Digitalisation of DHC

Optimising a Demand Driven System

Digitalisation is the topic of the day in many industrial sectors, and district heating and cooling is no exception. Digitalisation promises to facilitate a transformation to a data driven approach in data management and online analysis, and to create intelligent and sustainable energy systems. Understanding the technological power and pitfalls helps to unleash the potential of digitalisation and makes it an important part of more efficient DHC networks.

Can digitalisation actually fulfil the seemingly lofty promises publicly associated with the concept, or is it just another buzzword? As always, the answer probably lies somewhere in between. As an industry buzzword, digitalisation was preceded by the related concept of Big Data, and in both cases, there seems to be a general confusion about what these concepts actually mean.

There is a joke about Big Data, saying that it is like teenage sex in that everybody talks about it, nobody really knows how to do it, everybody thinks everyone else is doing it and so everyone claims they are also doing it. The same can be said about digitalisation. One factor contributing to the confusion is that, contrary to what seems to be common perception, neither digitalisation nor Big Data is an end in itself, but rather a means to an end.

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A machine learning algorithm in itself will not save the day, unless you know how to apply it in your specific domain. Collecting a large set of data will not provide you with more understanding of your system, unless you know how to distil information and knowledge from that set of data. Only when your end purpose is clearly defined, it will be meaningful to talk about any possible benefits of digitalisation.

For the district heating sector the primary end purpose is to increase the efficiency, and integrate more sustainable energy sources. These targets can only be achieved by lower system temperatures. The decrease of system temperatures has been the driving force for innovation throughout the history of district heating. This is still the primary motivation for the transition from the current 3rd generation networks to the more sustainable low-temperature 4th generation networks of the future.

So how does it tie together?

Consider the fact that district heating networks are by definition demand driven systems, and that the primary constraints of the network, including the system temperature requirements, are essentially set by that demand. However, from an overall system perspective only the production (network supply temperature) and distribution (pressure head) are controlled and optimised in any structured, system-wide way.

The consumption that drives the demand, is currently managed by autonomous heating controllers in individual buildings throughout the district heating grid, without any real operational information passing among themselves or towards distribution and production systems.

So, how can we ever hope to fully optimise a demand driven system, if the demand itself is not explicitly part of the real-time operational optimisation process? How do you connect all the data streams from all those buildings, how do you manage all that data, and how can it ever be possible to extract information and knowledge from that data stream in a real time fashion. Well, this is where digitalisation comes into the picture.

For district heating and cooling, digitalisation is really all about the merging of digital technologies with traditional engineering solutions. This is facilitated by converging trends of increasingly affordable computational power and more accessible industrial grade solutions for both wired and wireless communication. This creates the possibility to build flexible yet robust IT-based platforms for communicating, analysing and controlling data streams among a large amount of distributed devices and actors. Such platforms are required to facilitate the emergence of intelligent energy systems, including tools for operational demand side management and machine learning based analytics.

What makes a system intelligent?

The question of the intelligence of a system has many potential answers, but from a district heating network controller and analyser perspective there are at least three basic requirements of such a system. First of all the system needs to have the ability to measure, communicate and manage relevant data across all the participating network devices and system processes. Secondly, it needs to be able to analyse this data and use it to extract information and knowledge, either for use within the system itself or visualised for human operators as a decision support tool. This second step is normally where machine learning and data mining technology can provide decisive benefit, as they help to automate the ability for the system to formulate conclusions about the operational behaviour of the system. The third step involves the ability to act on these conclusions. This might, for example, involve either input to human operators or technicians, or automated actions taken by smart grid controllers using real-time demand side management. These steps are then continuously re-iterated to adapt to changes in the environment in which the system operates.

Actually, the ability to be self-learning and automatically adapt to changes is a vital part of any such intelligent system. One of the ongoing research projects Noda participate in is specifically focused on the challenges on identifying and quantifying deviations from proper operational behaviour resulting from manual changes of substation control settings [1].

The first part of that project was started due to rather pragmatic reasons; the energy efficiency controllers Noda and Vito develop benefit from being able to automate the detection, and adapt to manual changes in the temperature program in substation controllers. This is a problem that is closely related to what in machine learning is called concept drift, in which the statistical properties of the target value is changing over time.

