ARTICLE IN PRESS

Sustainable Cities and Society xxx (xxxx) xxx

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Adaptive hot water production based on Supervised Learning

Amirreza Heidari [a,*], Nils Olsen [a,b], Paul Mermod [a,b], Alexandre Alahi [b], Dolaana Khovalyg [a]

[a] Thermal Engineering for the Built Environment Laboratory (TEBEL), Ecole Polytechnique Fédérale de Lausanne (EPFL), Lausanne, Switzerland
[b] Visual Intelligence for Transportation Laboratory (VITA), Ecole Polytechnique Fédérale de Lausanne (EPFL), Lausanne, Switzerland

ARTICLE INFO

Keywords:
Domestic hot water
Intelligent hot water system
Adaptive control
Occupant behavior
Machine Learning
Neural network

ABSTRACT

A major challenge in the common approach of hot water generation in residential houses lies in the highly stochastic nature of domestic hot water (DHW) demand. Learning hot water use behavior enables water heating systems to continuously adapt to the stochastic demand and reduce energy consumption. This paper aims to understand how machine learning (ML) can predict the stochastic hot water use behavior, and to investigate the potential reduction in energy use by an adapting hot water system. Different ML models are implemented on a data set of 6 residential houses, and their average performance is compared. Ten different models were evaluated, including four single models (Random Forest, Multi-Layer Perceptron, Long-Short Term Memory Neural Network, and LASSO regression), four Sequential Multi-Task models combining classification and regression models, and two Parallel Multi-Task models based on Random Forest and Multi-Layer Perceptron. Dynamic simulation of a smart hot water supply system, which adapts to the predicted demand, shows that adaptive hot water production can provide significant energy use reduction.

1. Introduction

The energy demand for space heating and cooling has decreased significantly in new generations of houses, which is mainly due to a better-insulated house envelope and more efficient energy systems (Zhou et al., 2018). However, the energy use for hot water production has not changed significantly over time. For example, the share of hot water energy demand to the total heat requirement in Switzerland has increased over different generations of houses, from 10 % in old houses (over 45 years old) to more than 70 % in modern low energy rated houses (Suisse Energie, 2016). Generally, hot water demand is a non-deterministic phenomenon that could depend on many parameters such as time-related factors, environmental factors, household type, lifestyle, personal habits, and background. The significant dependency of DHW demand to the behavior of occupants creates a challenge for the common approach of hot water generation systems (). Conventional approaches to hot water production have to take some considerations to be able to meet stochastic DHW demand whenever it happens. In these approaches, hot water is produced and stored in huge volumes before the demand, or it is produced by the use of lower-efficiency *on-demand* hot water production systems. Any of these strategies results in significant energy waste (Hohne, Kusakana, & Numbi, 2019), mainly because there is no prior knowledge about hot water use behavior of occupants.

In recent years, there has been a growing interest in the energy behavior of occupants as a major factor influencing the building energy performance (Laaroussi, Bahrar, El Mankibi, Draoui, & Si-Larbi, 2020). However, a review of occupants behavior research field show that in most of the previous studies the interaction of occupants and building systems has been focused on windows use, shade use, thermostat set point, lighting use, and plugs, while the hot water use behavior has been overlooked (Li, Yu, Haghighat, & Zhang, 2019). Human behavior is influenced by many external drivers, as indicated in Calvache, Santos, Antunes, and Santos-Reis (2018)), and, therefore, is very hard to be predicted (Sanchis-Cano, Romero, Sacoto-Cabrera, & Guijarro, 2017). However, in the case of hot water use behavior, a few studies indicate that there are some regularities in the hot water use behavior of occupants. For example, the correlation analysis on the hot water use data in studies of Costil et al., Delorme-Costil and Bezian (2017), Gelažanskas and Gamage (2015a, 2015b) shows that the pattern of hot water use on the same day of different weeks has strong similarities. As another example, the pattern of daily hot water use usually has two peaks, one in the morning and the other one in the evening (Gelažanskas & Gamage, 2015b). These regularities show that hot water use patterns include useful information about water use-related habits of occupants, which can be extracted by data mining and ML methods to predict hot water use before the actual event.

* Corresponding author.
E-mail address: amirreza.heidari@epfl.ch (A. Heidari).

https://doi.org/10.1016/j.scs.2020.102625
Received 20 August 2020; Received in revised form 21 November 2020; Accepted 23 November 2020
Available online 1 December 2020
2210-6707/© 2020 Elsevier Ltd. All rights reserved.

Please cite this article as: Amirreza Heidari, *Sustainable Cities and Society*, https://doi.org/10.1016/j.scs.2020.102625

Nomenclature

COP	Coefficient Of Performance
DHW	Domestic Hot Water
EMA	Exponential-Moving-Average
LSTM	Long-Short Term Memory
ML	Machine Learning
MLP	Multi-Layer Perceptron
$p \in [0-1]$	Probability of hot water use for the next hour
R	Pearson's Correlation Coefficient
RMSE	Root Mean Squared Error
RF	Random Forest
$V\ (l)$	Volumetric hot water demand
$y_{c1} \in \{0,1,2\}$	The proportion of predicted demand to the total demand of that day
$y_{c2} \in \{0,1,2\}$	The proportion of predicted demand to the total demand based on the quartiles of the distribution of hourly demand

1.1. Related works

Space cooling and heating have been considered as the major energy demand in the building sector, so it has been the focus of many studies on the built environment (Carvalho, Moura, Vaz, & de Almeida, 2015; Heidari, Roshandel, & Vakiloroaya, 2019; Heidari, Rostamzadeh, & Avami, 2019; Heidari, Rostamzadeh, Khovalyg, 2019). Hence, the application of ML methods in buildings mostly has focused on the predictions of space heating (Guo et al., 2018; Roy, Roy, & Balas, 2018) and cooling demand (Ngo, 2019; Thinsz, 2019), while the energy use for hot water supply has been overlooked so far (Marszal-Pomianowska et al., 2019). The literature review shows that only a few researches have focused on the prediction of stochastic hot water demand and optimal operation of water heating systems based on learning the demand. The available studies on prediction level either focused on the prediction of volumetric hot water use or energy use for hot water production. Maltais and Gosselin (2019) developed an ML model to predict the hourly volumetric hot water demand in a 40 unit residential building in Quebec City, Canada. The primary analysis of the data showed that the hot water use profile includes an important noise component. Therefore, a Sequential Multi-task ML model was developed, including a recurrent neural network to predict the filtered trend, and Random Forest (RF) to predict the noisy part. Dmy et al. (2019) evaluated 7 different statistical models as well as a Support Vector Machine for the prediction of hourly and daily hot water demand in a hotel in Oslo, Norway. Gelažanskas and Gamage (2015b) explored the possibility of forecasting volumetric hot water demand at the individual building level. To this aim, a data set of hot water use in 120 residential buildings in the UK was analyzed through various stochastic models, such as exponential smoothing, seasonal autoregressive integrated moving average, seasonal decomposition, and a combination of them to forecast the demand 24 h ahead. In another study of Gelažanskas and Gamage (2015b), the authors evaluated the potential of an artificial neural network to predict the energy demand profile of individual water heaters. Data from a hundred dwellings were analyzed using the autocorrelation technique. The most appropriate time lags were then chosen and different topologies of the neural network were tested and compared. Delorme-Costil and Bezian (2017) used an artificial neural network to predict the energy use for domestic hot water production 8 min and 64 min ahead. Three different neural network models were analyzed, varying in their architecture and input parameters. Fischer, Wolf, Scherer, and Wille-Haussmann (2016) coupled behavioral and energy balance models to generate hourly profiles of space heating and hot water energy use in German households. These demand profiles were useful for better sizing and operation of thermal supply systems in buildings. Dong, Munk, Cui, Boudreaus, and Kuruganti (2018) evaluated three different ML models, including Support Vector Machine, Gaussian Naive Bayes, and RF, to predict the power use of a 9 kW electric water heater. Prediction of hot water energy use is even more challenging when a renewable energy source is integrated into the system. In such cases, the energy demand is affected by two stochastic phenomena, which are occupant's behavior and renewable energy availability. To evaluate the feasibility of energy demand prediction in such systems, Heidari and Khovalyg (2020) evaluated the energy demand prediction of a solar-assisted heat pump. A novel neural network, combining time series decomposition and attention mechanism was developed and compared to the conventional models. Ritchie, Engelbrecht, and Booysen (2020) developed a probabilistic hot water usage simulator to generate usage profiles with an hourly resolution, which can be used for several applications such as demand-side management.

