Online short-term heat load forecast

– An experimental investigation on greenhouses

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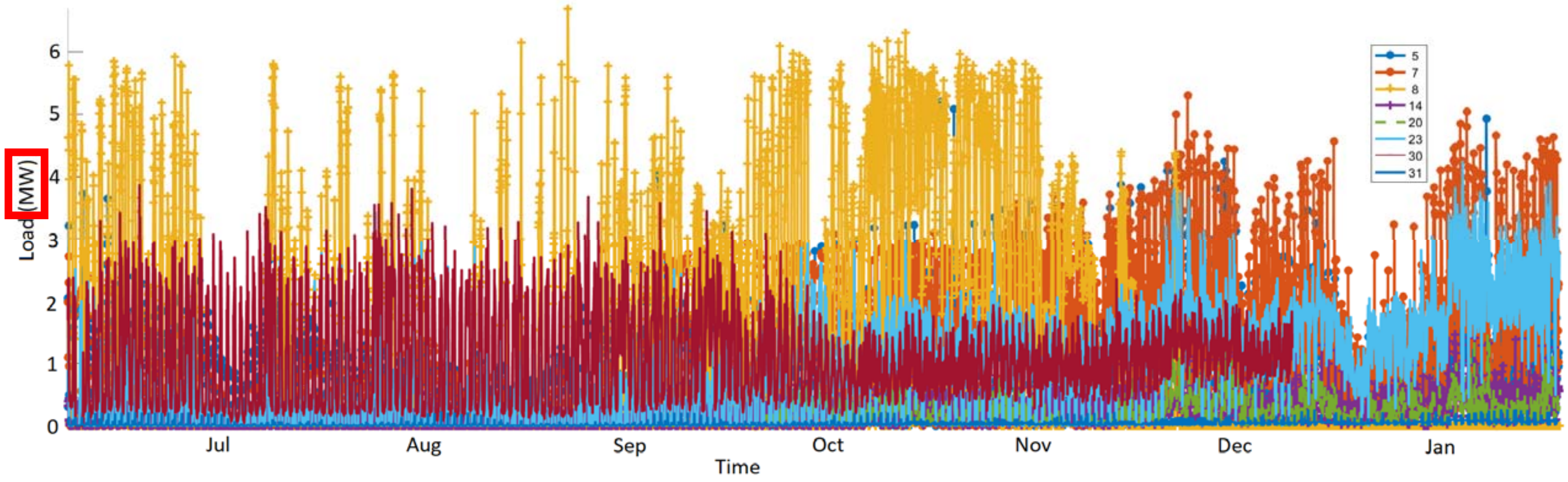
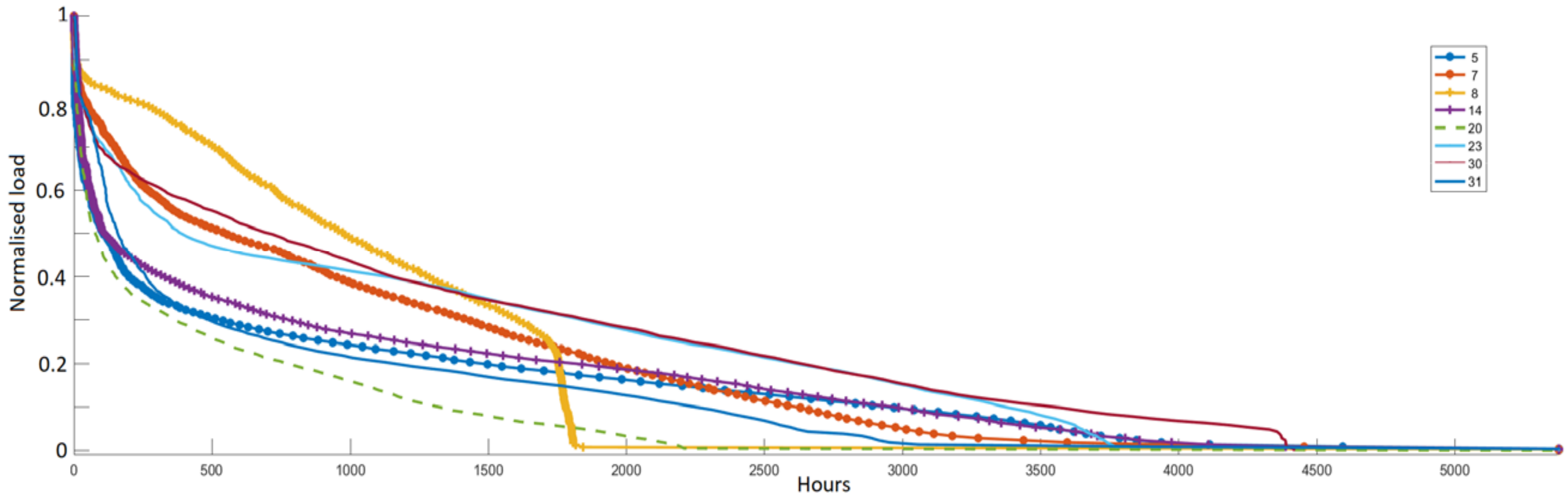
Greenhouses are major, sensitive and inhomogeneous heat loads



