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

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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.

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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 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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Nomenclature

CHP	Combined Heating and Power
GP	Gaussian Processes
LSTM	Long short term memory
ML	Machine Learning
MLP	Multi-layered perceptron
NN	Neural network
PGU	Power Generation Unit
PI	Probability of Improvement
RMS	Root Mean Squared
RNN	Recurrent Neural Network
SMBO	Sequential Model-Based Optimization
TS	Thermal Storage
α	learning rate in gradient descent algorithm
σ	sigmoid function serving as a gating function
σ_g	standard deviation associated with GP prediction
$\circ$	element-wise vector multiplier.
γ	fraction of heat recovered in heat recovery unit that is routed to TS
γ^{opt}	optimal value of γ at a given timestep t
γ^{GP}	value of γ at a given timestep t predicted by GP
η_{PGU}	electric efficiency of PGU
η_{rec}	thermal efficiency of the heat recovery unit
ζ	factor accounting for energy losses outside of heat recovery unit
ρ	density of water
a	acquisition function for Bayesian Optimization
A_c	cross-sectional area of each node (m^2)
c_p	specific heat capacity of water (J/Kg K)
$\mathbf{c_t}$	transient 'memory' value in LSTM function
d_i	inner diameter of heat exchanger (mm)
d_o	outer diameter of heat exchanger (mm)
e	mean squared error in predicting electricity consumption
E_{gen}	electricity provided to the building
f_t	targets in training data for GP
f_e	predictions made by GP
$\mathbf{g}$	input activation function in LSTM
$\mathbf{h_t}$	output of LSTM function at given timestep t
h_j^m	value of hidden node in a neural network in node j, layer m
h_i	inner heat transfer coefficient (W/m^2 K)
h_o	outer heat transfer coefficient (W/m^2 K)
H	height of storage tank (m)
$\mathbf{i}$	input gate in LSTM
k	thermal conductivity of water (W/mK)
k_{mat}	thermal conductivity of heat exchanger material (W/mK)
M_I	minimum size of training data corresponding to case I $Q_{rec} \geqslant Q_d$ for GP to predict $\mathbf{x^{opt}}$
M_{II}	minimum size of training data corresponding to case II $Q_{rec} < Q_d$ for GP to predict $\mathbf{x^{opt}}$
N	total number of nodes
$\mathbf{o}$	output gate in LSTM
Q_d	heating demand in building
Q_{rec}	heat recovered in heat recovery unit
Q_{st}	heat stored in thermal storage tank
$Q_{T,bldg}$	total heat delivered to the building
$Q_{TS,out}$	heat delivered by thermal storage to building
s	parameter to describe discrepancy between electricity consumption in test data and that in the corresponding training data
T	stored water temperature (K)
T_m	mean stored water temperature (K), computed using temperatures specific to each node
T_h	hot water temperature (K)
T_c	cold water temperature (K)
$T_{c,in}$	inlet temperature of water in the cold heat exchanger (K)
T_i	temperature of stored water in node i (K)
$T_{h,i}$	temperature of hot water in node i (K)
$T_{h,in}$	inlet temperature of water in the hot heat exchanger (K)
$T_{h,in}^{opt}$	optimal inlet temperature of water in the hot heat exchanger (K) at a given timestep t
$T_{h,in}^{GP}$	optimal inlet temperature of water in the hot heat exchanger (K) at a given timestep t
$T_{c,i}$	temperature of cold water in node i (K)
UA	overall heat transfer coefficient of heat exchanger (W/m^2 K)
$\dot{V}_h$	volume flow-rate inside the hot heat exchanger
$\dot{V}_c$	volume flow-rate inside the cold heat exchanger
$\dot{V}_c^{\,opt}$	optimal volume flow-rate inside the cold heat exchanger
$\dot{V}_c^{\,GP}$	volume flow-rate inside the cold heat exchanger, as predicted by GP
$\dot{V}_c^{\,max}$	maximum possible value of $\dot{V}_c$
$\mathbf{s}$	date-related variables used as inputs to the deep RNN model
w_{ji}^m	weight connecting j in layer m to node i in layer $m-1$
$\mathbf{w}$	weather variables used as inputs to the deep RNN model
$\mathbf{X}$	input features to the deep RNN model
$\mathbf{x_t}$	input to LSTM activation corresponding to a previous layer and current timestep t
$\mathbf{X_t}$	training input for a given ML algorithm
$\mathbf{X_e}$	test input for a given ML algorithm
$\mathbf{x^{opt}}$	set of optimal operational variables at a given timestep
$\mathbf{x_I^{opt}}$	set of optimal operational variables at a given timestep, corresponding to case I: $Q_{rec} \geqslant Q_d$
$\mathbf{x_{II}^{opt}}$	set of optimal operational variables at a given timestep, corresponding to case II: $Q_{rec} < Q_d$
$\mathbf{x^{GP}}$	set of approximations to optimal operational variables at a given timestep as predicted by GP
$\mathbf{x_I^{GP}}$	set of approximations to optimal operational variables at a given timestep as predicted by GP, corresponding to case I
$\mathbf{x_{II}^{GP}}$	set of approximations to optimal operational variables at a given timestep as predicted by GP, corresponding to case II
$\mathbf{X}$	feature vector used as inputs to the deep RNN model.
y_p	predicted value of electricity consumption
y_a	actual value of electricity consumption
$\mathbf{z_{I,train}}$	training input for GP in optimization scheme corresponding to case I: $Q_{rec} \geqslant Q_d$
$\mathbf{z_{I,test}}$	training input for GP in optimization scheme corresponding to case I: $Q_{rec} \geqslant Q_d$
$\mathbf{z_{II,train}}$	training input for GP in optimization scheme corresponding to case II: $Q_{rec} < Q_d$
$\mathbf{z_{II,test}}$	test input for GP in optimization scheme corresponding to case II: $Q_{rec} < Q_d$

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