Optimal control of the water heating systems considering the predictions of the demand side is another topic considered in the literature. Studies on the optimal control of building energy systems based on the demand learning either focus on the cost optimization for reducing total energy demand (Bünning, Huber, Heer, Aboudonia, & Lygeros, 2020) or cost optimization for shifting the peak of energy demand (Luo et al., 2020). Few studies have focused on the optimal control for reducing the total water heating energy demand. Kazmi, Mehmood, Lodeweyckx, and Driesen (2018) developed a reinforcement learning model to optimize hot water production for the stochastic hot water demand. The application of this model to 32 houses in the Netherlands reduced energy use for hot water production by roughly 20 % with no loss of the comfort of occupants defined as the water supply of at least 45 °C. To address the legionella growth risk in the control system, Kapsalis and Hadellis (2017) developed a control algorithm which combines a convolutional neural network for demand prediction and a cognitive Supervisor considering Legionella risk. The control system regulates the tank's temperature to reduce bacteria formation with the minimum increase in energy consumption.

Regarding the energy storage potential of water heating systems, they are interesting building systems for load shifting. Therefore, few other studies have also considered dynamic pricing in optimization, which results into the load shifting of water heating systems. Kapsalis and Hadellis (2017) developed a scheduling algorithm based on Dijkstra's algorithm to optimize the energy cost of electric water heaters under dynamic pricing. Ruelens et al. (2016) used an auto-encoder network together with a well-established batch reinforcement learning algorithm, called fitted Q-iteration, to reduce the cost of energy consumption of a 2.36 kW electric water heater by finding an optimal control strategy. Compared to a default thermostat controller, the proposed method reduced the energy cost by 24 % using day-ahead prices and by 34 % using imbalance prices.

Despite the growing importance of hot water energy demand, on the one hand, and recent advances in artificial intelligence and ML, on the other hand, the potential of implementing ML models to predict hot water use behavior is not well explored. Early prediction of hot water use behavior by the use of ML can eliminate energy overuse while maintaining the satisfaction of occupants. Thus, the objectives of this paper are summarized below:

- To implement a set of 10 different ML models on 6 different houses to identify which model has a better performance for prediction of highly-stochastic hot water use behavior;
- To quantify energy reduction potential by early prediction of hot water use through dynamic simulation of the smart learning-based system and two conventional approaches of hot water production.

This paper is structured into three main sections. The first section presents the methodology, including a description of the dataset, different machine learning models, and a dynamic energy simulation approach. The second section describes the results in two main parts - the performance of different ML models and the potential energy reduction by the smart system. The final section summarizes the results of this work and draws conclusions.

2. Methodology

The methodology section is divided into 3 main sections. The first section presents a description of the dataset. The second section introduces ML modeling, starting with the explanation of inputs and output of the model, different examined models, hyper-parameter optimization, and the evaluation metrics. The third section explains the modeling approach to dynamic energy simulations.

2.1. Description of the dataset

The dataset used in this study contains the volumetric hot water demand of 94 households having electric water heaters in South Africa during 8 months of operation from early August 2017 to the end of March 2018. The dataset was collected by Booysen, Engelbrecht, Ritchie, Apperley, and Cloete (2019) using smart IoT-based control systems, which were designed for optimal control of water heating systems described in Booysen et al. (2019) and peak load management described in Roux, Naude, Booysen, and Barnard (2017). The dataset is publicly available in Booysen and Roux (2019). Background information such as the size of the households and type of occupants is not available. As shown in Fig. 1, the smart control system measures real-time power use, inlet, and outlet water temperature, and the inlet water flow rate. The systems are electric water heaters with a pressurized tank. The smart control system was connected to a mobile network and transferred data to the database in which data from all water heaters were collected.

As the first step of data analysis, visualizations and descriptive statistics are done on the volumetric hot water supply of all 94 water heaters. Fig. 2(a) shows the average and standard deviation of hourly hot water demand over all 94 water heaters and all the days of the week. Fig. 2(b) shows the same average profile but is separated by weekdays. As expected, the patterns clearly show that there are two peaks in the daily hot water use, one in the morning and the other in the evening.

Separated profiles in Fig. 2(b) show that the hot water demand during the weekends has lower values, and the morning peaks are shifted in time. To better understand the similarity of demand patterns during different days, the correlation factors between different days are calculated, as shown in Fig. 3. As can be seen, each working day has a high correlation with the other working days and a low correlation with the weekend days. Similarly, each weekend day (Saturday and Sunday) also has a high correlation with other weekend days and a low correlation with the working days. Therefore, the demand for the same hour in the last week can be a useful feature to predict the next hour's demand.

Studies (Delorme-Costil & Bezian, 2017; Gelažanskas & Gamage, 2015b) on hot water use profiles show that hot water consumption varies significantly between different houses because the domestic hot water demand profile is highly dependent on occupants' behavior and the schedules (Hendron & Burch, 2007). Hence, a generic model (a model which is trained on some houses to predict other houses) cannot provide good accuracy. Therefore, the model should be house-specific, learn the hot water use behavior of occupants in a particular house to predict the future behavior of the same occupants. Hence, in this research 6 houses exhibiting very different patterns are selected from the dataset of 94 households and used for training and testing of each of the proposed models independently. Fig. 4(a) and (b) show the box plots of hot water demand showing the mean and variance of demand for different days of the week and for different hours of the day, respectively. As can be seen, hot water demand profiles are significantly different between the selected houses, and therefore the average performance of the models is a good representative for comparison. House 6 shows a very irregular pattern, compared to the other houses. This house is included to investigate how different models will perform in case of exceptional patterns.

To explore the repetitive patterns in hot water use profiles and optimal choice of input features, the autocorrelation factor of selected houses is shown in Fig. 5. In this figure, the k_{th} lag is the time period that has happened "k" time points before time t. In all houses (except house 6, which is an abnormal pattern), there are two peaks in the autocorrelation factor, one at the 168 h lag and the other at the 24 h lag. It shows weakly and daily routines in hot water use profile, which demonstrates that the profile of one week before and one day before contain useful information for the model to predict the next hour demand. These findings are considered in the feature selection step. House 6 however, doesn't show a significant autocorrelation factor, and therefore it has no routine.

2.2. Machine learning models

The machine learning models in this study aim to use the previous hourly data of hot water demand to predict one hour ahead. Therefore, in the modeling approach first, the various features are extracted from the data to extract useful information, then different models are designed to use these features to predict future demand. In this part, first, the model inputs and output are explained, and then different evaluated models to perform this prediction are presented.

2.2.1. Inputs and output

The main parameter affecting hot water demand is users' behavior, which can be affected by many factors such as everyday habits. So, the selected features should well extract the routines and habits of users from the data. The only data available from case study houses was the hourly data of hot water demand, and other data like occupancy were not available. Therefore, representative features from the time-series data should be extracted, which show the behavior and habits of occupants in terms of hot water demand. Different extracted features can be categorized into *short-term inputs*, *long-term inputs*, and *temporal inputs*, as explained below:

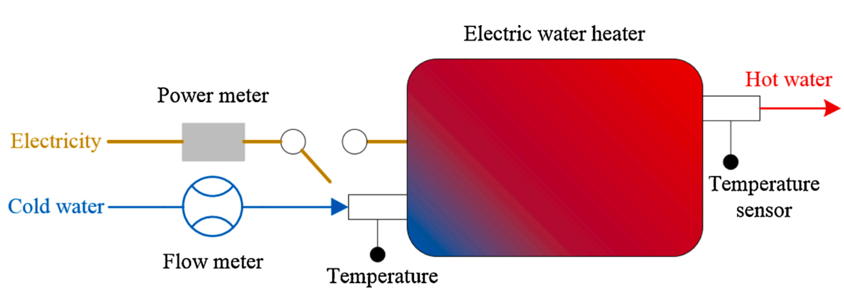
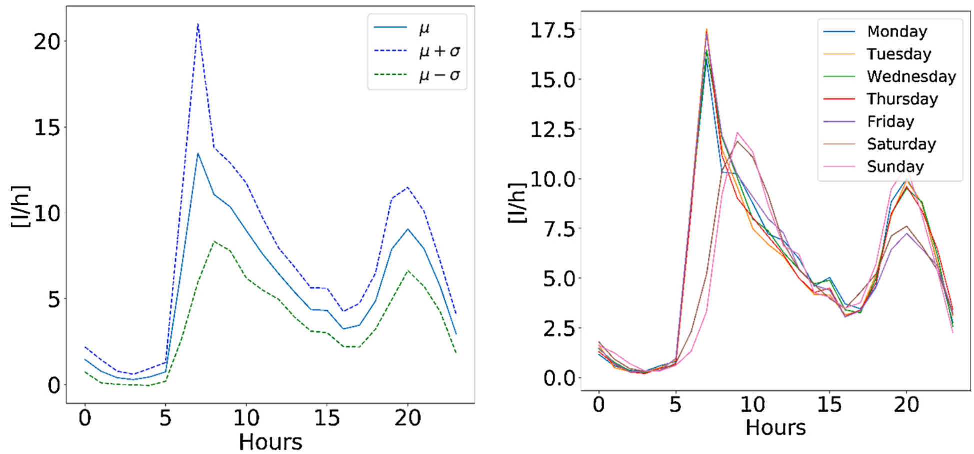


Fig. 1. Data acquisition setup on individual electric water heaters.