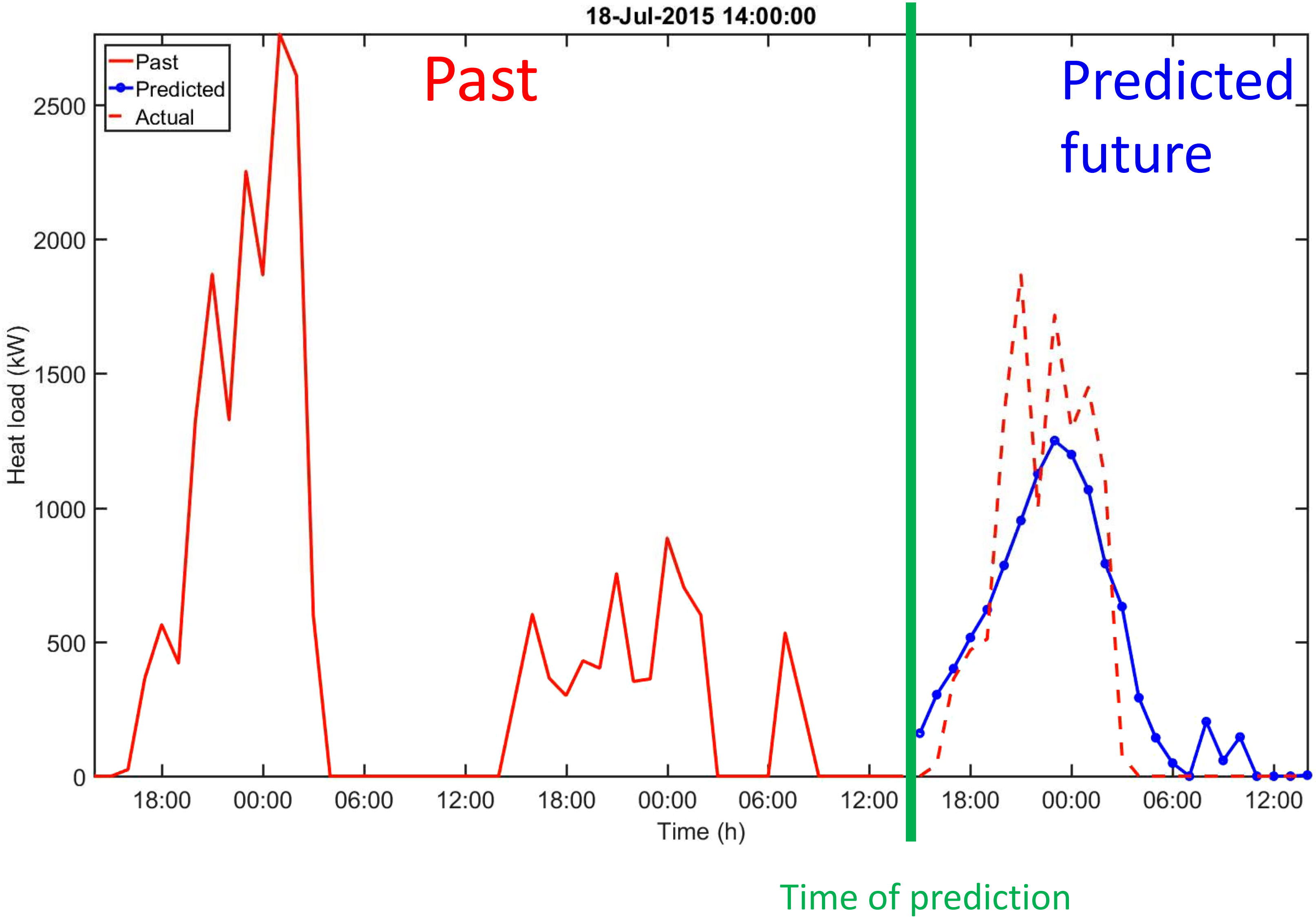


[Data from Funen (DK), provided by Fjernvarme Fyn]

This study used field data from a Danish environment

Data	Provider	Details	Sample time
Greenhouse heat load	Fjernvarme Fyn (DH system operator)	Heat load, flow rate, supply/return temperatures (5 greenhouses selected)	15-60 min
Weather measurements (central station)		Temperature, relative humidity, global irradiance, wind speed, atmospheric pressure	60 min
Weather forecast service	ENFOR A/S	Temperature, relative humidity, global irradiance, wind speed (prediction horizon of 147h)	

Online short term adaptive forecast is made in receding horizon



Recursive least squares is a low complexity method for online adaptive short term forecast

Model (linear form)

$$Y[k] = X[k]^T \, \hat{\theta}[k-1]$$

Model coefficients

Heat load at time k

Vector of explanatory variables at time k

Recursive update (with forgetting)

Adapt:

$$\hat{\theta}[k] = \hat{\theta}[k-1] + R[k]^{-1} X[k] \underbrace{[Y[k] - X[k]^T \, \hat{\theta}[k-1]]}_{\text{Prediction error}}$$

Forget:

