



Using ensemble weather predictions in district heating operation and load forecasting



Magnus Dahl^{a,b,*}, Adam Brun^b, Gorm B. Andresen^a

^a Department of Engineering, Aarhus University, Inge Lehmanns Gade 10, 8000 Aarhus C, Denmark

^b AffaldVarme Aarhus, Municipality of Aarhus, Bautavej 1, 8210 Aarhus V, Denmark

HIGHLIGHTS

- Ensemble weather predictions are introduced in district heating operation.
- A heat load forecast model with dynamic weather-based uncertainties is developed.
- Dynamic forecast uncertainties are applied to the operation of area substations.
- The supply temperature can be lowered while retaining security of supply.
- Area substations with smaller pumping capacity benefit most.

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ABSTRACT

Ensemble weather predictions are introduced in the operation of district heating systems to create a heat load forecast with dynamic uncertainties. These provide a new and valuable tool for time-dependent risk assessment related to e.g. security of supply and the energy markets. As such, it is useful in both the production planning and the online operation of a modern district heating system, in particular in light of the low-temperature operation, integration of renewable energy and close interaction with the electricity markets. In this paper, a simple autoregressive forecast model with weather prediction input is used to showcase the new concept. On the study period, its performance is comparable to more complex forecast models. The total uncertainty of the heat load forecast is divided into a constant model uncertainty plus a time-dependent weather-based uncertainty. The latter varies by as much as a factor of 18 depending on the ensemble spread. As a consequence, the total forecast uncertainty varies significantly. The forecast model is applied to the operation of three heat exchanger stations. Applying an optimized temperature control can significantly lower supply temperatures compared to current operation. Improving the temperature control with dynamic time-dependent weather-based uncertainties can lower the supply temperature further and reduce heat losses to the ground. The potential benefit of using dynamic uncertainties is larger for systems with relatively smaller pumping capacities.

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1. Introduction

District heating systems exist in most countries in the Northern Hemisphere but are most widespread in the Nordic countries and in the former Soviet Union [1]. In the EU, district heating covers about 13% (2010) of the total domestic heating demand. It has been estimated that this could potentially be increased to 50% by 2050 [2]. Unlike individual house heating, district heating requires

investment in city-wide distribution networks. As a consequence, district heating is not competitive in low density areas, but has a significant potential in many high heat density urban areas, despite reduced heat demand from future building energy retrofit solutions [3].

District heating can limit the use of high exergy fuels such as oil and gas for heat-only applications. This is due to its ability to utilize low-quality energy sources such as municipal waste and excess heat from heavy industrial processes and electricity production. Increasing the use of biomass and solar thermal energy in the district heating sector is useful in the process of decarbonizing the energy sector. Combined use of large-scale heat pumps and electric boilers allows district heating systems to utilize electricity

* Corresponding author at: Department of Engineering, Aarhus University, Inge Lehmanns Gade 10, 8000 Aarhus C, Denmark.

E-mail address: magnus.dahl@eng.au.dk (M. Dahl).

Nomenclature

$\delta\hat{P}$	uncertainty on the heat demand forecast \hat{P} [MW]	Q^{ref}	reference volume flow rate for security of supply [m^3/h]
\hat{P}	forecasted heat load, production or consumption [MW]	Q_{max}	water flow capacity of a heat exchanger station [m^3/h]
\mathcal{L}	likelihood function	rh	relative humidity [%]
ρ_w	density of water [kg/m^3]	t	subscript denoting hourly time steps
σ	standard deviation of forecast errors [MW]	T^{out}	outside temperature [$^{\circ}\text{C}$]
σ^{m}	standard deviation of model-based errors [MW]	T_{ret}	return temperature [$^{\circ}\text{C}$]
σ_t^w	standard deviation of the ensemble of heat demand forecasts in time step t [MW]	T_{sup}	supply temperature [$^{\circ}\text{C}$]
σ_t^{tot}	combined standard deviation, based on σ_t^w and σ^{m} in time step t [MW]	$T_{\text{sup}}^{\text{min}}$	minimum supply temperature as a function of outside temperature [$^{\circ}\text{C}$]
a, b, c, d	heat load model parameters	v^{wind}	wind speed [m/s]
c_w	specific heat of water [MW h/kg. $^{\circ}\text{C}$]	AIC	Akaike Information Criterion
I^{sun}	solar irradiance [W/m^2]	MAE	mean absolute error [MW]
k	number of model parameters, used when evaluating AIC	MAPE	mean absolute percentage error [MW]
P	heat load, production or consumption [MW]	RMSE	root mean square error [MW]
Q	volume flow rate [m^3/h]	Sc. i	superscript denoting Scenario i

generated from wind and solar power for heating in situations with surplus generation [4,5].