(a) (b)

Fig. 2. Average of hourly hot water demand over 94 water heaters: (a) averaged over all days of the week, (b) separated by the days.

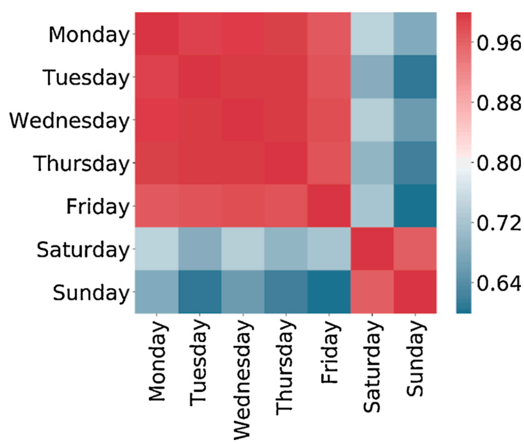


Fig. 3. Correlation factor of hot water demand over the weekdays.

2.2.2. Short-term inputs

Hot water demand in future hours is affected by how much water has been used so far. For example, if an occupant has taken a shower during the last 10 h, it is less probable to take a shower again during that day. Also, occupants typically have some daily routines, like taking a shower every morning or washing dishes every evening. Examining specific hours in the preceding day or week can reveal these habits. Accordingly, the following features, as short term inputs, are considered to explore this kind of habits by looking at a short period of up to one week:

- $\boldsymbol{DHW_{1h}}$, $\boldsymbol{DHW_{2h}}$, $\boldsymbol{DHW_{12h}}$: The volume of domestic hot water (in liters) consumed 1 h, 2 h, and 12 h ago, respectively.
- $\boldsymbol{DHW_{1D}}$, $\boldsymbol{DHW_{1W}}$: The volume of domestic hot water (in liters) was consumed one day ago and one week ago at the same hour, respectively. DHW_{1D} and DHW_{1W} were selected based on the correlation factor diagram, as the value of hot water demand at each hour best correlates with the hot water demand of 24 h and 168 h ago.
- ***Proportional*** $\boldsymbol{DHW_{1D}}$, ***Proportional*** $\boldsymbol{DHW_{1W}}$: The proportion (%) of hot water demand in that specific hour to the total use of the one day ago and one week ago, respectively. This feature provides the model with information about the usual share of consumption of that specific hour in the day.
- ***Binary*** $\boldsymbol{DHW_{12h}}$, ***Binary*** $\boldsymbol{DHW_{24h}}$: These binary variables (0 or 1) indicate if there was any consumption during the last 12 h and the last 24 h, respectively. While there was no data on occupancy, these binary variables were useful to identify if the occupants are away.

2.2.3. Long-term inputs

While the *short-term* features provide insight into hot water demand behavior up to one week ago, information about more time steps before provides insight into the changes in habits and routines in a longer period. To this aim, Exponential-Moving-Average (EMA) was used, which embodied the information of long-time previous time steps while giving more weight to the recent data. Two following features were extracted accordingly:

- **Hourly EMA:** The Hourly EMA variable is independent of the weekday and represents the hourly moving average for one specific hour of the day. Hourly EMA was computed by combining the Hourly EMA ($EMA_{H,t-24}$) and the measured consumption (DHW_{t-24}) of the previous day as below. α_H is the weighting given to the most recent data.

$$EMA_{H,t} = (1 - \alpha_H)EMA_{H,t-24} + \alpha_H DHW_{t-24} \text{ with } \alpha_H = 1/30 \tag{1}$$

- **Daily-Hourly EMA:** The daily-hourly EMA was computed similar to the hourly EMA, but this time for a specific hour for a given day. Daily Hourly EMA takes into account both the previous Daily Hourly EMA and the hot water consumption at the same hour of the previous week. α_{DH} is the weighting given to the most recent data:

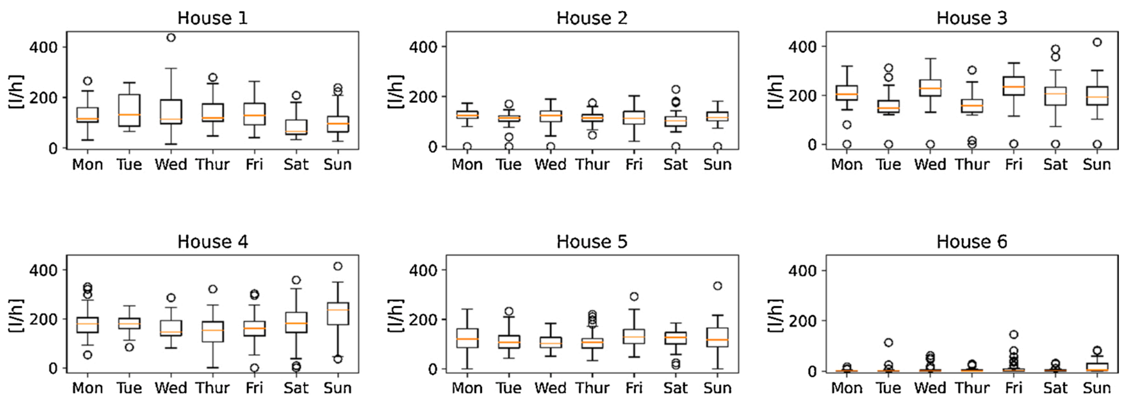
$$EMA_{DH,t} = (1 - \alpha_{DH})EMA_{DH,t-168} + \alpha_{DH} DHW_{t-168} \text{ with } \alpha_{DH} = 1/4 \tag{2}$$

2.2.4. Temporal inputs

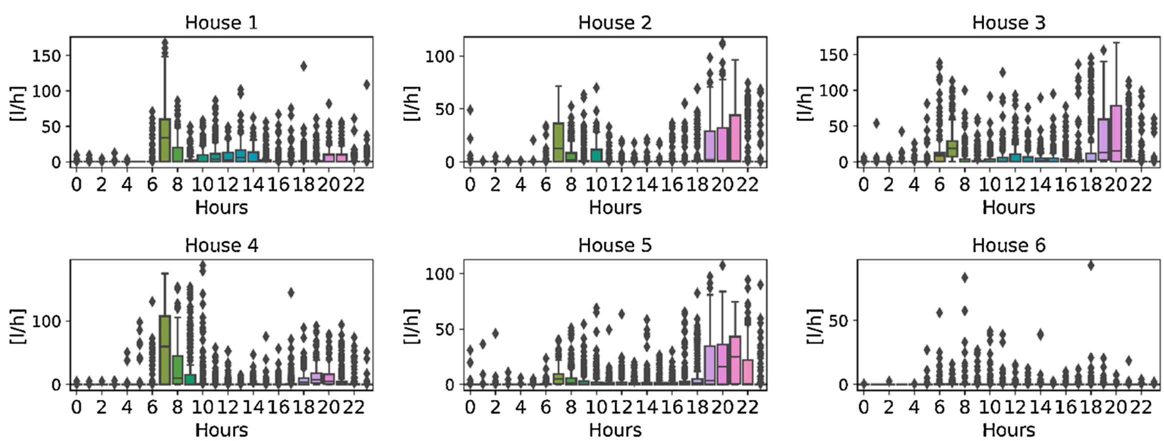
As shown in the primary analysis of data, the hot water demand is very dependent on the temporal variables like the hour of the day. The following features provide temporal information about the demand to be predicted:

- **Weekday:** Dummy variables that indicated the number of the day in the week. While an integer variable can be used for this feature, dummy variables are more suitable as they show the cyclic feature of days in a week and the fact that the time difference between all of each day and the previous day is the same regardless of their number (e.g. [1,0,0,0,0,0,0] as Monday) ;
- **Workday:** A binary variable to indicate the working day;
- **Holiday:** A binary variable to indicate the holiday;

The different models in this study aim to use these inputs to predict one hour ahead of hot water demand. Fig. 6 shows the general framework of the models in this study. Different candidate models to perform this task are explained in the next section.



(a)



(b)

Fig. 4. Box plots of hot water demand showing the mean and variance of demand throughout the 8 months of measurements (a) for different days of the week (b) for different hours of the day.