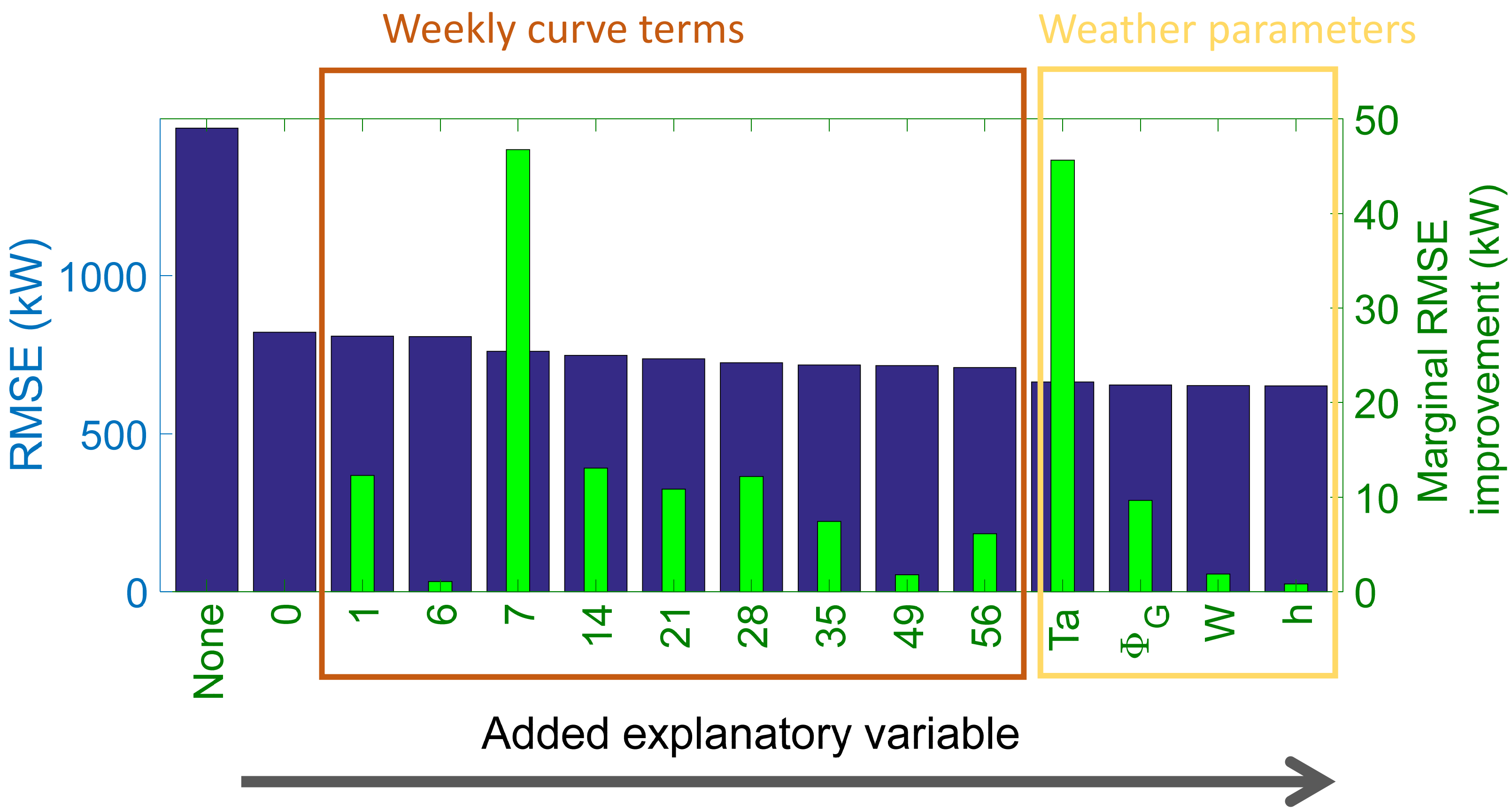
$$R[k] = \lambda R[k-1] + X[\mathrm{k}] \, X[k]^T$$

[Chap. 11 of : H. Madsen, "Timeseries Analysis", 2008, Chapman & Hall CRC]

A broad selection of explanatory variables is available

Type	Variables
Time dependency (weekly curves)	Constant term
	$C_T(k) = \cos\left(2\,\pi\,k\,\frac{T}{T_0}\right)$ $S_T(k) = \sin\left(2\,\pi\,k\,\frac{T}{T_0}\right)$ Where T_0=1 week & $k \in [1:83]$
Weather	Ambient temperature (°C)
	Global horizontal solar radiation (W/m²)
	Wind speed (m/s)
	Relative humidity (%)
	Atmospheric pressure (hPa)

