and evaluating the model for multi-class classification. The process involves several stages, including data preprocessing, model architecture design, training, and evaluation.

2.2.1. Data pre-processing

To address class imbalance, Random Under Sampling (RUS) was applied to the dataset [17]. The dataset, initially consisting of features X_0 and labels Y_0, was combined into a single DataFrame. The RandomUnderSampler from the imblearn package was used to balance the dataset by reducing the instances in the majority class, ensuring that the class distribution was even across the training and testing sets. Mathematically, the goal is to make the sizes of the majority class and the minority class equal. Additionally, One-Hot Encoding was applied to the target variable Y, converting categorical labels into binary vectors. Furthermore, input features X were standardized to have zero mean and unit variance. This scaling ensures that all features contribute equally to the model, which is particularly important for models that use gradient-based optimization.

2.2.2. Feature importance analysis using random forest

To enhance leak localization accuracy in the DHN model, a RF-based feature selection layer was integrated prior to the ANN. This hybrid approach leverages RF's ability to identify the most important features, which are then fed into the ANN for improved pattern recognition and leak detection and localisation. In this study, the features consist of data collected from temperature and pressure sensors installed along the DHN, providing critical insights into the network's operational state. Additionally, this approach was used to evaluate the pertinence of pressure sensors installed in the return pipes of the DHN, determining their contribution to fault localization using the ANN. This methodology offers several benefits, including interpretability, reduced dimensionality, and improved model performance, by focusing on the most relevant sensor data.

RF was trained on the pre-processed dataset to calculate feature importance based on their contribution to reducing impurity (e.g., Gini impurity) across decision trees [18]. The importance of feature j is computed as :

$$Importance(j) = \frac{1}{N_{trees}} \sum_{T} \sum_{t \in T} \Delta Impurity(j, t) \tag{2}$$

where N_{trees} is the number of trees, T represents a tree, and t is a node in T. The top k features with the highest importance scores, derived from temperature and pressure sensor data, were selected for input to the ANN. This process highlighted the significance of pressure sensors in the return pipes, quantifying their relevance in fault localization.

2.2.3. ANN model architecture

The model architecture is structured as a feed-forward ANN comprising multiple hidden layers [6]. Non-linear activation functions, such as the relu, tanh, and sigmoid, are applied within the hidden layers to enable the network to learn complex, non-linear relationships within the data. The output layer utilizes the softmax activation function to produce a normalized probability distribution over the target classes, facilitating multi-class classification.

Each hidden layer can be described by the equation:

$$z_i = W_i x + b_i \tag{3}$$

where W_i and b_i are the weights and biases of the $i-th$ layer, and x is the input vector. The softmax activation for the output layer is given by:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \tag{4}$$

where z_i is the input to the softmax layer for class i, and C is the number of classes.

2.2.4. Model training

The model is trained using the Adam optimizer [4], which adapts the learning rate during training. The training objective is the categorical cross-entropy loss, given by:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{5}$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability. Training continues until convergence or until early stopping halts the process. Early stopping monitors the validation loss and stops the training when no improvement is observed after a set number of epochs. Additionally, learning rate scheduling is used, where the learning rate is reduced by a factor when the validation loss plateaus, helping the model converge more effectively.

2.2.5. Model evaluation

After training, the model is evaluated on the test set using multiple metrics such as accuracy, precision, recall, and F1-score to provide a comprehensive assessment of the model's performance [19], [20]. A confusion matrix is also generated to visualize the classification performance [4]. This matrix breaks down the number of true positives, false positives, true negatives, and false negatives for each class, providing deeper insights into model errors and the overall performance across all classes.