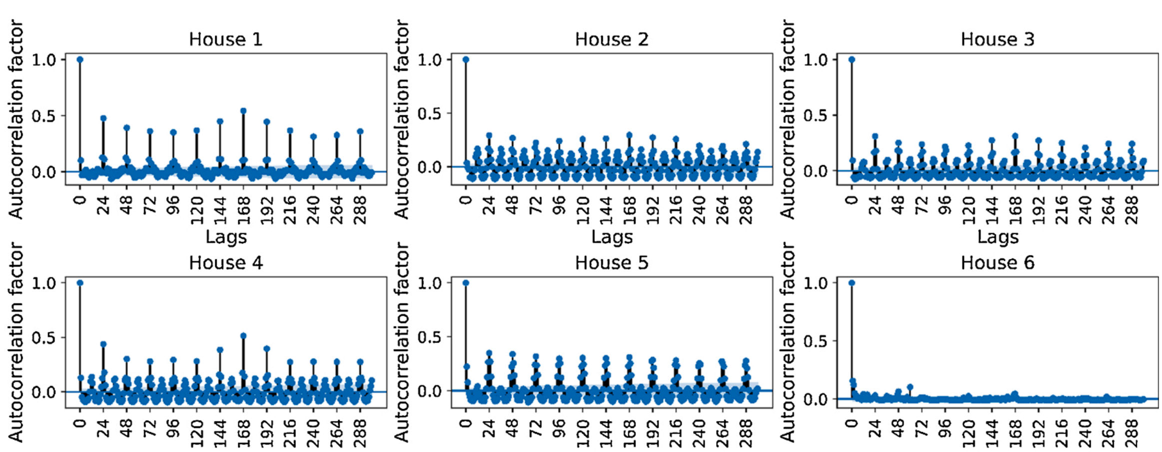


Fig. 5. Autocorrelation factor of hot water demand data in selected houses.

2.2.5. *Different models*

In this research, several machine learning models have been evaluated to investigate which model shows the best performance for this highly stochastic problem. Different evaluated models are categorized into three groups: Single models, Sequential Multi-task models, and Parallel Multi-task models.

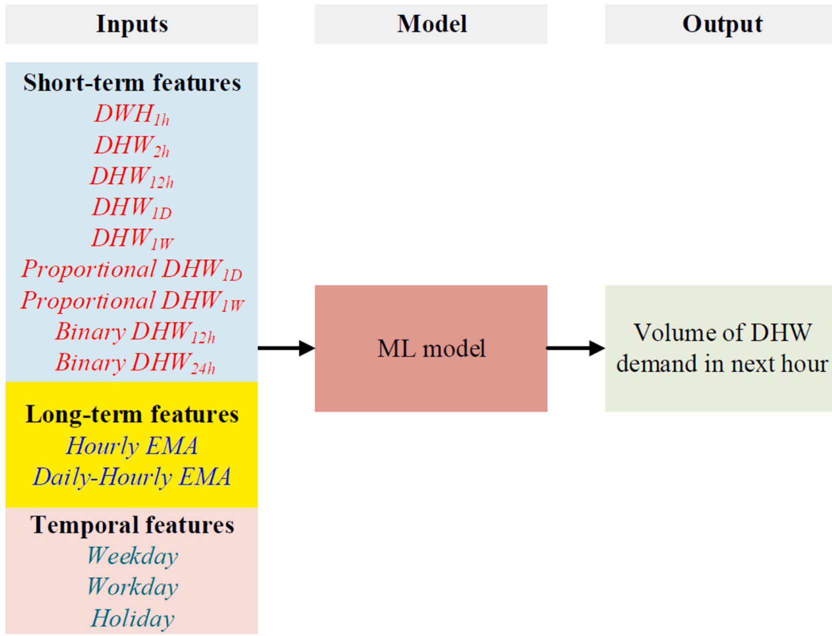


Fig. 6. Model inputs and output for the prediction of hour-ahead hot water demand.

2.2.6. Single models

Single models include a single algorithm that uses the inputs into a regression model to predict the hot water demand of one hour ahead. Different algorithms used in this part include Random Forest (RF), Multi-Layer Perceptron (MLP), Long-Short Term Memory neural network (LSTM), and LASSO regression (LASSO).

2.2.7. Sequential multi-task models

Sequential Multi-task models aim to use a classification model to predict a class that can be useful for the regression model. To this aim, at first, the classification model uses the inputs vectors to predict a class of future hot water use. This class can be a binary number (Y_b), which shows if a demand instance is predicted to happen or not, or can be an integer number which shows the level of predicted hot water use as low (indicated as 0), medium (indicated as 1) or high (indicated as 2). This level is either based on the proportion of predicted demand to the total demand of that day (y_{c1}), or based on the quartiles of the distribution of hourly demand (y_{c2}). In the first case (y_{c1}), the low category corresponds to hours where the demand is less than 2 % of total daily demand. Similarly, medium denotes the ratio from 2 % to 20 %, and high denotes the ratio of above 20 %. In the second case (y_{c2}), the first quartile is considered as low, the second and third quartiles are considered as medium, and the fourth quartile is considered as high. These classes are considered to include very short-time usages like hand washing in the first class, medium time usages like cooking in the second class, and the long-time usages like the shower in the third class. For classification models, the cross-entropy loss function is used. The predicted class, as well as the other inputs, is then supplied to the regression model to predict the volume of hot water demand in the next hour. The main purpose of this approach is to provide additional information to the regression model to examine if it helps to improve the model accuracy. Based on the type of classification output, and also the algorithm used different combinations are evaluated as follow:

- **RF binary-RF**: The combination of RF classification and RF Regression, in which the classification output is the binary variable.
- **MLP binary-MLP:** The combination of MLP classification and MLP regression in which the output of classification is a binary variable.
- **RF percentage-MLP:** The combination of RF classification and MLP regression in which the output of classification is the level of usage based on the percentage (y_{c1}).
- **RF quartile-MLP:** The combination of RF classification and MLP regression in which the output of classification is the level of usage based on the quartile (y_{c2}).

The output of the regression model in all of these combinations is the volumetric hot water demand in the next hour.

2.2.8. Parallel multi-task model

In the Sequential Multi-task models, a classifier and a regressor are trained in series. On the other hand, the Parallel Multi-task model aims to perform the same tasks of classification and regression, but in parallel. In Parallel Multi-task, the classification model predicts the probability of hot water demand in the next hour, and the regression model predicts the volumetric demand for hot water. The model outputs are the probability of hot water use ($P \in [0-1]$) and a real-value prediction, the loss function in this model is a combination of the classification and regression errors. The loss function of the network is a weighted combination of classification and regression losses as below

$$Multitask\ loss = w_1.MSE + w_2.CEL \tag{8}$$

In which, $w_1$and w_2 are the weights of regression and classification errors, according to the relative importance of each model in the overall loss. CEL is the cross-entropy loss (CEL) of classification to be minimized, which in turn maximizes the likelihood of the predictions:

$$CEL = -\sum_{t=1}^{N} \log(y_{\bar{c}t}) \tag{9}$$

In where $\bar{c}$ is the ground-truth class of observation t. MSE also is the mean squared error of the regression to be minimized, which is calculated as follow:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2 \tag{10}$$

In which N is the number of samples, y_i is the predicted value and $\bar{y}_i$ is the correct value.

The underlying concept of this model is that if two outputs are correlated or share information, then the joint training can potentially improve predictive performance compared to the independent training. This approach has been successfully implemented in many domains, such as autonomous vehicles (Kenway et al., 2016), but it is overlooked in energy applications. In this study, two Parallel Multi-task models are implemented, including a model based on RF (called RF parallel) and a model based on MLP (called MLP parallel).

The schematics of all different models are shown in Fig. 7.

2.3. Hyper-parameter optimization

The choice of hyper-parameters significantly affects network performance (Jiang et al., 2018). Carefully tuning the hyper-parameters of a conventional model can result in a model with better performance than many recently proposed models that are claimed to be state-of-the-art (Rahman, Srikumar, & Smith, 2018). In this paper, the grid search method is used to tune the hyper-parameters. In practice, a model should be first tuned; then, it can be used to learn the hot water use behavior in each house. Therefore, with a practical point of view, the model architecture should be first decided for all houses and cannot be changed for every house. In addition, the models of the same family but with different hyper-parameters are actually different models, as hyper-parameters have a significant effect on the performance. Therefore, if the hyperparameters are different for each house, their performance cannot be averaged on all the houses. Due to these two reasons, the hyper-parameters of each model are tuned on house 5, and they are used for all the houses.

2.4. Metrics

2.4.1. Regression metrics

Root Mean Squared Error (RMSE) and *Pearson's Correlation Coefficient* (R) are used to measure the accuracy of regression models. RMSE is a frequently used measure of the average difference between the predicted values and the real values, as shown in Eq. (11).