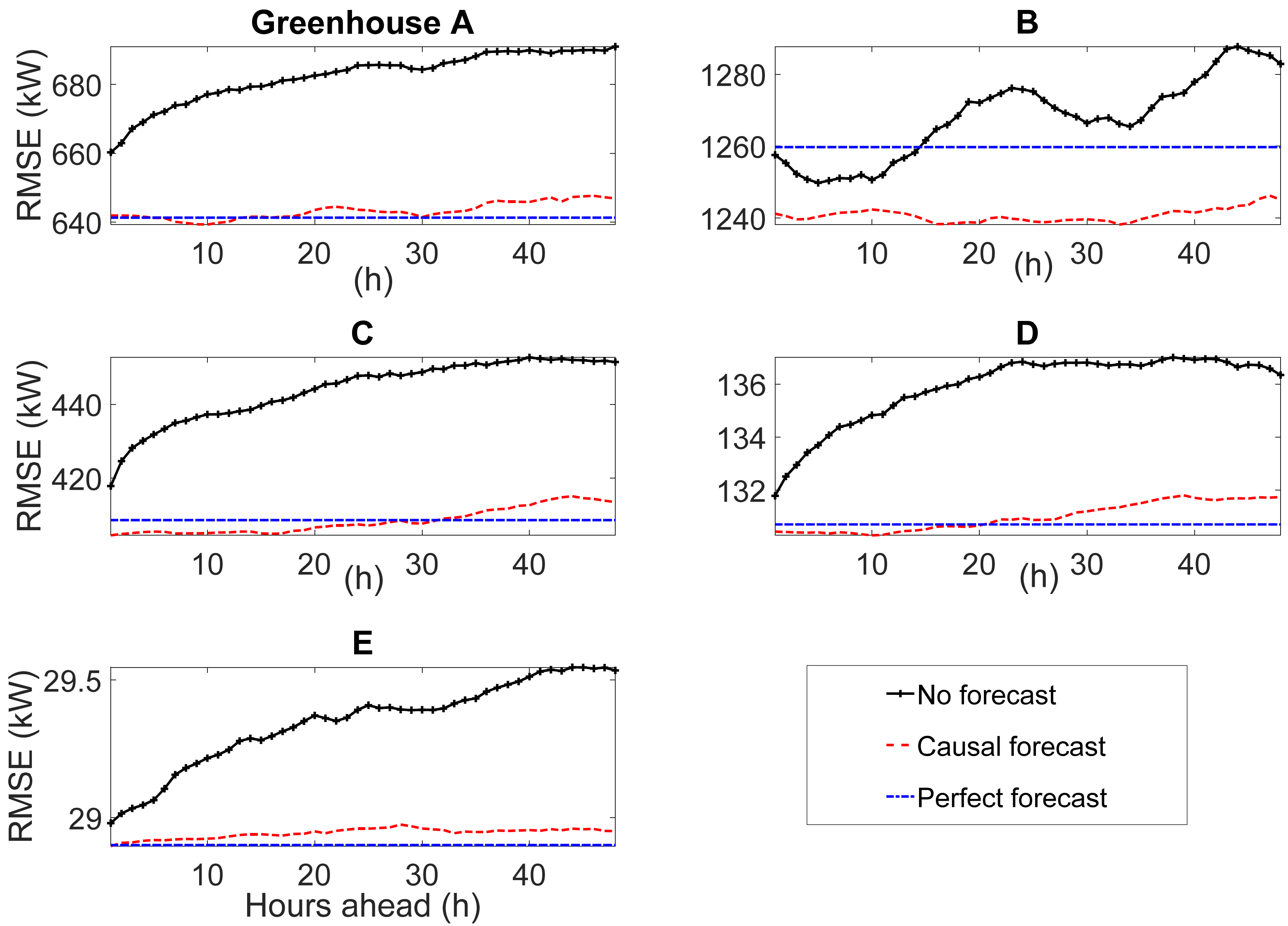
Explanatory variables were selected in a forward selection manner



