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# A benchmark for the simulation of meshed district heating networks based on anonymised monitoring data

R Boghetti<sup>1,2</sup>, Jérôme H. Kämpf<sup>1,2</sup>

<sup>1</sup> L'IDIAP Laboratory, École polytechnique fédérale de Lausanne (EPFL), Station 14, CH-1015 Lausanne

<sup>2</sup> Energy Informatics Group, Idiap Research Institute, Marconi 19, 1920 Martigny, Switzerland

E-mail: roberto.boghetti@idiap.ch

**Abstract.** With the increasing interest in District Heating Networks (DHNs) as a potential solution to decarbonize heating, new simulation tools are being developed, raising the need for standardized benchmarks to validate their performance. Currently, the main benchmark used for DHN simulation models is the DESTEST, which consists in an inter-model comparison on the simulation of a toy radial network. However, no common benchmarks based on monitoring data from a meshed network exist at the moment, which would be needed to complement the DESTEST. To address this issue, this paper presents aggregated monitoring data from a medium-sized meshed DHN and proposes a benchmark based on this data. While aggregating the data and assuming steady-state conditions is not a suitable strategy for representing locally high dynamic behaviours, applying the benchmark to an existing simulation tool showed that the simulation results are coherent with the published monitoring data, as a low difference in temperature across most available sensors is found. The published data and the proposed benchmark aim to encourage the development of more accurate models for DHNs and to facilitate the evaluation of the performance of different simulation tools and enable their optimization, which will ultimately lead to more efficient and reliable DHNs.

## 1. Introduction

The urgent necessity of reducing the carbon footprint of space heating and domestic hot water in buildings has led to a recent surging interest from policy-makers and researchers in District Heating Networks (DHNs) [1]. As a consequence, a growing body of literature is developing on efficient methods for the simulation and analysis of these systems, with several new tools being developed and released. Being able to thoroughly test and benchmark these tools is, however, a challenging task. In fact, contrarily to other similar applications, such as building simulations, very few initiatives are targeted at providing common benchmarks for DHN simulation tools. A notable exception is the recent development of the DESTEST [2], a series of Common Exercises (CEs) aiming at providing a framework for comparing the results of different District Energy Simulation (DES) tools. CEs are divided into two categories, focusing on buildings and network simulation respectively, with increasingly complex exercises. Throughout the whole benchmark, a small district with 16 buildings connected to a radial DHN is used. In each CE, a set of Key Performance Indicators (KPIs) is given for comparing the outputs generated by the benchmarked tools with a corresponding reference value calculated as the mean of the outputs. While the

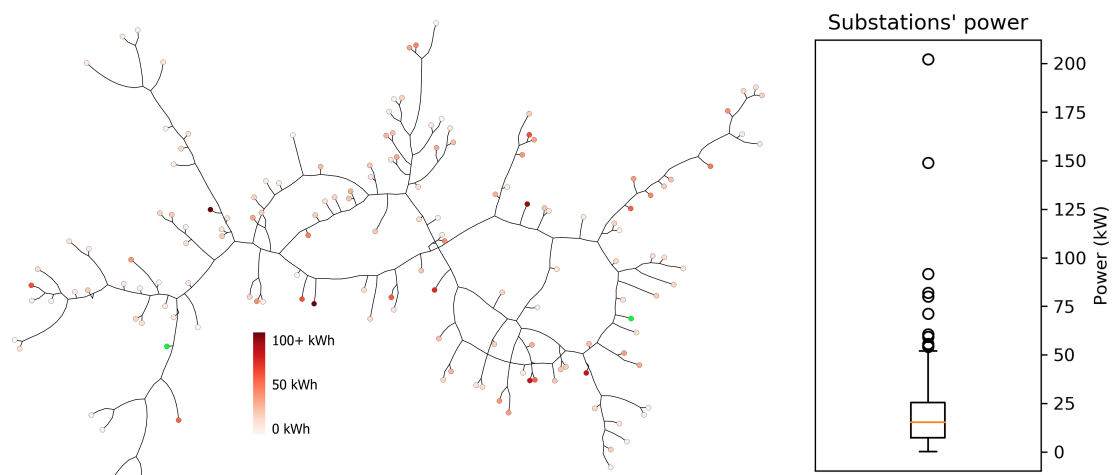


DESTEST is a much needed and useful inter-model benchmarking framework, it does not give any information on the scalability of the tools to the simulation of complex meshed DHNs and is very sensitive to outliers in the reference data, which are - in an inter-model benchmark - the results of models and not measurements. For a more comprehensive evaluation, the DESTEST therefore should be complemented with experimental data. However, this is not always available to researchers. Moreover, even when monitoring data is available, it is usually not accessible to other researchers for reproducing the results or establish common benchmarks due to the privacy concerns involved in sharing such data.