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2\right]^{\frac{1}{2}} \tag{11}$$

RMSE shows the average error of all predictions. Pearson's Correlation Coefficient is another common metric for regression models, which is calculated as the covariance divided by the square root of the product of predicted and actual variances, as shown in Eq. (12). The value of R varies between –1 to +1, where a value closer to –1 and +1 shows the perfect relationship, and a value closer to zero shows a weak relationship.

$$R = \frac{Conv(X, Y)}{Std(X) \cdot Std(Y)} \tag{12}$$

These two metrics are implemented on the test data set to assess both the average error of prediction and the correlation of predicted and

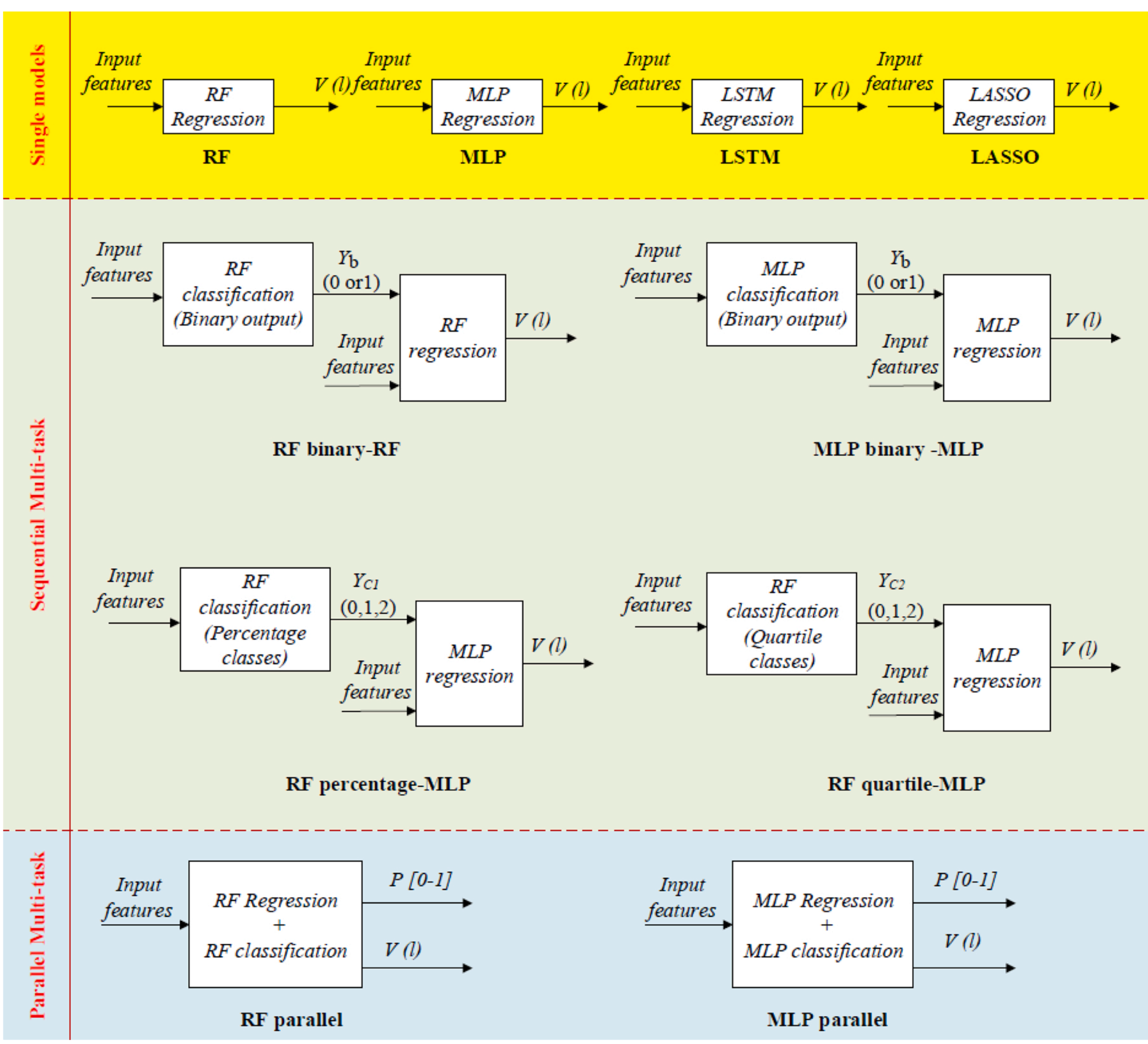


Fig. 7. Schematics of all different models.

actual values.

2.4.2. Classification metrics

The score F_1 is a commonly used measure for classification accuracy, which is consisted of *Precision* and *Recall*. *Precision* is the ratio of correct positive results to all positive results returned by the classifier, and *recall* is the ratio of correct positive results to all samples that should have been identified as positive. The balanced F_1 -the score is a harmonic mean of precision and recall, as shown in Eq. (13):

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{13}$$

As the classification models in this research are multi-class models, $macro - F_1$ the score is used, which is the average of all classes.

2.5. Dynamic energy simulations

Once the prediction level is done by ML models, the next step is the decision level. In the decision level, it should be decided how to make use of predictions for more rational hot water production. The predictions can be used by a smart hot water system specifically designed to work based on predictions or to retrofit the current conventional systems by modifying their operational strategy. To quantify the energy-saving potential, an adaptive hot water system, in which the operation is always adapted to the predicted demand, is simulated and compared with two conventional systems with rule-based control for all six homes. Following, the operational principle of two conventional approaches, as well as the proposed adaptive approach, is explained.

Generally, conventional approaches for hot water generation can be divided into two main categories of *with-tank* and *on-demand* systems, as shown in Fig. 8(a) and (b), respectively.

a) **With-tank systems:** In these systems, hot water is generated and stored in a storage tank. Once there is a demand, hot water is drawn from the top of the tank, and the cold water with the network pressure is supplied to the bottom of the tank. Therefore, the level of the tank remains always full, but the temperature drops. Therefore, the heating system switches ON whenever the tank temperature falls below a set-point level to maintain the temperature on a set point. A major challenge in this approach is that water with a temperature between 25 ℃ and 45 ℃ provides a favorite environment for the multiplication of legionella bacteria (SIA.381/1, 2011). Therefore, to kill the legionella bacteria and prevent health problems, the World Health Organization (WHO) suggests keeping the temperature of the hot water tank above 60 ℃ (Sernhed, Johansson Kallioniemi, Wollerstrand, Ottosson, & Karlsson, 2018). Accordingly, in this approach, a large amount of hot water is produced in advance and heated to keep the temperature above 60 ℃. The early hot water production and the need for compensation of storage heat losses is mainly because there is no prior knowledge of future demand.
b) **On-demand systems:** on-demand systems heat water instantaneously when there is a demand. Examples of on-demand systems are electric resistance or gas-fired heaters with efficiency less than 1 and limited peak flowrate production (Brazeau & Edwards, 2011). This approach eliminates the need for storing hot water in the tank for a long time. However, as the hot water needs to be produced instantaneously, only electric element or gas-fired water heaters (with efficiency of between 0.9–1) can be currently used. Heat pumps, with a much higher COP between 2–5, are not applicable for instantaneous water heating due their thermal and mechanical inertia (Ju et al., 2018), and also complexity to meet a variable demand instantaneously.

The *smart hot water system* aims to learn the hot water use behavior and eliminate these inefficiencies. The main objectives of this smart approach are:

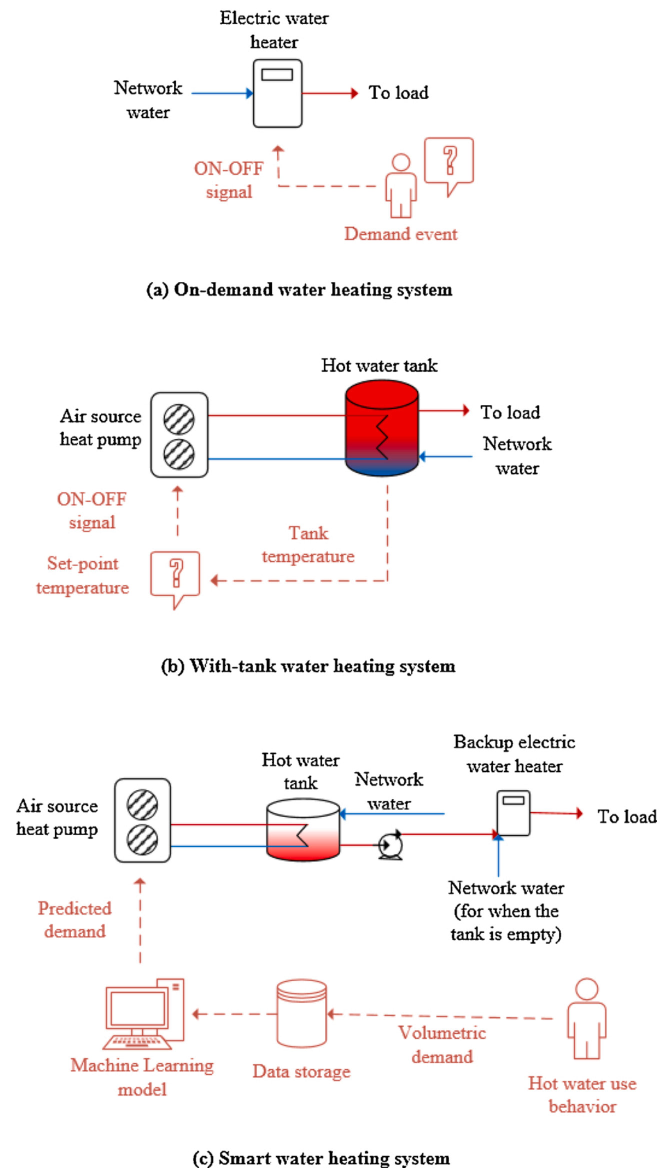


Fig. 8. Schematics of hot water production systems: (a) a conventional with-tank, (b) a conventional on-demand, (c) a smart system.