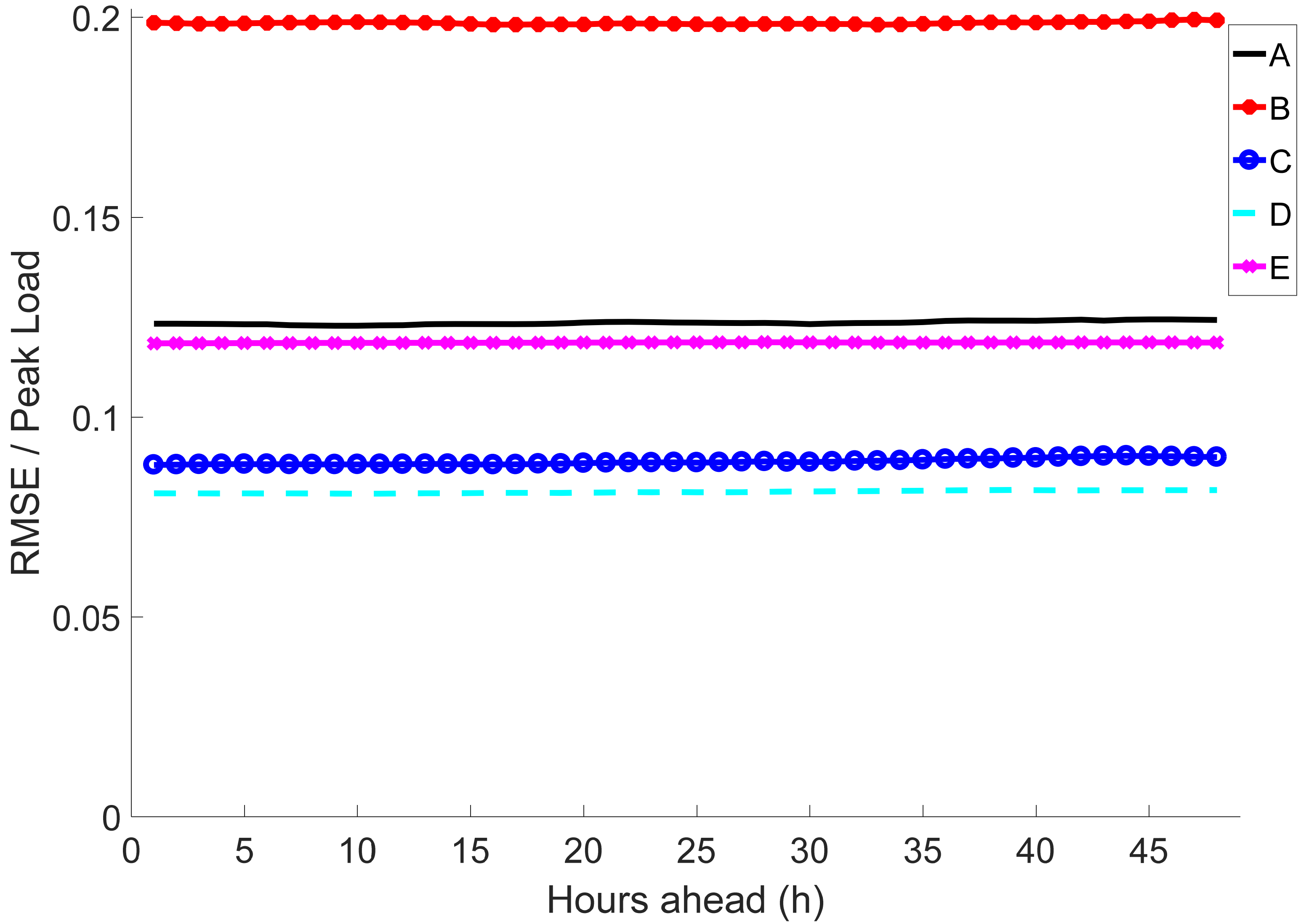
Relevant explanatory variables differed among greenhouses

Greenhouse	Relevant weekly curve terms	Weather inputs			
		Ambient temperature	Global solar irradiance	Wind speed	Relative humidity
A	**0, 1**, 6, **7, 14, 21, 28, 35, 49, 56**	X	X	X	X
B	**0, 1**, 2, 3, 4, 5, 6, **7**, 8, 9, 13, **14, 21**	X	X	X	X
C	**0, 1**, 6, **7**, 8, 13, **14, 21, 28, 35, 42, 56, 77**	X	X	X	X
D	**0, 1**, 6, **7, 14, 21, 28, 35, 42, 49, 56, 63, 70, 77**	X		X	
E	**0, 7, 14, 21, 28, 35, 42, 49, 56, 63, 70, 77**	X			