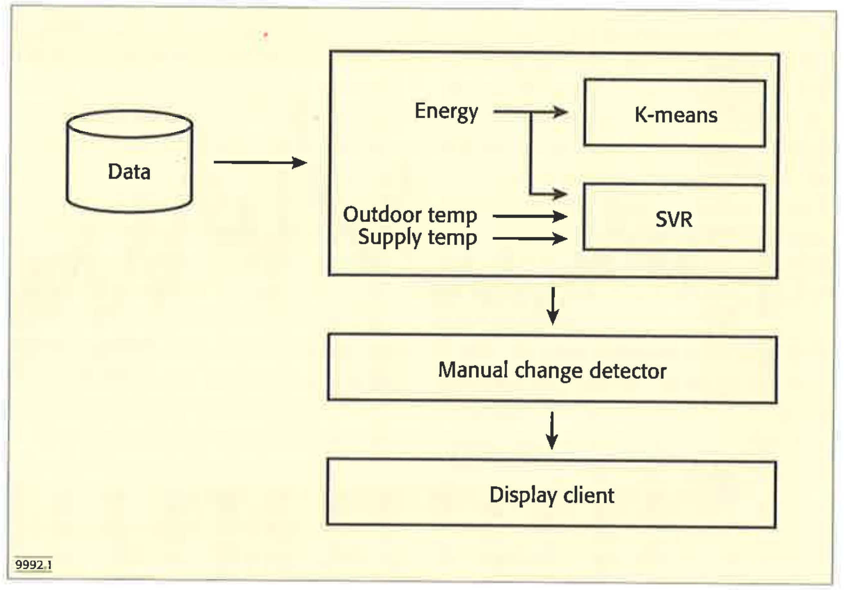

Figure 1. A process overview for detecting and quantifying changes in substation controller parameters

To solve this specific issue, a two-step classifier was used which integrated into a decision support tool for human operators [2]. The first classifier is based on the k-means algorithm, which belongs to a group of distance based clustering methods. In this step, the algorithm decides if the space heating is on or off, which is important since, in this case, the system shouldn't be taught to react on deviations occurring when district heating is only used for domestic hot water.

The second classifier is then used to predict the radiator supply temperature in relation to the outdoor temperature, which provides a baseline for detecting deviations in the actual measured supply temperature. This second step is based on an algorithm called support vector machines (SVM), which is a supervised learning method used in machine learning for classification, pattern recognition and regression analysis. Together these steps provide a simple and scalable way to detect changes in substation controller parameters. *Figure 1* shows the basic flow of this process.

This system is a rather simple application of machine learning in the context of district heating. However, it is a clear example of the benefits enabled by digitalisation in this domain. This specific project has since expanded into other related areas of interest, but the core focus is still based on the ability to separate de-