1 **Producing hot water at the right time with the right volume:** using the predicted amount of hot water demand for the next hour, the water heating system can produce hot water one hour before the expected demand and store it in a small storage tank. Production of hot water at the right time reduces the heat losses to the environment.
2 **Enabling the use of heat pumps for on-demand generation of hot water:** While heat pumps are very energy efficient, in practice there are several issues to use them for instantaneous hot water production. A heat pump needs a high heat exchange area, as well as an oversized compressor, to meet the demand instantaneously. In addition, a variable speed compressor would be required to meet the varying demand. But if the demand is predicted, a typical heat pump can be used to produce hot water just before the demand. This has the potential to replace current low-efficient on-demand systems with the heat pumps that have 3–4 times higher efficiency.
3 **Adaptive control**: In contrast with the conventional rule-based control which neglects the occupant's behavior, the proposed control approach tries to adapt to the stochastic behavior of occupants in real-time.

The schematic of the proposed smart system is shown in Fig. 8(c). In this system, an air-source heat pump is connected to a small hot water tank. The heat pump heats the predicted amount of hot water expected to be used in the next hour, and stores it in a small tank. Therefore, despite the conventional tanks which are always full and push hot water to demand with the pressure of inlet water, the small tank in the proposed system can be partially full, and therefore needs a pump to supply hot water. If the tank is empty, the tank pump stops, and cold water is supplied to the backup heater directly. It should be noted that there are always some instances of wrong predictions by the ML models, both in case of volume or time of predicted demand. Therefore, a fast-responding backup system such as an electric heater should be considered in combination with the heat pump system. The prediction data used in the simulation are based on the ML model which shows the highest accuracy between the different evaluated models.

Both conventional approaches were considered as baselines for comparison with the smart hot water system, and the dynamic hourly simulation of all three systems was performed using TRNSYS16. The main parameters used for dynamic simulations of three systems are listed in Table 1. The capacity of on-demand and with-tank systems (heat pump) is considered as 7 kW and 1.7 kW, respectively. The systems are rated based on the maximum demand in houses, to ensure that they can deliver enough heat during the hour of peak demand. The on-demand system includes a direct electric heater in which the efficiency is between 0.9–1, while the heat pump efficiency (COP) is more than 1. Therefore, to deliver the same heat to meet the maximum demand, the heat pump requires a lower rated power. Accordingly, the heat pump is rated lower than the instantaneous system. For storage tanks, the volume is also calculated based on the maximum demand, considering that the effective volume is usually considered as 70 % of the total volume (Bhatia, 2020). For on-demand hot water systems, TRNSYS uses the following equation to calculate the heat loss to the environment:

$$Q_{loss} = UA\left(\frac{T_{in} + T_{setpoint}}{2} - T_{env}\right) + (1 - \eta_{th})Q_{max} \tag{14}$$

In which, UA is the overall loss coefficient (Given in Table 1), T_{in}, $T_{setpoint}$ and T_{env} are the inlet, set point and environment temperatures, respectively. η_{th} is the thermal efficiency of water heater, and Q_{max} is the maximum heating rate of the heater.

For smart hot water system, the overall heat loss coefficient of the tank is calculated based on average heat loss coefficient of wetted and dry areas of the tank at the current time step. In addition, as TRNSYS performs transient simulations, the wall temperature is calculated at each time step based on the thermal conductance of the wall which therefore takes into account the cyclic heating and cooling of the tank.

Table 1
Parameters used in TRNSYS simulation.

Parameter	Value
On-demand system	
Capacity	7 kW
Thermal efficiency	0.98
Overall loss coefficient (UA)	2.51 W/K
With-tank system	
Heat pump capacity	1.7 kW
COP	4.8
Volume of the storage tank	120 L
Diameter and height of the tank	0.32 m × 1.5 m
Thermal conductance of tank	2.5 kJ/h × m^2×K
Setpoint temperature for the tank	60 °C
Smart system	
Heat pump capacity	1.7 kW
COP of heat pump	4.8
Nominal power of pump	0.3 kW
Volume of the storage tank	100 L
Diameter and height of the tank	0.29 m × 1.5 m
Capacity of the backup system	7 kW
Thermal efficiency of backup heater	0.98
Wetted loss coefficient	2.5 kJ/h × m^2×K
Dry loss coefficient	1.6 kJ/h × m^2×K

3. Results and discussion

The first part of this section discusses the performance of the ML models in detail, and the second part focuses on the potential energy reduction by the smart system considering the demand prediction.

3.1. Performance of ML models to predict DHW demand

Developed ML models are trained and tested on each of the selected houses, independently. Then the average of metrics over all 6 houses is used to compare the relative performance of the developed models. The dataset includes 8 months of hourly hot water demand in each house. The first 7 months are used for training and internal validation, then, the final month (equal to 12.5 % of the data) is used for testing. The performance of single, Sequential Multi-task and Parallel Multi-task models are presented in this section.

3.1.1. Single models

Table 2 shows the selected hyper-parameters by the grid search optimization method. These hyper-parameters are used for all 6 houses.

The performance of the single models on each house is presented in Table 3. As mentioned before, the house 6 has a very irregular pattern, which is included to evaluate the performance of different models in irregular conditions. However, as this house is not a representative case, it is not included in the calculation of the average performance for each model.

As can be seen in Table 3, a model can perform better than the other for one house but perform worse for another house. For instance, LASSO shows the best performance for both metrics on the house 5 while RF performs the best on the house 4. So, the average of all 5 houses should be used for comparison. According to the average value of RMSE and R, the RF model shows the best performance, followed by MLP, Lasso, and LSTM. While LSTM has a more complex structure, it is performing worse than other models. LSTM model usually performs better when there is a long-term dependency in data, and therefore the model needs to preserve it in its memory well. The performance of RF and MLP are very close to each other, with RF slightly better on average. The RF model, however, is faster and, therefore, better for the control hardware. The value of RMSE increases by an increase in the hourly demand. So, the low value of RMSE in house 6 compared to other houses is due to the very low demand in this house, and it does not show a higher prediction performance than other houses. For this house, the value of R is a better basis for comparison. In the case of house 6, with an irregular pattern, the RF model again shows the best performance, followed by LASSO, MLP, and LSTM.

3.1.2. Sequential multi-task models

Table 4 shows the optimal hyper-parameters for each model. The hyper-parameters of RF percentage-MLP and RF quartile-MLP are similar because they are actually the same models but with different

Table 2
Selected hyper-parameters for each model.

Model	Hyper-parameter	Value
RF	Number of trees	100
	Main samples split	17
Lasso	α	0.01
MLP	Number of neurons for the first layer	64
	Number of neurons for the second layer	32
	α	0.01
LSTM	Number of hidden layers	1
	Number of neurons	16

Table 3
Performance of single models for prediction of hot water use behavior.

Model	House ID						
	1	2	3	4	5	6	Average[a]
	RMSE						
Lasso	6.77	9.91	16.28	15.21	10.05	2.36	11.64
RF	6.71	9.16	15.78	14.22	10.29	2.35	**11.23**
MLP	6.69	9.16	15.27	15.12	10.17	2.41	**11.28**
LSTM	6.93	10.46	16.21	15.66	10.91	2.51	12.03
	R						
Lasso	0.65	0.53	0.62	0.66	0.58	0.21	0.61
RF	0.66	0.62	0.65	0.71	0.55	0.23	**0.64**
MLP	0.66	0.62	0.67	0.66	0.58	0.11	**0.64**
LSTM	0.64	0.52	0.63	0.64	0.49	0.06	0.58

[a] House 6 with abnormal pattern is not considered in the average.

Table 4
Selected hyper-parameters for Sequential Multi-task models.

Model	Hyper-parameter	Value
RF binary-RF	Number of estimators in classifier and regressor	100
	Minimum samples split	17
MLP binary-MLP	Number of hidden layers in classifier and regressor	2
	Number of neurons per layer 1 and 2 of classifier and regressor	16 and 32
RF percentage-MLP	Number of estimators (RF classifier)	500
	Maximum depth (RF classifier)	9
	Number of hidden layers (MLP regression)	1
	Number of units per layer (MLP regression)	16
RF quartile-MLP	Number of estimators (RF classifier)	500
	Maximum depth (RF classifier)	9
	Number of hidden layers (MLP regression)	1
	Number of units per layer (MLP regression)	16

classes as the classification output.

In two of the Sequential Multi-task models (RF binary-RF and MLP binary-MLP), the classification algorithm just classify the usage of hot water as a binary value (0 – no use, 1 – in use), while in two others (RF percentage-MLP and RF quartile-MLP) the classification algorithm is supposed to predict the level of future hot water use. Hence, in the second case, it is a more difficult task for the classification model. Following, the performance of this classification model is discussed in detail prior to the whole model. A dummy classifier that always predicts the low-level consumption (dominant class) is also used as the benchmark model.