Forecasting of both production and demand is becoming increasingly important in the energy sector due to: (i) the growing share of wind and solar energy and (ii) the focus on coupling the electricity, heating and transportation sectors in smart energy networks [6]. In this context, a good forecast can be used to plan the operation of flexible assets to minimize costs and environmental impact. The uncertainty of the forecast can be used to quantify financial risk in the energy market or operational risk related to security of supply [7]. Forecast uncertainty can be estimated using the technique of ensemble forecasting. Ensemble forecasting has previously been used for electricity load forecasting, both in a linear [8] and in a neural networks context [9]. It has also been applied to wind [10,11] and solar power forecasting [12] to estimate the forecast uncertainty. In this paper, the technique of ensemble forecasting is adapted to district heating load forecasting for the first time. We are also the first to demonstrate how dynamic forecast uncertainty could be applied to operate existing heat exchanger stations with increased efficiency while retaining security of supply.

1.1. Heat load forecast uncertainty

District heating production planning and operation involve decision making under uncertain conditions. Hence, accurate forecasts of daily variations in the heat load are needed in the district heating sector.

Variations in the heat load are caused by changing weather and consumer behavior [13], and forecasting district heating demand or heat load has been studied in a multitude of papers. A number of commercial tools for this purpose also exist. Within academic studies, machine learning approaches to top-down forecasting of district heating demand have gained popularity in recent years. Multilayered neural networks are used to predict heat load in [14,15], and to predict cooling load in a district heating and cooling system in [16]. In [17], the authors compare a number of different supervised machine learning algorithms and conclude that support vector regression performs best. Other studies such as [18] take a more traditional statistical approach. In [18], physical knowledge is used to limit the model space and statistical analysis is used to refine the model and estimate the parameters. Stochastic time series methods have also been successfully applied to heat load forecasting. This includes general transfer function models [19] and

seasonal autoregressive integrated moving average models (SAR-IMA) [20,21]. The paper [22] demonstrated that decent forecast performance can be achieved by simple autoregressive methods with weather input. In [21], a comparison between a number of linear regression models and a SARIMA model with exogenous input favors a simple linear regression model using weekly heat demand patterns. On the building level, [23] presents a heat demand forecast that is a hybrid model using both physical, autoregressive integrated moving average models (ARIMA) and singular value decomposition methods.

While all of these studies benchmark the performance of their models by some standard measure, not all of them address the forecast uncertainty directly, e.g. through the use of prediction intervals. In [20,23], prediction intervals are provided for the forecast models, but these are estimated from the statistical uncertainty on the model parameters only, and they do not take the unpredictability of the weather input into account. In [21,22], for instance, a perfect weather forecast is assumed when benchmarking the model. However, weather forecasts are never perfect, and a heat load forecast model that depends on a weather forecast is bound to propagate some of the uncertainty in the weather forecast into an uncertainty on the heat load forecast. The authors of [15] estimate weather-based prediction intervals for one of their forecast models. These prediction intervals are constant in time and are estimated by simply adding Gaussian noise with mean 0 and standard deviation 1 to each of the weather variables in a Monte Carlo simulation.

In this paper, we present a heat load forecast model with prediction intervals that vary in time, due to the time variation in the uncertainty of an ensemble weather forecast. An ensemble weather forecast consists of multiple independent forecasts that ideally cover the full range of possible weather conditions in a given period. It can be used to estimate the most likely scenario and quantify the time-dependent uncertainty of the weather variables. Each ensemble member represents an internally consistent weather configuration based on a sophisticated meteorological model which means that cross-correlations between different weather variables are naturally captured.

A heat load forecast with dynamic prediction intervals is a new and valuable tool for the district heating sector. Augmented with cost estimates, it will allow production planners to take calculated risk in unit commitment situations or when trading on the electricity market. From an operational perspective, knowing the dynamic uncertainties of a forecast enables operators to know when to push

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