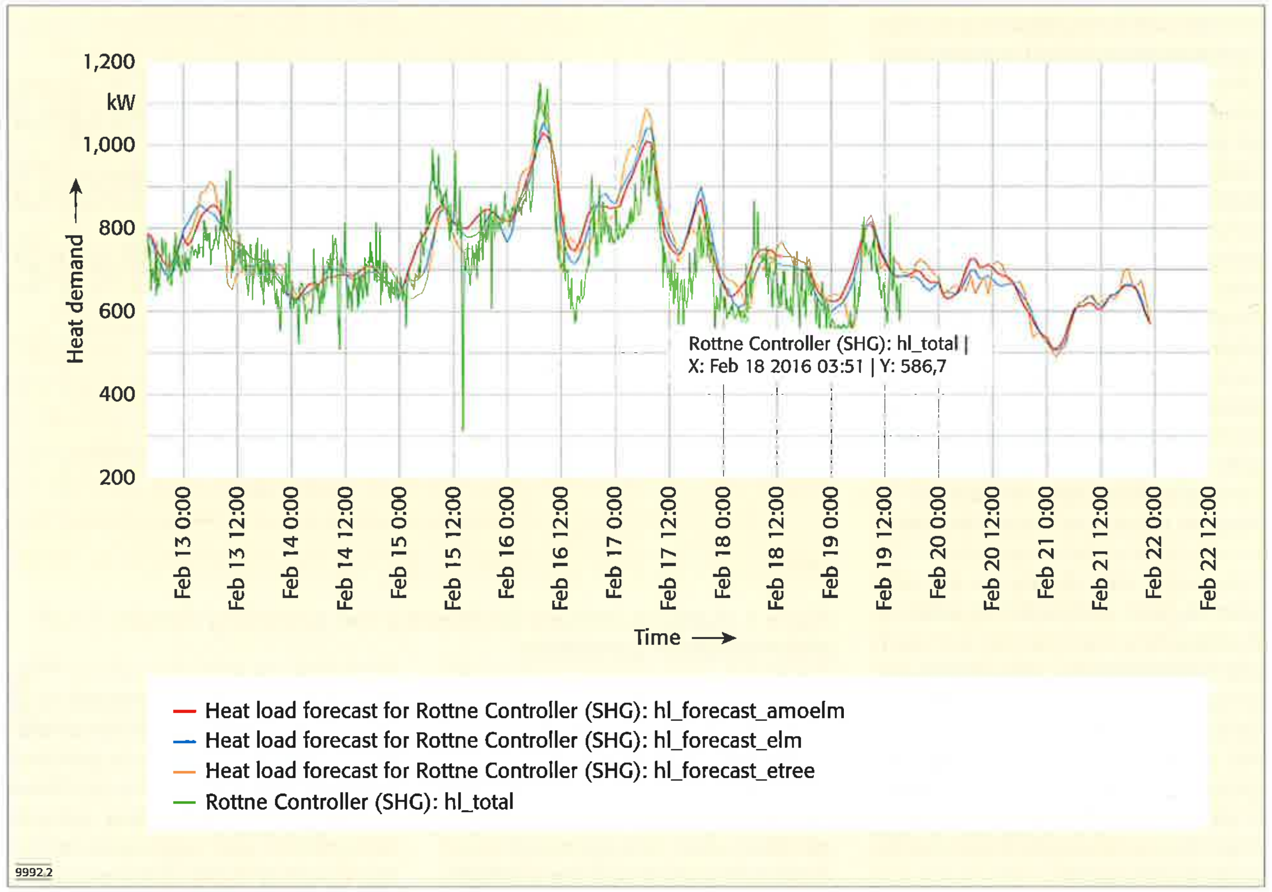

Figure 2. Operational heat demand forecasts shown in a screenshot from the Storm smart grid controller – the red, blue and orange lines show the results of three different forecaster algorithms based on machine learning techniques, while the green line shows the actual consumption in the network