The goal of this paper is to propose a complementary exercise for benchmarking DHN simulation tools, to be used along the DESTEST, that is based on anonymized monitored data from a meshed DHN.

## 2. Reference network

The chosen reference network is a DHN serving the Swiss alpine resort of Verbier. At present, the network is connected to 165 substations and has 3 heating plants. The topology is of meshed type, with 6 internal loops and a maximum difference in altitude of around 125 m. The network is mostly made of underground, pre-insulated pipes, buried at an average depth of 0.8 m, however, a minority of aerial pipes, passing for example through basements, are also present. Given the sensitive nature of the true coordinates of different elements in the network, the equivalent layout shown in Figure 1, generated through Graphviz [3], is instead used in this work. Note that only the primary network up to the customer's property is modeled, while the exact configuration of the connection between the network and the substations is not known. Furthermore, the altitude differences in the network are neglected, as they are not known with sufficient accuracy.



**Figure 1.** Anonymized topology of the network of Verbier, as used in the benchmark, and distribution of energy demand.

For the benchmark, the network is encoded as a directed graph where edges are pipes, consumers and heating plants, while vertices represent junctions between these elements. Pipes form two subgraphs, respectively the supply and return line, while consumers and heating plants connects vertices of the two subgraphs.

**Table 1.** List of pipe characteristics contained in the respective file.

Variable	Data type	Description	Unit
pipe_id	string	Unique identifier of the pipe.	-
startpoint	string	Unique identifier of the starting node.	-
endpoint	string	Unique identifier of the ending node.	-
is_supply	boolean	Boolean indicating if the pipe pertains to the supply line.	-
is_aerial	boolean	Boolean indicating if the pipe is an aerial pipe.	-
length	float	Length of the pipe in meters.	m
d_int	float	Diameter of the internal pipe in meters.	m
t_int	float	Thickness of the internal pipe in meters.	m
t_ins	float	Thickness of the insulation in meters.	m
t_ext	float	Thickness of the external casing in meters.	m
lambda_ins	float	Thermal conductivity of insulation.	W/(K·m)
roughness	float	Roughness of the internal surface of the pipe.	mm

The graph is given in tabular format as four CSV (Comma-Separated Values) files respectively for junctions, pipes, consumers and heating plants. Descriptive data is only given for pipes, as the characteristics and limits of consumers and heating plants are potentially sensitive or competitive information. A list of the pipe characteristics shared for modelling the network is given in Table 1.

### 3. Monitoring data

Along with the network characteristics, monitoring data from one point in time is given for the benchmark. Available measurements include mass flow  $\dot{m}$  (kg/s) and inlet and outlet temperature  $\theta_{in}$  and  $\theta_{out}$  (°C) of all substations and heating plants. Flow sensors have a tolerance of  $\pm(2 + 0.02 \cdot Q_p/Q)\%$ , where  $Q_p/Q$  is the ratio between the limit and current flow, bounded to  $\pm 5\%$ . Temperature sensors have a tolerance of  $\pm(0.3 + 0.005 \cdot \theta)^\circ\text{C}$  where  $\theta$  (°C) is the temperature of the water. The heat exchange rate  $\dot{Q}$  (W) is computed from the measurements:

$$\dot{Q} = \dot{m}c_p(\theta_{in} - \theta_{out}) \quad (1)$$

where  $c_p$  (J/(K·kg)) is the specific heat capacity computed at the average temperature using the relationship given in [4].

For data protection concerns, the dynamic profiles are not shared, and no information on the date and time of the measurements is given. Instead, the benchmark data is taken as a 1-hour mass flow-weighted average of the measurements. The weighted averaging has also the scope of reducing the impact of the thermal transient while imposing the conservation of energy.

