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INTERNATIONAL ENERGY AGENCY
TECHNOLOGY COLLABORATION PROGRAMME ON
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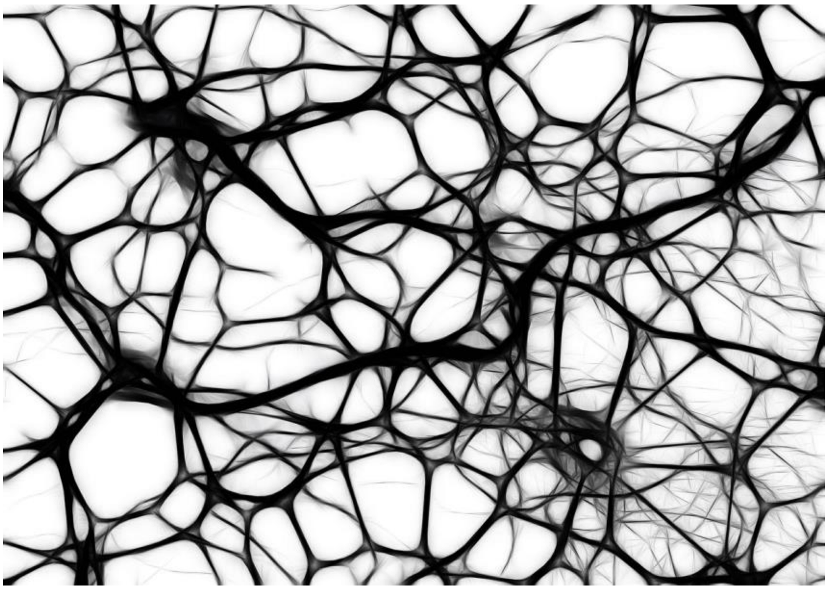

SUMMARY FOR NON-TECHNICAL AUDIENCES

AI FOR FAILURE DETECTION AND FORECASTING OF HEAT PRODUCTION AND DEMAND IN DISTRICT HEATING NETWORKS

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CONTENT

1 INTRODUCTION

AI is a rapidly growing field of research and application in many areas of daily life. It is probably one of the fastest growing businesses in the world.AI is also being used more and more in heating networks. This work is intended to support the further development of AI applications in this area. AI, especially "self-learning" approaches like Artificial Neural Networks (ANN) could contribute to a large extent to improve energy efficiency and fault detection in district heating networks.

The project "AI FOR FAILURE DETECTION AND FORECASTING OF HEAT PRODUCTION AND DEMAND IN DISTRICT HEATING NETWORKS" developed AI methods for forecasting heat demand and heat production. and evaluate algorithms for detecting faults which can be used by interested stakeholders (operators, suppliers of DHC components and manufactures of control devices).

Regarding fault detection, CEA LITEN has been investigating traditional methods based on modelling and simulation for several years. However, detecting faults in DH networks and components remains a challenge, and best performance can only be achieved when combining different approaches.

While AI methods alone face the difficulty of a lack of accurate fault data for most systems, this project will investigate a relevant combination of simulation and experimental data for "self-learning" fault detection algorithms.

Regarding forecasting, Fraunhofer ISE has previously developed an ANN-based control algorithm for single family house heating systems including renewable energy which showed energy savings of up to 12%. The ANN approach provides a "self-learning" capability allowing to create automatically black-box models just from measurement data. Such a low effort/low-cost forecast approach provides the basis of a simple upgrade of current District Heating Network (DHN) control and is particularly important when fluctuating renewable energies are integrated into DHN enabling maximizing renewable heat yields, minimizing flow temperatures, optimizing demand side, minimizing faults and reducing cost. In this project more sophisticated ANN approaches are developed and evaluated in the DHN context.

The methods for forecasting and have been developed and evaluated based on data from a real District Heating Network at Stiftung Liebenau Meckenbeuren, Germany with multiple heat sources (CHP, natural gas, oil, waste combustion) and a variety of heat sinks (residential, laundry, green house, workshop, medical station). The fault detection methods were elaborated mainly based on synthetic data.

AI allows for a combination of low-cost implementation, significant reduction of CO2 emission and economic benefits. Its application is neither limited to any technology nor to any local conditions. Implementation can be done within a short period without changing infrastructure. Thus, AI provides a powerful approach to an economically viable and fast pathway for DHN towards a transition to a carbon-neutral, sustainable energy system.

The following executive report describes the main findings of the project. More details can be found in the full report.

2 FORECASTING

Potential for energy saving by integrating forecasting into the control of Liebenau DHN was conservatively estimated to 3-4% of the whole energy production. An AI based algorithm with a prediction horizon of 4-6 hours should be very helpful to raise this potential. One of the main goals of this project was to develop methods to predict relevant time series data of a DHN in order to provide the network operation with supporting information. The most important one of these quantities is the heat demand of single consumers, of cumulated parts of the network or of the network as a whole. For this, a DHN forecasting software framework containing 4 different ANN architectures (single-shot/autoregressive CNN (Convolutional Neural Network)/LSTM (Long Short-Term Memory) was implemented in Python using the open-source Machine Learning library “TensorFlow”. The developed methods by Fraunhofer ISE are applied to collected real-world data from an existing DHN (Stiftung Liebenau) with many different heat producers and consumers.

