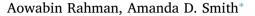
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Predicting heating demand and sizing a stratified thermal storage tank using deep learning algorithms



Site-Specific Energy Systems Laboratory, Department of Mechanical Engineering, University of Utah, Salt Lake City, UT 84112, USA

HIGHLIGHTS

- A deep recurrent neural network (RNN) model is used for medium-term thermal load prediction.
- The deep RNN model outperforms a simple multilayer perceptron for time series forecasting.
- An optimization framework is proposed for sizing a thermal storage tank to meet thermal loads.
- The optimization method can be used in selecting a thermal storage tank for use with a building.
- The combined predictions and optimization allow for estimating performance of the tank.

ARTICLEINFO

Keywords: Building energy modeling Machine learning Recurrent neural networks Deep learning Heating load prediction Thermal energy storage

ABSTRACT

This paper evaluates the performance of deep recurrent neural networks in predicting heating demand for a commercial building over a medium-to-long term time horizon (>1 week), and proposes a modeling framework to demonstrate how these longer-term predictions can be used to aid design of a stratified thermal storage tank. The building sector contributes significantly to primary energy consumption in the US, and as such, there is a need to predict heating demand in buildings over longer time horizons, and to develop methods that can facilitate installation, planning and management of distributed generation and thermal storage to meet these heating demands. Key objectives of this paper are: (a) Investigate how a deep recurrent neural network model performs in predicting heating demand in campus buildings at University of Utah over multiple weeks, and (b) develop an optimization framework that which can provide definitive guidelines on sizing a stratified thermal storage tank without requiring high performance computing resources. The results showed that the predictions by the deep RNN are comparatively more accurate than those by a 3-layer MLP, and that these deep RNN predictions can adequately serve as proxy for future demand while considering sizing in the design of a complementary stratified thermal storage tank.

1. Introduction

The building sector is responsible for a significant fraction of the primary energy consumption and greenhouse emissions in the U.S [1] - a good portion of which is contributed by space and water heating, as well as gas equipment usage [2]. With increasing application of distributed generation and storage systems in order to meet these demands, there is a need for forecasts of heating demands across different time horizons [3]. Such time horizons for forecasts could be (i) short-term (< 1 week), which is useful for real-time control and optimization of building energy components, short-term maintenance and immediate scheduling and management of generation capacity and storage [3–6] or (ii) medium-to-long term, which concerns planning, installation and

* Corresponding author. *E-mail address:* amanda.d.smith@utah.edu (A.D. Smith).

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management of distributed generation and storage systems [7], and decision-making related to demand response strategies [3].

This paper concerns the use of longer-term predictions in aiding design of a stratified thermal storage. Conventionally, deterministic energy simulation packages such as eQuest and EnergyPlus are used to estimate the heating and cooling loads in a building over a longer time horizon [8]. These physics-based models compute these loads by considering transient mass and energy balance between different connecting zones in a building. However, these energy simulation packages often require detailed knowledge of building construction and operational schedules - which are often not available in practice. Thus, these energy simulation packages often do not accurately predict future demands [9]. As these energy simulation packages require inputs which







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GIP Combined Heating and Power GP Gaussian Processes STM Logs short term memory 7 ML Mukhine Learning 7 MLP Mukhine Learning 7 MLP Mukhine Learning 7 MLP Mukhine Learning 7 MLP Mukhine Learning 7 ML Anoreastant deviation astign			Q _{TS,out}	heat delivered by thermal storage to building
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Q_d heating demand in building $\mathbf{z}_{II,train}$ training input for GP in optimization scheme corre- sponding to case II: $Q_{rec} < Q_d$ Q_{rec} heat recovered in heat recovery unit $\mathbf{z}_{II,train}$ training input for GP in optimization scheme corre- sponding to case II: $Q_{rec} < Q_d$ Q_{st} heat stored in thermal storage tank $\mathbf{z}_{II,test}$ test input for GP in optimization scheme corresponding to case II: $Q_{-sc} < Q_d$			1,0050	
Q_{d} heating defining in building Q_{rec} heat recovered in heat recovery unit Q_{st} heat stored in thermal storage tank $Z_{II,test}$ input for GP in optimization scheme corresponding to $C_{rec} < Q_{d}$ $C_{II,test}$ test input for GP in optimization scheme corresponding to $C_{rec} < Q_{d}$			ZII train	
Q_{st} heat stored in themal storage tank $z_{II,test}$ test input for GP in optimization scheme corresponding to case II: $Q_{st} < Q_{st}$			11,114111	• • •
Q_{st} heat stored in the main storage tank case II: $0 < 0$		-	ZII tast	
$Q_{T,klas}$ total heat delivered to the building		ě	11,1081	
	$Q_{T,bldg}$	total heat delivered to the building		

are often uncertain or difficult to obtain, they are often used as comparative tools, often prior to the building construction.

As such, machine learning (ML) models that predict future loads based on past observed data are often employed by energy researchers and modelers [10]. In prior literature, ML algorithms such as simple and multivariate linear regression [10,11], non-linear regression [10–12], multi-layered perceptron neural networks [10,13–15], autoregressive techniques [13,16], Gaussian Processes [17] and hybrid models combining ML models with deterministic thermal networks [18] have been used to predict electric, heating and cooling loads in buildings. While these methods, in general, have been successfully employed in short-term forecasts, comparatively limited work has been Download English Version:

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