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# Learning the dynamic of clusters of vertices in a graph for District Heating Network simplification

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## ABSTRACT

District Heating Networks (DHNs) provide very efficient and flexible solutions to produce and supply heat energy for local uses but are computationally expensive both to optimize and simulate. Leveraging the formulation of a DHN as series of graphs with time series signals on its vertices, the objective of this work is to reduce such computational costs by aggregating identified vertices. We investigate recurrent neural network model to learn and mimic the temporal dynamic of the signals of aggregated vertices.

## INTRODUCTION

Despite its existence for more than a century, *District Heating* (DH) is still a niche technology [1]. The purpose of DH is to transport heat energy by connecting heat production facilities (*producers*) to end users (*consumers*) with two inversely-oriented parallel distribution pipes (supply and return) forming the *District Heating Network* (DHN). Traditionally, the evaluation of optimal scenarios in the design and/or management of a DHN (*e.g.*, optimal design and power management of production units constrained by the consumer demands, or heat losses minimization in the pipes) requires complex algorithms which combine mathematical optimization and physical simulation [2] [3]. Since, these algorithms require a full description of the network, run on short time steps (*e.g.*, 10 minutes) and large time window (*e.g.*, a year), they tend to be computationally intensive in terms of memory and computational time.

To tackle this problem, we propose to simplify the topological description of the DHN by aggregating identified vertices of the graph, and performing a cluster-level regression of this aggregate of vertices. We then reduce the size of the network but preserve the energetic properties of the DHN. In this first work, we study the case of a simple cluster of two adjacent vertices, and propose a regression methodology to learn their behavior in the network. Future work will use clustering techniques on graphs.

## GRAPH FORMULATION

Physical values describing the state of a DHNs are time series data modeling the demand at the various vertices of the graph, and are obtained through physical simulation. Inspired by related work [4], [5], we formulate the DHN as a series of graphs  $\mathbf{W} \in \mathbb{R}^{T \times N \times N}$ , where  $T$  is the number of time observations and  $\forall t : \mathbf{W}_t \in \mathbb{R}^{N \times N}$  is the weights matrix of the graph at instant  $t$ . Due to the physical structure of the considered application, all graphs in  $\mathcal{W}$  share the same  $N$  vertices and edges support  $\mathcal{E}$  (*i.e.*, for two  $t$  and  $t'$ , only non-zero entries of  $\mathbf{W}_t$  and  $\mathbf{W}_{t'}$  may differ). Moreover, we consider that all graphs are symmetric and have no self-loops.

For each time instant  $t$ , we determine the weights of  $\mathbf{W}_t$  through Equation 1, derived from the resolution of the heat transfer equation under the hypothesis of no thermal inertia of the pipes wall [6], that gives the decay and delay of the temperatures signals through the pipes, and hence gives a physical similarity measure of two adjacent vertices:

$$\forall i, j, t : \mathbf{W}_{t,i,j} \stackrel{\text{def}}{=} \begin{cases} \exp\left(-\frac{\pi \mathbf{H}_{i,j} \mathbf{L}_{i,j} \mathbf{D}_{i,j}}{C \mathbf{M}_{t,i,j}}\right) & \text{if } (i,j) \in \mathcal{E} \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where  $\mathbf{H}$  is the matrix of convective heat loss coefficients,  $\mathbf{L}$  and  $\mathbf{D}$  are respectively the lengths and diameters of the pipes,  $\mathbf{M}$  is the tensor of mass flow rate of water traversing the pipes, and  $C$  is the water specific heat capacity. These values are given and model the properties of the studied DHN.

On each vertex, we observe four multi-variate time series signals  $\{\mathbf{X}^s, \mathbf{X}^r, \mathbf{X}^p, \mathbf{X}^d\} \in \mathbb{R}^{4 \times T \times N}$ , respectively modeling the available temperature of the hot water  $\mathbf{X}^s$  (*supply* pipe), the temperature of the cold water  $\mathbf{X}^r$  (*return* pipe) after consumption [2], the *produced* power  $\mathbf{X}^p$  and the *demand* power  $\mathbf{X}^d$ .

## PROPOSED METHODOLOGY

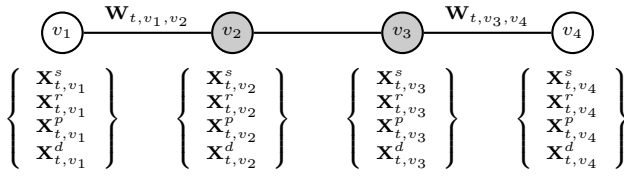
A cluster of DHN vertices is an ensemble of vertices, aggregated as a single one with the edges inside the cluster. The external edges (entering and exiting) of the cluster are kept unchanged. This new vertex mimics the temporal dynamic of the original vertices within the cluster. The aggregation is therefore a two fold process: 1) similar vertices are aggregated in a cluster (either by hand or through a clustering approach);

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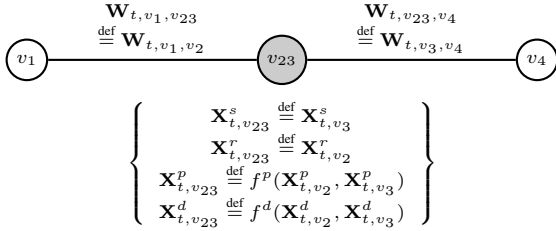
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and 2) a cluster-level supervised learning approach aims to learn how to reproduce the dynamic of the cluster. In this work, we focus on step 2.