The time step to be used in the benchmark is then chosen such that the network conditions are as close as possible to a steady-state. The selection procedure was carried out as follows. First, the maximum absolute gradients of temperature (inlet for the substations, outlet for the heating stations) and mass flow over a rolling 3-hour window were computed. The time frame of 3 hours is chosen as it is the average time taken for the water to complete a closed loop around the network. Then, the time steps were ranked in increasing order of gradient value for both the temperature and mass flow, and the first time step to appear in both rankings - corresponding to the one in which the network is the most similar to a steady state condition - was finally

taken. Branches with no mass flow during these steps were removed from the data, reducing the number of substations to 150 and the number of heating stations to 2. While the choice of a time window with low gradients is a reasonable strategy for ensuring that most of the resulting data is as close as possible to a steady-state situation, a subset of values might still be estimated from monitoring data with a highly dynamic behaviour. It is the case for some substations which have non-conventional uses, such as outdoor deicing or secondary heat sources. When this occurs, the weighted average of the values might not be close to the corresponding steady-state. This effect is more evident in large networks with longer transport time, where due to the different traveling speeds of pressure and thermal waves there might be a delay between a change in operating conditions and the attainment of a steady-state for the temperature. The issue is also worsened by the fact that the data of mass flow and temperature is registered by the sensors with different granularity. As a consequence of these effects, for these substations the averaged values and those that would be measured in a steady-state situation might differ significantly.

An additional source of uncertainty are the errors that can be caused by sensor faults, loss of calibration, or environmental factors that affect the sensors' performance. While these effects, if sparse enough, are usually negligible in measures taken with high granularity (such as those taken at the heating stations), they have a significant impact on the resulting value where the average was taken on only few signals, as it is the case in a minority of substations.

#### 4. Verification procedure

Using the provided data, we propose a common benchmark for the verification of DHN simulation tools. Similarly to the DESTEST, the proposed verification procedure consists in comparing the simulation results and the monitoring data on a selection of KPIs. One of the main challenges in using real data for benchmarking is that the metrics chosen need to account for the possible presence of errors and uncertainties. As discussed in the previous section, these can arise from both issues with the sensors and as a consequence of averaging data with high gradients and poor granularity. To mitigate the effect of outliers and ensure the robustness of the benchmark, appropriate metrics that can handle the uncertainty and variability of the data must then be used. As these effects are usually negligible in heating stations but not in substations, KPIs for the latter are given in form of metrics on the whole set, rather than on local measures. In particular, computing the error as the difference between the *simulated* and *reference* inlet temperature, the following metrics over the error distribution are considered: a. the median, b. the 5% trimmed standard deviation c. the 5<sup>th</sup> percentile and d. the 95<sup>th</sup> percentile. In addition, the following KPIs are considered for the heating stations: e. the difference between the *simulated* and *reference* return temperature of *HS0* and f. the difference between the *simulated* and *reference* return temperature of *HS1*. For the simulation, we estimated the soil class at the depth of the network from the records in the geocadast repository (<https://geocadast.crealp.ch>) to be mostly loamy sand, for which a thermal conductivity value of 2.4 W/(K·m) is suggested [5]. The air and ground temperature are estimated to be 0°C and -2.5°C respectively.

#### 5. Test with PyDHN

The benchmark was tested using PyDHN. For this work, we used a decoupled model based on the loop method for the hydraulic simulation and the conservation of energy in nodes for the thermal part. These models, including references to more detailed publications, are available in the project repository (<https://www.github.com/idiap/pydhn>)

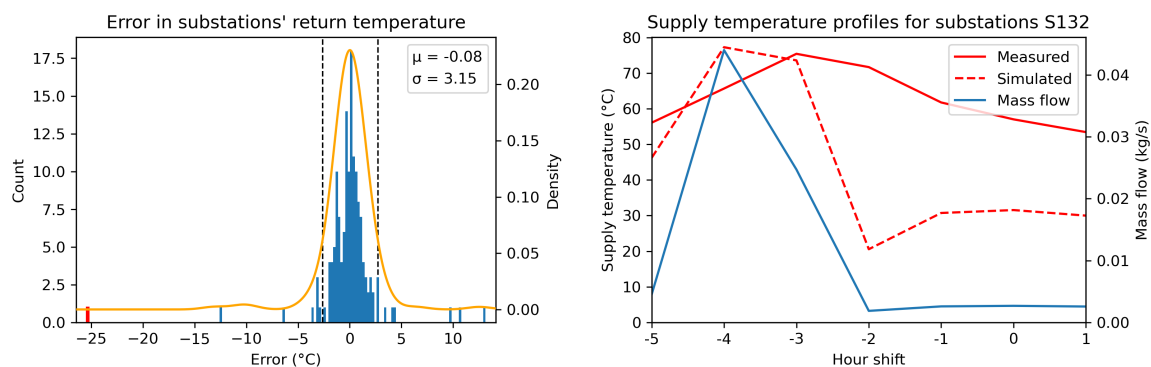
In general, the simulation seems to very slightly underestimate the heat losses. A difference of around 0.3°C between the simulation outputs and the benchmark values was found for both heating stations, which is within the tolerance of the temperature sensors. Overall, the distribution of the error on substations had a median of 0.07°C and a 5% trimmed standard