As discussed before, the prediction of usage level (as low, medium or high) in these classification algorithms are either based on the percentage (y_{c1}) or quartiles (y_{c2}). For each of these scenarios, an MLP and an RF model are evaluated to indicate which one performs better to be used by the Sequential Multi-task model. The actual share of these levels for each house is presented in Table 5. The percentage of low consumption levels in all houses is significantly higher than other classes, showing that most of the hot water demand instances are associated with short uses like hand washing, and longer instances like dishwashing happen rarely. It forms an unbalanced data, which in turn is more difficult for classification since most of the instances will be predicted as the dominant class.

Table 6 presents the F1-score of classification methods for each house. As can be seen, all the models outperform the baseline model. Also, classifying the consumption based on percentage levels (y_{c1}) shows a better performance than classifying based on quartile levels (y_{c2}). On average, the RF model shows the best performance in classifying future levels of hot water usage. Accordingly, in the case of two Sequential Multi-task models where the classifier is used to predict the consumption level, the RF algorithm has been used.

The performance of Sequential Multi-task models is shown in Table 7. As can be seen, the RF percentage- MLP model shows the best performance between the Sequential Multi-task models. This is mainly because the RF classification based on the percentage levels has the best performance in classification, and therefore provides more accurate input to the regression model. However, compared to the single RF model, all the Sequential Multi-task models show a lower accuracy. This lower performance is because of two reasons. Firstly, the classification output, which is used by the regression model, is not always true. In this problem, it is expected that the negative impact of wrong classifications has been higher than the positive impact of the right classifications. Secondly, it is expected that the single RF model already extracts useful information from features, and therefore the classification model provides unnecessary information, which reduces the generalization of the regression model. To asses this hypothesis, we evaluated the performance of RF percentage-MLP using an ideal classifier, which predicts all the instances of hot water demand properly, on the house 2. In this case, the RF percentage-MLP will perform significantly better than the single RF model, with a 19 % lower RMSE and a 24 % higher R coefficient. Therefore, better performance of classifiers can result in higher accuracy of Sequential Multi-task models than single models. It can be achieved by the use of more input data, like hourly occupancy of the house, which is, however, not available in this study.

The performance of Parallel Multi-task models is shown in Table 8. The performance of the RF parallel is better than the MLP parallel

Table 6
Performance of classification methods on different demand patterns.

Class types	House ID						
	1	2	3	4	5	6	Average[a]
	RF						
Percentage method	0.58	0.53	0.65	0.69	0.62	0.43	0.62
Quartiles method	0.61	0.51	0.65	0.68	0.61	0.37	0.61
	MLP						
Percentage method	0.34	0.39	0.5	0.51	0.50	0.39	0.45
Quartiles method	0.31	0.37	0.49	0.51	0.45	0.32	0.43
	Dummy classifier						
Percentage method	0.25	0.28	0.24	0.26	0.25	0.29	0.25
Quartiles method	0.26	0.28	0.22	0.26	0.23	0.32	0.25

[a] House 6 with abnormal pattern is not considered in the average.

Table 5
Actual percentage of each DHW consumption level in each house.

Parameter		House ID						
Categorization method	Usage level	1	2	3	4	5	6	Average[a]
Categorizing based on percentages (y_{c1})	Low	77.2	85.8	72.5	79.3	75.1	87.8	78
	Medium	15.1	6.2	21.6	14.1	16.5	96.2	14.7
	High	7.6	7.9	5.8	6.5	8.3	6.8	7.2
Categorizing based on quartiles (y_{c2})	Low	78	85.2	66.9	78.8	70.8	96.2	76
	Medium	17	10.2	22.7	14.4	18.8	2.3	16.6
	High	4.8	4.4	10.2	6.8	10.2	1.4	7.3

[a] House 6 with abnormal pattern is not considered in the average.

Table 7
Performance of Sequential Multi-task models in different houses.

Model	House ID						
	1	2	3	4	5	6	Average[a]
	RMSE						
RF binary-RF	7.62	10.79	16.12	15.41	10.41	2.42	12.07
MLP binary-MLP	8.61	10.51	18.49	16.94	10.65	2.49	13.04
RF percentage- MLP	**6.74**	**9.71**	**16.74**	**14.88**	**10.2**	**2.38**	**11.66**
RF quartile-MLP	6.85	9.92	16.7	14.77	10.14	2.35	11.68
	R						
RF binary-RF	0.59	0.47	0.62	0.65	0.56	0.10	0.58
MLP binary-MLP	0.28	0.44	0.44	0.55	0.51	0.07	0.44
RF percentage- MLP	**0.66**	**0.55**	**0.58**	**0.68**	**0.57**	**0.16**	**0.61**
RF quartile-MLP	0.65	0.54	0.58	0.69	0.57	0.23	0.61

[a] House 6 with abnormal pattern is not considered in the average.

Table 8
Performance of Parallel Multi-task models in different houses.

Model	House ID						
	1	2	3	4	5	6	Average[a]
	RMSE						
RF parallel	7.11	10.07	17.39	16.73	10.74	2.37	12.41
MLP parallel	9.00	10.64	18.75	15.94	10.74	2.42	13.02
	R						
RF parallel	0.66	0.56	0.60	0.60	0.58	0.19	0.6
MLP parallel	0.22	0.41	0.43	0.62	0.50	0.09	0.44

[a] House 6 with abnormal pattern is not considered in the average.

model, which again shows the superiority of RF for this problem. However, its accuracy is lower than the best case of single and Sequential Multi-task models. It shows that sharing information between classification and regression tasks does not result in higher accuracy in this problem.

Considering the results from all three groups of models, it can be concluded that a single RF model is the best model for the prediction of hot water use behavior when the only available data is the historical data of hot water use. In addition, RF offers great potential for practical implementation in control systems or the Internet of Things, as it is faster than other models to train, so it does not require high computational capacity.

For a visual comparison of different models, the hourly predictions by the best model of each approach are presented in Fig. 9 for one week in March of 2018. It can be seen that in most cases, the models predicts the time of hot water demand but underestimates the volume. Therefore, the volumetric demand, which is very challenging to be predicted properly, is the main source of difference in the accuracy of different models. Fig. 9 also highlights that in case of implementing the prediction models in practice, either a backup system should be used or the hot

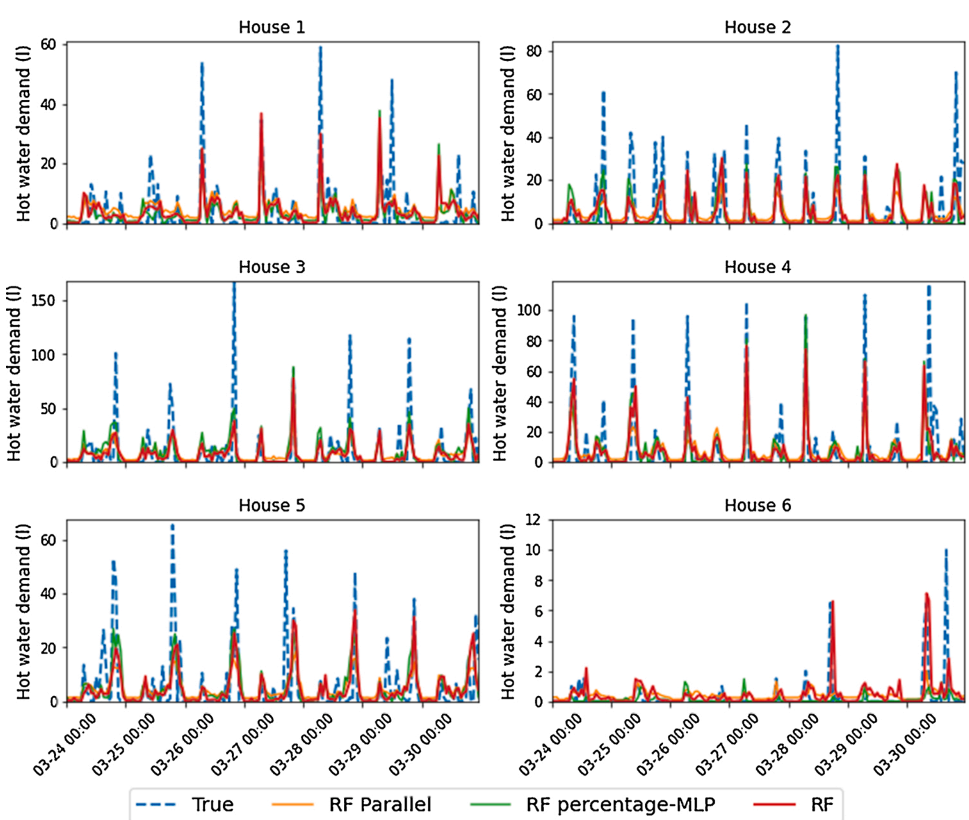


Fig. 9. Hourly predictions by the best model of each approach.

water should always be produced with a percentage higher than the predicted volume to ensure the user satisfaction. It will be better illustrated in the next section.