Given the objective task, a good clustering must allow to significantly decrease the overall simulation cost of the DHN and its replacement by a clustered vertex shall not perturb the rest of the DHN from an energetic point of view. To enforce these settings, in this preliminary work, we consider a simple cluster of two vertices manually selected by experts for their pertinence w.r.t. the objective, to train the supervised regression model. The goal of this supervised regression is to train a neural network model to learn the temperature signals ( $\mathbf{X}_s$  and  $\mathbf{X}_r$ ) from the cluster to each of its output edges, given its input edges. This is illustrated in Figure 1. The quality of the regression is evaluated using a mean absolute error.



(a) Original graph, for a time  $t$ . Vertices to group in a cluster are identified in grey. The four signal entries associated with the vertices are represented below.



(b) Graph where the two identified vertices have been clustered, in the case where supply flows from  $v_1$  to  $v_4$  and return from  $v_4$  to  $v_1$ . We indicate how signals and weights are merged. Here,  $f^p$  and  $f^d$  denote functions of the production and demand of aggregated vertices, taking heat losses and stocking properties into consideration. Details are beyond the scope of this abstract.

Fig. 1: Illustration of vertices aggregation process.

## EXPERIMENTS

We consider here the two-vertex cluster illustrated in Figure 1. Note that this is a simple example for demonstration. The cluster of vertices can be more complex, by aggregating more vertices, a higher number of connections, loops... The goal is now to train a regression model to predict  $\mathbf{X}_{t,v23}^s$  and  $\mathbf{X}_{t,v23}^r$  from  $\mathbf{X}_{t,v3}^d$ ,  $\mathbf{X}_{t,v3}^s$ ,  $\mathbf{X}_{t,v1}^r$ ,  $\mathbf{X}_{t,v4}^r$ ,  $\mathbf{W}_{t,v1,v23}$ , and  $\mathbf{W}_{t,v23,v4}$ . Note that power and demand signals of adjacent vertices (*i.e.*,  $\mathbf{X}_{t,v1}^p$ ,  $\mathbf{X}_{t,v1}^d$ ,  $\mathbf{X}_{t,v4}^p$ ,  $\mathbf{X}_{t,v4}^d$ ) are not used as input as, physically, they do not influence directly the dynamic of the temperatures at the clustered vertex.

We introduce a neural network model made of two-layers of Gated Recurrent Unit [7] of 20 units, max length of 10 step, dropout rate of 0.2, followed by one dense layer of 60 units and the output dense layer. Dense layers are activated

with ReLU. Chosen hyperparameters are the result of grid search tuning and the ones that are not mentioned are using the default values provided by Keras implementation. The loss to minimize is a mean absolute error (MAE) between predicted values of  $\{\mathbf{X}_{t,v3}^s, \mathbf{X}_{t,v2}^r\}$  ( $\forall t$ ) and their actual values, optimized using Adam with a 0.001 learning rate and a batch size of 25.

Here, we consider a dataset of  $T = 240,000$  time-steps, for which values are derived by simulation of the whole network (modeling a DHN of  $N = 71$  vertices). The cluster we aim at modeling is the one shown in Figure 1. Our model is trained with the first 70% of the dataset and tested with the remaining last 30%. It is trained with a maximum of 50 epochs and a validation split of 0.3. Figure 2 shows the performance of the model to infer the dynamic of the return temperature signal  $\mathbf{X}_{t,v23}^r$  on the test set. It achieves a satisfying performance to learn the physical dynamic of both temperatures signals with a MAE of  $0.0074^\circ\text{C}$  on the test set.

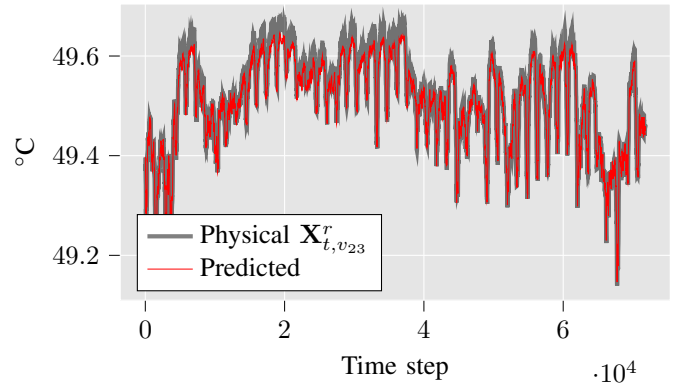


Fig. 2: Illustration of the model performance on the test set. Results on  $\mathbf{X}_{t,v23}^s$  show an even lower MAE.

## COMPLEMENTARY DISCUSSIONS

Leaning on the results of the supervised regression, in the following work, we will investigate Graph Neural Network clustering techniques to identify clusters of vertices with good properties with respect to the considered problem, *i.e.*, which replacement results in minimal error on the conservation of the DHN energetic properties.

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