3. Results and Discussion

3.1. Relevance of temperature and pressure sensors in leak localization

Based on the bar plot of the RF importance scores presented in Figure 2, several conclusions can be drawn regarding the relevance of temperature and pressure sensors in leak localization. The localization of leaks in DHNs relies heavily on the data provided by temperature and pressure sensors installed along the network. Pressure sensors, in particular, play a critical role in leak detection due to their sensitivity to changes in the hydraulic conditions of the network. As depicted in Figure 2, pressure sensors pres_ret_2 to pres_ret_10 have the highest importance scores, making them the most effective features for locating leaks. When a leak occurs, the pressure drop propagates through the pipes, and the magnitude of this drop varies depending on the leak's location and size. This makes pressure sensors highly effective for pinpointing leaks. However, not all pressure sensors contribute equally to leak localization. For instance, pressure sensor pres_ret_1, installed at the heat production plant, maintains a constant value of 5 bar due to its role in regulating the network's supply pressure. As a result, pres_ret_1 provides no meaningful variation in data and thus has no contribution to leak localization, as confirmed by its near-zero importance score in the RF feature importance analysis.

Temperature sensors, while less directly sensitive to leaks compared to pressure sensors, still provide valuable information. They capture thermal dynamics within the network, which can indirectly indicate anomalies such as leaks. For For example, temperature sensors installed at the last substation (Substation 10) on the primary side, along with power demand data, exhibit moderate importance scores in the RF analysis. Although their scores are not as high as those of pressure pressure sensors, they still contribute to the overall leak localization process, particularly in scenarios where pressure data alone may be insufficient.

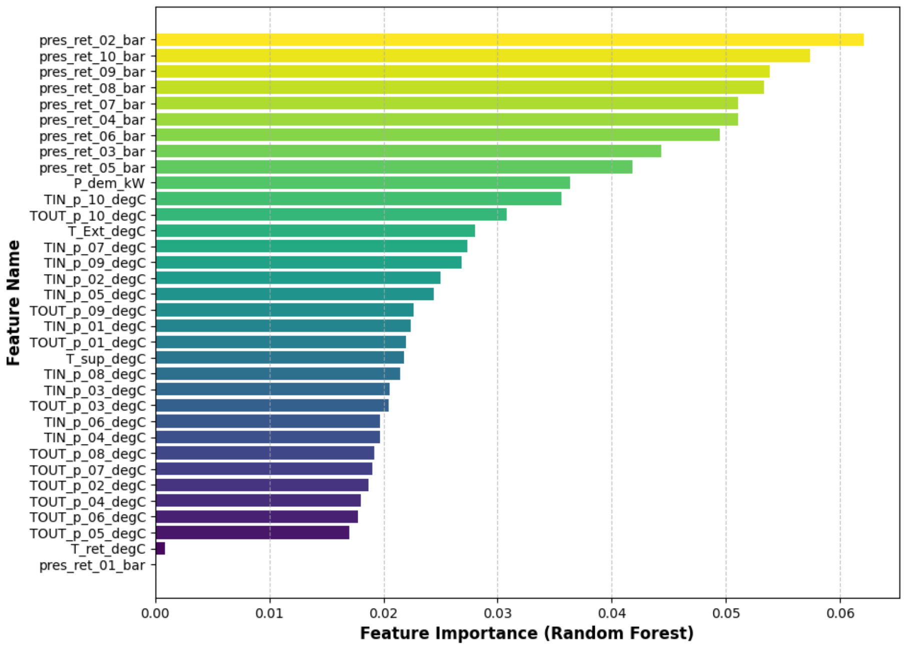


Fig. 2: Sensors importance using Random Forest analysis.

3.2. Influence of input feature selection on leak localization performance

To further investigate the impact of input feature importance on the performance of the leak localization model, three input scenarios were designed based on the RF importance scores. In the first scenario, only the nine most important features were selected, corresponding to the highest-scoring pressure sensors (e.g., from pres_ret_02_bar to pres_ret_10_bar). The second scenario expanded upon this by including three additional features: the power demand (P_dem_kW) and the temperatures measured on the primary side at substation 10 (TIN_p_10_degC and TOUT_p_10_degC), resulting in a total of twelve features. The third scenario incorporated all the features presented in Figure 2, excluding T_ret_degC and pres_ret_01_bar, as these exhibited negligible importance scores according to the RF analysis. For each input scenario, a systematic hyperparameter tuning process was carried out to ensure the optimal configuration of the ANN. This comprehensive evaluation enables a better understanding of how feature selection, guided by feature importance analysis, influences the overall effectiveness of the leak localization model.

