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Operational Demand Forecasting In District Heating Systems Using Ensembles Of Online Machine Learning Algorithms

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Abstract

Heat demand forecasting is in one form or another an integrated part of most optimisation solutions for district heating and cooling (DHC). Since DHC systems are demand driven, the ability to forecast this behaviour becomes an important part of most overall energy efficiency efforts.

This paper presents the current status and results from extensive work in the development, implementation and operational service of online machine learning algorithms for demand forecasting. Recent results and experiences are compared to results predicted by previous work done by the authors. The prior work, based mainly on certain decision tree based regression algorithms, is expanded to include other forms of decision tree solutions as well as neural network based approaches. These algorithms are analysed both individually and combined in an ensemble solution. Furthermore, the paper also describes the practical implementation and commissioning of the system in two different operational settings where the data streams are analysed online in real-time.

It is shown that the results are in line with expectations based on prior work, and that the demand predictions have a robust behaviour within acceptable error margins. Applications of such predictions in relation to intelligent network controllers for district heating are explored and the initial results of such systems are discussed.

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1. Introduction

Operational data analytics where traditional engineering and modern data science solutions are merged is a driving force behind the development of innovative 4th generation district heating networks as well as the upgrading of current 3rd generation systems [1]. A key aspect of most such energy efficiency schemes is the ability to predict future behaviour within the network. Since district heating, by basic design, is demand driven, it follows that demand predictions are vital to the success of such endeavours. Heat demand is also an important support tool for traditional optimisation schemes due to the substantial time delays in heat delivery throughout a district heating system. By using heat demand forecasting in such situations it is possible to increase the efficiency of heat generation in relation to the actual heat demand within the dispersed topology of the heating grid. Furthermore, the ability to control the demand is at the core of many operational optimisation solutions relating to smart grid technology such as demand side management and active load control, which further increases the value of heat demand forecasting [2].

1.1. Demand forecasting in district heating

The heat demand in a district heating system generally originates from space heating and tap water heating. While space heating is primarily weather dependent, the tap water usage is related to social behaviour [3]. This combination leads to a nonlinear, stochastic and non-stationary characteristic of the system that increases the complexity of any sufficiently good solution [4]. Furthermore, the development of modern real-time supervision systems increase the availability of real-time data, which although providing a valuable resource for extensive data analytics also increases the complexity of the situation.

Demand forecasting in district heating systems is not a new subject. Throughout the years a number of forecasting approaches have been proposed, including statistical models as well as machine learning solutions such as neural networks [5]. The statistical approach is normally focused on trying to separate the weather dependent heating demand from the tap water usage based on social behaviour. Such solutions can range from rather simple solutions, featuring linear functions, to more complex solutions combining physical knowledge of the system with statistical modelling [6, 7]. Using the physical knowledge of the network as a basis together with statistical models for identifying system parameters is also underpinning other similar approaches [8], in which the Box-Jenkins methodology is applied to an autoregressive moving average model (ARMA). The use of statistical models for demand forecasting also includes the application of seasonal autoregressive integrated moving average models (SARIMA) in which the forecasting values are derived using Kalman filtering [9].

The other major branch of demand forecasting is based on more machine learning related approaches such as neural networks or support vector machines [10, 11, 12]. This should in theory increase the ability of the solution to handle nonlinear and non-stationary behaviour in the data. These ideas have since been further explored, e.g. by introducing recurrent neural networks to improve the ability to handle non-stationary heat demands [13].

There are many influencing factors making up the total heat demand in a district heating system and it is in practice impossible to make an exact model of this behaviour. This is a contributing factor to the use of both statistical models and machine learning approaches in which exact physical models are not required. Furthermore, in addition to being dependent on the quality of historical data, the forecasting is also conditioned on the quality of the influencing factors during operational usage. For example, many demand forecasting models make use of an outdoor temperature forecast, which in itself can be of varying quality.

1.2. Machine Learning

Machine Learning is a methodology for finding and describing structural patterns in data [14]. Machine learning is a subfield of computer science and is usually regarded as a part of artificial intelligence research. The basic idea