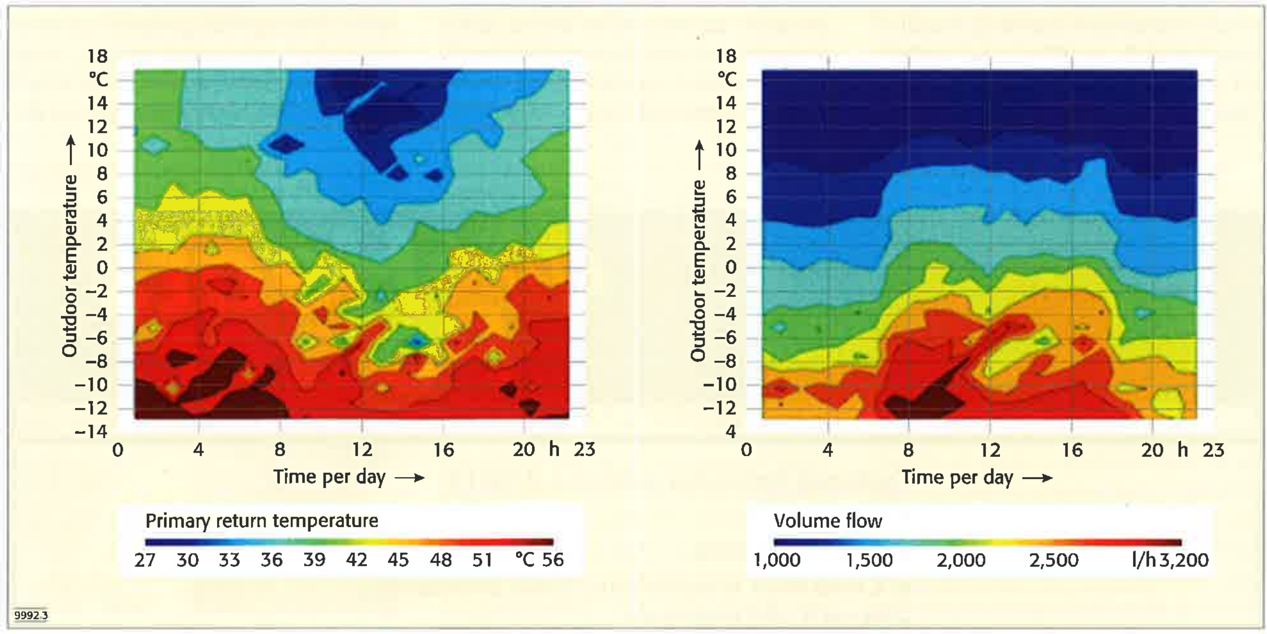

Figure 3. Contour maps relating the four dimensions of time of day, outdoor temperature, primary return temperature and mass flow over the heat exchanger

viations from expected operational behaviour.

Digitalisation projects

Most of the innovation projects that Noda and Energyville – Vito are involved in relate to digitalisation in one aspect or another. Digitalisation is a prerequisite for operational optimisation tools, such as smart grid controller technology, as well as current developments in machine learning based analytics. The machine learning part is important since it can not only be used to create tools for advanced analytics and decision support tools for human operators, but also facilitates ancillary services for the smart grid controllers and associated technologies.

An example of such ancillary services is the recent advances in technology for forecasting heat demand and available thermal flexibility. These kinds of forecasts are of utmost importance for smart grid technology in general. Indeed, to be able to optimize the operation of the system, the behaviour should be forecasted anyway. For instance, if one would like to get rid of expensive peak boiler operation in a network, at least these peaks should be forecasted in order to react on that. And this is really only made possible by the digitalisation effort in modern district heating systems.

In 2016, the authors presented a paper on online demand forecasting using ensembles of machine learning algorithms [3]. This work has since been expanded in other publications (under review), where additional algorithms are examined and added in combination with expert decision methods to further advance the ensemble behaviour. This work has primarily been fuelled by the requirements within the Horizon 2020 project Storm, in which a smart grid controller for district heating and cooling is being developed [4]. *Figure 2* shows an example of the operational heat demand forecast system used in the Storm project.

In October 2017 Noda and Energyville – Vito are part of a new Horizon 2020 project starting up, called Tempo (*Temp*erature Optimisation for Low Temperature District Heating across Europe), with the expressed purpose of developing tools and work processes for lowering system temperatures in district heating systems. The general basis of the project is the realisation that high system temperatures are primarily caused by sub-optimal behaviour at the demand side. By providing technical tools to identify, diagnose and correct that behaviour, it will also be possible to lower the system temperatures. The whole premise of such a project is based on digitalisation, and it will, to a large extent, build on the application of machine learning and data mining technology.

The basic idea is to combine a set of individual technologies into a solution package for different application areas, i. e. both new and existing networks. The implementation of the solution package in different district heating networks will be supported by a three-step process using (1) identification of sub-optimal behaviour primarily based on heat meter data, (2) diagnosis of the problem by adding more dimensions to the search space, such as data from the heating system or indoor climate and (3) to correct the sub-optimal behaviour by implementing relevant parts of the solution package.

A lot of work has already been done relating to the identification step, although in the project these techniques will be applied in a much larger scale based on the digitalisation effort. An example of such prior work is the use of contour maps to analyse the status of district heating substations, especially their ability to absorb heat by cooling the primary network water [5]. *Figure 3* shows an example of such a contour map.

So, digitalisation not just a buzzword then?

Although digitalisation is a powerful tool, it also comes with some pitfalls. A sometimes overlooked aspect is that of data security and end-user privacy, which becomes increasingly relevant as the amount of collected data increases and the data mining technologies are becoming more and more sophisticated. These are areas that many grid operators might currently not be fully equipped to handle, which makes it all the more important for technology provides to support them with their expertise.

However, there is no doubt that digitalisation is an important part of the future for district heating and cooling. This is especially true when building modern low-temperature networks for the future or refurbishing existing networks to make them more efficient and sustainable. In such cases each part of the energy chain has to be continuously optimised, and this will be impossible without embracing the potential of digitalisation.

So, no, digitalisation is not just another buzzword. It is an important part of the answer to how we create the intelligent and sustainable energy systems of the future. By providing this intelligence as a continuous service it will be possible to implement in both current and future district heating and cooling schemes, and help to make thermal grids an integrated part of a sustainable European energy supply chain.

References

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