3.3. Scenario-based results and analysis

The performance of the ANN models was assessed based on accuracy, precision, recall, f1-score, and confusion matrices for each of the three scenarios. It is important to note that the leak localization task is formulated as a classification problem, where classes 1 to 9 correspond to specific leak locations, and class 0 indicates the absence of a leak. The optimal hyperparameters, determined through RandomSearch optimization for each scenario [4], are presented in Table 1.

Table 1: Optimal Hyperparameters per Scenario.

Scenario	Hidden layers	Neurons per layer	Activation	L2 Regularization	Dropout Rate	Learning Rate
1	3	136-160-152	relu	$1.71\ 10^{-4}$	0.1	$1.25\ 10^{-4}$
2	3	192-112-96	relu	$3.29\ 10^{-5}$	0.2	$1.34\ 10^{-4}$
3	2	240-168	tanh	$3.38\ 10^{-5}$	0.3	$1.81\ 10^{-4}$

Scenario 1: Nine most important pressure sensors

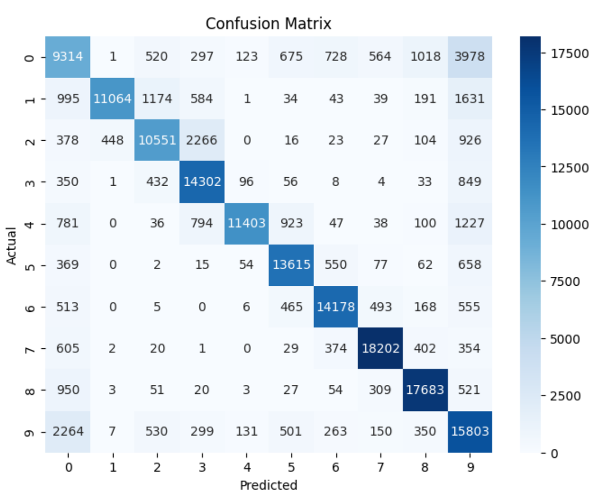
Using only the nine most important pressure features, the model achieved an overall accuracy of 80%. Classes corresponding to leak positions (1 to 9) were generally well classified, with precision and recall scores ranging from moderate to high. Notably, leaks located at positions 1, 4, and 7–9 achieved high precision and recall values, reflecting the strong discriminative power of pressure data for these locations. However, classification performance for class 0 (no leak) was significantly lower, with a precision of 0.56 and recall of 0.54. This indicates that using only pressure measurements, the model struggled to confidently identify the absence of leaks, likely due to the fact that pressure variations alone are not always sufficient to differentiate between normal operation and small leaks. The confusion matrix revealed some misclassifications between adjacent leak positions, highlighting a limitation in the model's spatial resolution when using a restricted set of features, Figure 3-a.

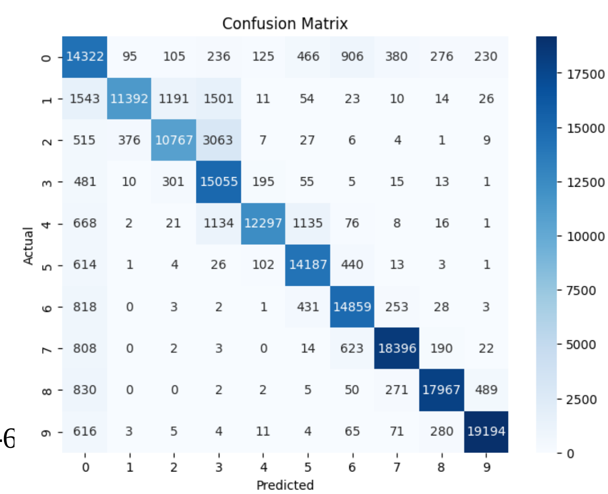
Scenario 2: Nine pressure sensors plus temperature and power demand data