The experiments lead to the conclusion that the implemented tool is able to predict heat demands of a DHN in different settings. The single-shot CNN is considered as the best choice amongst the 4 different models, although in some cases other methods slightly outperformed single-shot CNN. The heat demand of the total network for the next 12 h can be predicted with a relative Mean Absolute Error (MAE) of 5.84%. The model is able to capture and predict the trend of the heat demand, although short peaks and fluctuations are missed. Additionally, it can be observed that the prediction uncertainty does not increase for timesteps further in the future but remains roughly at a constant level. This means that even longer prediction horizons than 12 h could be feasible.

The direct comparison of the results achieved with the CNN approach with a previously developed LSI (Linear System Identification) + ANN (Artificial Neural Network) method show that the CNN method provides a superior prediction quality. The accuracy of CNN is almost twice as good as the LSI + ANN approach. Nevertheless, the finding that a very large part of the heat consumption in the DHN can be described with a simple linear system, is an important conclusion from these analyses, too. In future, these findings may open even more optimization potentials also for the CNN methods.

It has been shown, that applying predictive methods for the forecasting of heat demand can improve the energy efficiency of a DHN. An economic estimation of the benefit-cost ratio has been conducted for the avoidance of overheating in the reference case of the Stiftung Liebenau DHN. This leads to the conclusion that such an approach is very interesting also from an economic point of view, since the investment is relatively low.

For the evaluation of individual cost-benefit ratios of other DHNs it is necessary to simulate the networks. Such an evaluation has not been conducted within this project since this would have been gone beyond the planned resources.

The operator of the Stiftung Liebenau DHN is very interested in implementing and testing the descripted approach for operation. A future project may help to evaluate in detail the benefits which can be attained by the proposed approach.

An upcoming publication summarizes the findings regarding forecasting (Frison 2023).

3 FAILURE DETECTION

Regarding fault detection, CEA LITEN has been investigating traditional methods based on modelling and simulation for several years. However, detecting faults in DH networks and components remains a challenge, and best performance can only be achieved when combining different approaches.

While AI methods alone face the difficulty of a lack of accurate fault data for most systems, this project investigated a relevant combination of simulation and experimental data for "self-learning" fault detection algorithms.

In the particular network of the Liebenau district heating network, the potential for improved failure detection based on AI techniques does not seems very significant, especially when considering the additional costs for installing sensors and collecting data in this case. While localization of leaks in the buildings and in the network is considered as the top priority, infrared thermography using drones (for outdoor use) and portable cameras (for indoor use) is the most cost-efficient measure. Using Machine-Learning is still promising for speeding up leak detection and localization, especially for smaller leaks. For other types of faults, installing this equipment only for fault detection would not provide a good cost/benefits ratio. However, the picture may be radically different in a setting where data collection is already in place for other purposes.

Overall, this study provides a realistic picture regarding the potential and pitfalls for fault detection in DHN systems. While fault detection is desirable for the best performance of the systems, and to avoid degradation on the long run, DH operators may not be sufficiently focused in this direction, because the quantification of financial gains is very uncertain. However, especially when data is already available from standard monitoring, machine-learning models can accurately detect faults, as presented in the previous chapters. As presented in this report, using synthetic data is also beneficial to overcome the key limitation regarding the quantity and quality of the available data. In particular, pre-training models on synthetic data and using then for initial labelling of real data is a key step towards robust and easy to deploy fault detection solutions.

A key contribution of this work regarding fault detection is to thus to provide an Open synthetic dataset to enable further research and development in this field. The dataset was created mostly using Open Source simulation models, after carefully assessing the relevant faults and the fault simulation capabilities of more than 90 open source models.

In addition, this dataset was used as a basis for evaluating and comparing the performance of five "standard" Machine Learning (ML) models and 1 "deep learning" models on several binary and multi-class classification tasks for fault detection, diagnosis and localization. The result highlights are the following:

- Three of the binary classification cases are relatively easy to handle for most Machine-Learning models. For the boiler efficiency fault, the accuracy is over 90% and sometimes close to 100%. For the heat pump COP fault and substation fouling fault, the accuracy is over 85%. While this case could be handled using a more “traditional” technique (threshold on a value computed from available measurements) the obtained result illustrate that ML model are appropriate for identifying consistent relations in the data, without requiring manual engineering.

- Two of the binary classification cases are more difficult to handle, and both of them are related to heat losses. This is not surprising, since faults related to heat losses need to be very strong to be detectable in the data, even by a human operator, because they are strongly dependent on the boundary conditions. Moreover, in this comparative study we only consider the raw data from instantaneous records, while effects of heat losses usually take places over longer time periods.

- Trying to distinguish between several types of faults using multi-class classification in a single model is a more difficult task, and the classification performance is reduced. Although the case we test here is limited, this suggests that using several models and a “one-versus-rest” approach may provide better diagnosis results.

- Promising results can be achieved regarding leak localization using sensor data. However, it should be recalled that we consider here a very simplistic linear network model and that the data used as input of the classification models might not be available in the general case.

The dataset is provided online at https://www.kaggle.com/datasets/mathieuvallee/ai-dhc and the code used to produce it is available at https://github.com/mathieu-vallee/ai-dhc.