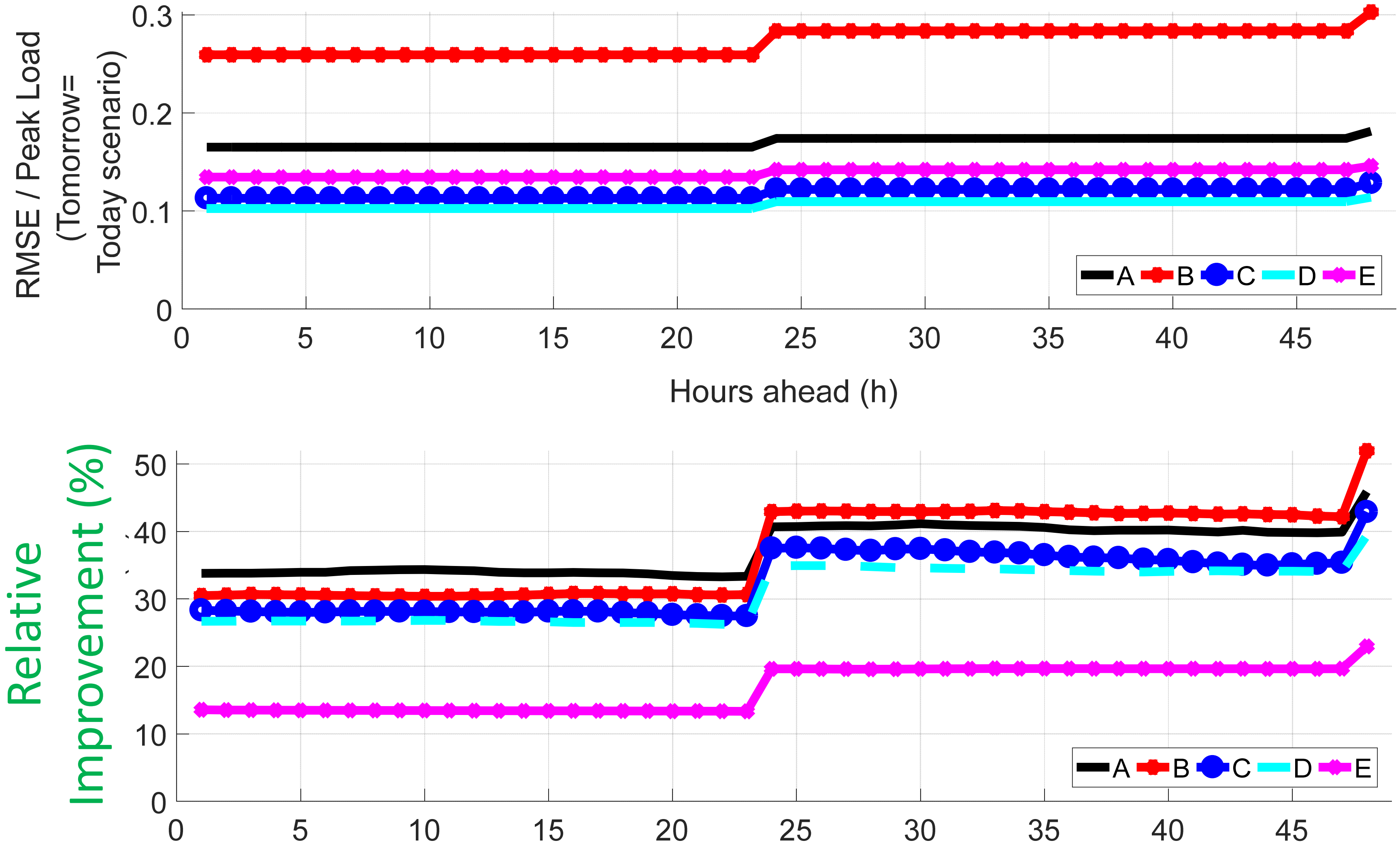
Use of a weather forecast improved the performance



Average error was within 8 - 20% of peak load



RLS performed 12–50% better than a naïve forecast



Further research remains

Limitations of the study:

- Reduced set of greenhouses
- Identification of relevant explanatory variables *a posteriori*
- Focused on average error/performance, not robustness

Take home messages

- Greenhouses can condition DH system operation, as they are large sensitive consumers of heat.

- ***Recursive least squares* forecast is relevant for** individual **load forecast** of greenhouses.
  - Adaptive and computationally simple
  - Low average error (RMSE within 8-20% of peak)
  - Significant improvement compared to naïve method

- Although **time periodicities** were **the most influential** explanatory variables, a **weather forecast improved performance**.

- **Different explanatory variables were identified** for the studied greenhouses, which justifies individual tuning of models.

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Full details of the study:

Vogler-Finck P, Bacher P, Madsen H,
"Online short-term forecast of greenhouse heat load using a weather forecast service", Applied Energy, 2017,
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