In the second scenario, the inclusion of temperature readings (TIN_p_10_degC, TOUT_p_10_degC) and power demand (P_dem_kW) led to a substantial improvement in model performance, with the accuracy increasing to 87%. Notably, the precision and recall of class 0 improved to 0.68 and 0.84, respectively. This confirms the complementary value of thermal and demand information in distinguishing between no-leak and leak scenarios, particularly when hydraulic indicators are insufficient. Leak positions, especially classes 3, 5, 6, and 9, benefited from higher recall values, suggesting that the added features captured additional system behaviors associated with different leak conditions. The confusion matrix showed fewer misclassifications compared to Scenario 1, Figure 3-b, demonstrating that combining hydraulic and thermal data leads to a more robust and accurate leak localization model.

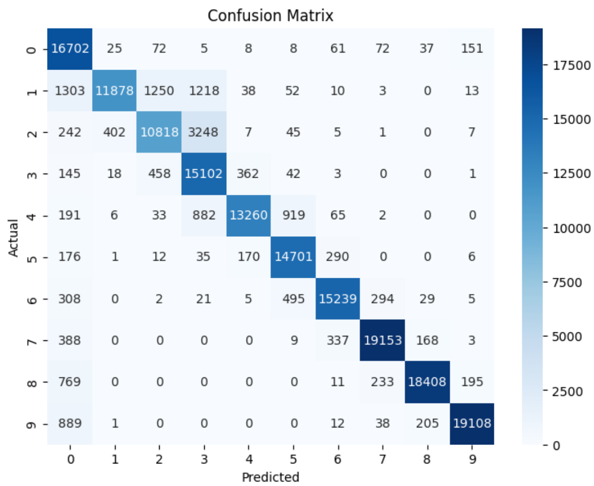
Scenario 3: Almost all features except low-importance ones

In the third scenario, where 32 features were used, the model achieved the highest accuracy of 90%. The performance across all classes improved, with class 0 reaching a precision of 0.79 and an outstanding recall of 0.97, indicating that the model became highly reliable in detecting the absence of leaks. Moreover, leak locations achieved uniformly high f1-scores, generally above 0.85, with several classes (especially classes 7, 8, and 9) reaching f1-scores close to 0.95–0.96. The confusion matrix showed minimal misclassification, Figure 3-c, confirming that a rich feature set capturing both hydraulic and thermal network behavior enables the ANN to learn highly distinctive patterns for each leak scenario. However, it is worth noting that while increasing the number of input features improved accuracy, it also increased the model's complexity, potentially leading to longer training times and a higher risk of overfitting if not properly regularized. The applied L2 regularization and dropout strategies proved effective in mitigating these risks.





(a) (b)



(c)

Fig. 3: Confusion matrices for (a) Scenario 1, (b) Scenario 2, and (c) Scenario 3.

4. Conclusion and Perspectives

The research emphasizes the significant role of AI techniques, particularly ANNs, in improving leak detection and localization within district heating networks (DHNs). The findings underscore the importance of precise sensor placement to enhance detection and localization accuracy and operational efficiency. By integrating AI and machine learning methods, it is possible to address key challenges in leak fault localization, thereby optimizing the performance and energy efficiency of DHNs. Looking forward, our current project focuses on developing an AI-driven automatic library for sensor placement determination. This tool will leverage advanced algorithms to identify the most relevant sensor locations, thereby improving machine learning performance for leak detection and localization systems. The application of such AI-based solutions is expected to enhance the accuracy, reduce costs, and improve the overall efficiency of monitoring and energy management in DHNs.

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