**Table 2.** Results of PyDHN on the proposed benchmark.

heating stations		substations			
HS0	HS1	median	trimmed std	5 <sup>th</sup> percentile	95 <sup>th</sup> percentile
0.37°C	0.24°C	0.07°C	1.07°C	-2.61°C	2.72°C

deviation of 1.07°C, indicating a good agreement between the outputs of the simulation tool and the aggregated data used in the benchmark. For most substations, the difference is in fact comparable to uncertainty on the water temperature given by the tolerances of the sensors. The 5<sup>th</sup> and 95<sup>th</sup> percentiles of the error were -2.61°C and 2.72°C respectively, which are reasonable considering the size of the network and the several assumptions made for treating the data. The complete distribution and the boundaries of the benchmark are given in Figure 2.

The figure shows the presence of outliers outside the trimmed range, with absolute values of up to 26°C. In particular, among the 150 substations, 13 were found to have a discrepancy between the simulated and actual supply temperatures of more than 3°C. Looking at the gradients of these outliers, we found that in all these cases a sudden change in mass flow or temperature happened between the benchmark hour and the previous one. For example, considering the substation *S132*, for which the highest discrepancy was found, the water flow had a sudden peak before the considered step, but the consequent effects on supply temperature would only be visible with a delay (Figure 2). At the considered time-step, the measured mass flow is close to 0 and the simulated temperature is decreasing sharply, as a consequence of the low mass flow. However, since a steady-state has not been reached, the temperature measured for that hour is still relatively high explaining the above 26°C of difference between simulation and measurement.



**Figure 2.** Left: overview of the error distribution on the whole set of substations, with limits indicating the thresholds used for the benchmark. The red bar indicates substation *S132*. Right: hourly profile of substation *S132* around the considered hour, indicated as 0.

## 6. Limitations of the approach

The presence of dynamic behavior of some substations, as presented in the previous section, constitutes a limitation of the proposed benchmark, which could be overcome by using dynamic data in the benchmark instead. Going towards sub-hourly values, and especially real-time monitoring, however, is frequently not feasible due to the sensitive and potentially competitive nature of the considered data.

Nevertheless, we argue that since these outliers are only a minority of cases, representing less than 10% of the whole dataset, their impact on the rest of the data, even if not negligible, remains within acceptable bounds. Therefore, we believe that the proposed benchmark constitutes a useful complement to the existing DESTEST, especially given the intrinsic limitations involved in collecting and sharing monitoring data of DHNs.

Although the results found by comparing PyDHN with the monitoring data seem within acceptable error bounds, we decided not to define acceptability thresholds for the benchmark at this stage. We hope that other researchers will be able to use the test to benchmark the tool and we leave hence the definition of maximum error bounds and acceptability thresholds to future work.

## 7. Conclusion

In this work, we presented a new open dataset for the verification of simulation tools for DHNs. The dataset is based on an operational meshed network with two active heat sources. It contains a single snapshot of averaged sensors' data for mass flow and temperature, chosen so that it is as close as possible to steady-state conditions.

We proposed a benchmark based on this data and applied it to the open-source simulation library PyDHN. Overall, the results obtained with the simulation tool were coherent with the monitoring data, and all the investigated KPIs were within reasonable bounds.


We then investigated the largest discrepancies between the simulated and reference data, and found that these were found in the supply temperature of substations with high temperature or mass flow gradients in the considered hour. As the steady-state simulation cannot reproduce such dynamic behaviour, but considering that this behaviour is limited to less than 10% of the dataset, we tolerate these outliers.

We believe that the proposed benchmark is a suitable complement for other existing test such as the DESTEST, and can provide additional information on the ability of the benchmarked tool to simulate complex networks, while also providing reference values based on monitoring data as open-data for other researchers.

The dataset is openly available on Zenodo (<https://doi.org/10.5281/zenodo.8058600>).

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