3.2. Energy reduction potential

Dynamic hourly simulations of three hot water systems are performed in TRNSYS16 simulation studio that provides an extremely flexible environment for dynamic modeling of different thermal systems. In TRNSYS simulation environment, rule-based control methods can be easily implemented by the use of available controller components, and model-free smart controls can also be implemented by integrating Python or MATLAB to TRNSYS. In this research, the hourly data of real and predicted demands are imported to TRNSYS for the simulation of conventional and smart systems, respectively. The prediction data are based on the single RF model, which indicated the best performance between different models.

Fig. 10 shows the hourly energy use of the 3 systems over one month. In the *with-tank system*, the control system monitors the average temperature of the water tank and switches ON the heat pump when the temperature falls below the 60 ℃ and turns it OFF when it goes higher than 65 ℃. Therefore, as can be seen in the figure even if there is no demand the *with-tank system* turns ON frequently to compensate the heat losses of storage tank. The hourly energy use of the *smart system* is more frequent than the *on-demand system* but lower in magnitude because the MLP model usually predicts more instances of demand than in reality but with lower volume. In the case of proper predictions, the *smart system* produces most of the required amount of hot water with a heat pump before the demand. In these cases, most of heating is done by the heat pump and the energy use of the backup system is very low. However, there are some cases when the model predicts the demand, but there is no actual demand. In such cases, the heat pump of the smart system repeatedly produces hot water and stores it in a small tank, where it gets cold and results in energy wasting. This is more problematic in case of long time absence of occupants, which has happened in house 2 between the hours 200–350. This can be solved by the integration of occupancy sensors in the smart system, or by manual adjustment of occupants before a long absence.

The cumulative energy use in different houses over one month is shown in Fig. 11 and the percentage of energy savings are shown in Table 9. The average accuracy of models is not the only factor that determines the relative potential of energy use reduction. One of the main factors that can affect the resulting energy use of a *smart system* is whether the wrong prediction is close to the actual demand in terms of volume and time or not. If the wrong prediction is close to the real demand, the preheated hot water will be used when it is still warm and therefore reduce the energy demand of the backup system. The results show that it often happens in houses 3 and 4 that have higher volume and more frequent hot water demand. Another important factor that reduces the potential of energy reduction by the *smart system* is the fact that, when the actual demand is zero, the RF model sometimes predicts a low amount of water use. Therefore, this low amount will be produced and stored by the heat pump system. This amount of hot water gets cold after some time, and when the next volume of hot water is predicted, newly generated hot water is supplied to the tank and drops in temperature by mixing with cold water remained in the tank. It happens more in the case of house 4, thus resulting in a lower energy use reduction. This can be improved by implementing additional control rules, such as draining the small tank once it is cold.

Between the conventional systems, the with-tank system shows lower energy use because in this system, although there is a heat loss by a storage tank, hot water is produced with a heat pump with significantly higher efficiency compared to instantaneous heater. As can be seen in Fig. 11, the smart system consumes lower energy than conventional systems in houses 1, 3, 4 and 5. This is because in these houses there is no long-time interruption over the month, and therefore the smart control system can better learn and adapt to the demand pattern. In house 2, however, the smart system consumes 2.4 MJ higher energy than the conventional system because of the long time of no demand in this house. Similarly, in house 6, the smart system consumes significantly higher energy than the conventional systems because in this house there are only a few instances of demand and, therefore, the demand prediction model is not able to learn the demand, accordingly most of the instances of hot water production by the smart system results to the energy waste.

Summing up the results, it can be concluded that if the house is occupied and there is no long time interruption in demand pattern, the smart hot water system can learn the pattern and provide energy use reduction compared to conventional approaches. While both of the with-tank and smart systems use a heat pump as the main part of water

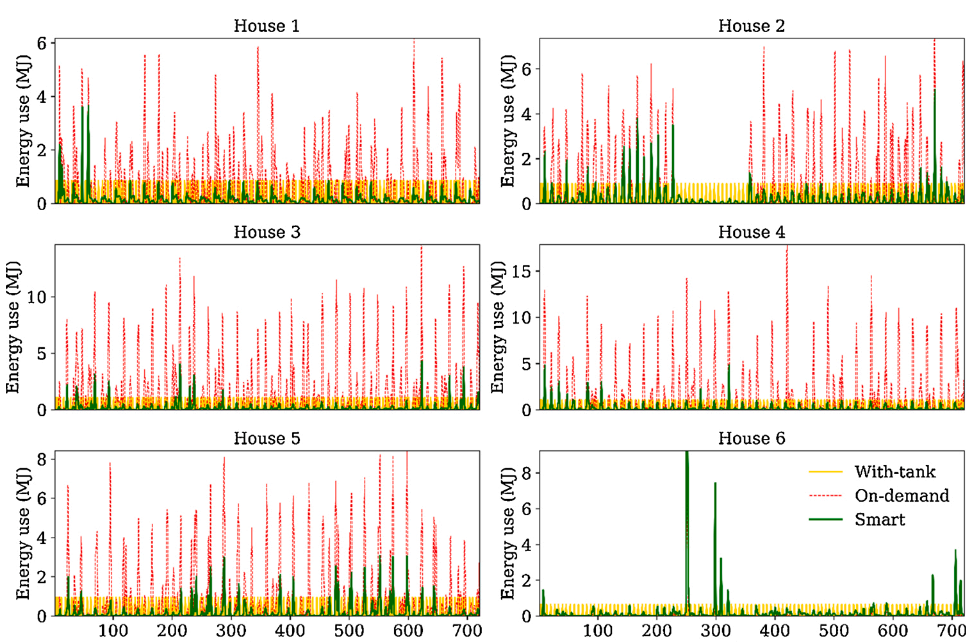


Fig. 10. Hourly energy use of three systems in 6 houses over one month.

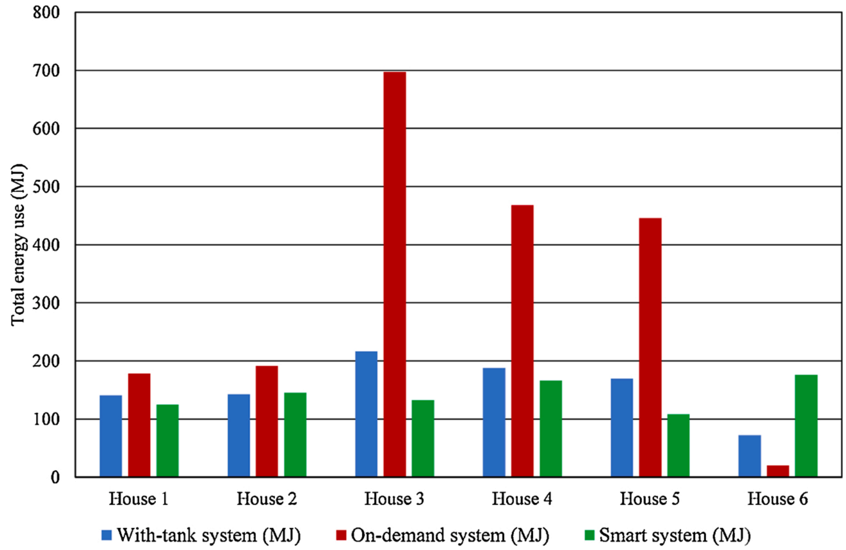


Fig. 11. Total energy use by different systems over one month.

Table 9
Energy saving percentage by smart system in different houses.

	House 1	House 2	House 3	House 4	House 5	House 6
Saving compared to on-demand	30.09	24.11	80.96	64.47	75.76	−769.20
Saving compared to with-tank	11.33	−1.68	38.67	11.48	36.46	−143.57

heating, maximum energy savings using the smart system corresponds to the tank heat losses of the with-tank system. In case of the buildings with long time interruptions, the smart system can be equipped with occupancy detection methods to adjust to the absence periods automatically, or can be manually adjusted by the occupants before a long absence.

4. Conclusions

The common challenge of conventional domestic hot water production strategies lies in the stochastic nature of hot water-related use behavior of occupants. Consequently, the energy demand for hot water production has not decreased over time and accounts for a significant share of energy use in modern, well-insulated houses. This research explores the performance of different ML models for learning this highly stochastic behavior and the associated energy reduction potential by the learning-based hot water generation. A set of single, Sequential Multi-task and Parallel Multi-task models were covered by this study. The following conclusions based on the results can be drawn:

- Predicting the real value of hot water demand is very challenging; hence all the ML models, with optimized architecture and engineered features, do not reach high accuracy;
- The optimized single models (MLP, RF, LSTM) show a better average performance than Sequential Multi-task and Parallel Multi-task models. The poor performance of Sequential Multi-task models is mainly caused by the wrong predictions of the classification model, which is fed to the regression models;
- The single RF model, with the RMSE and R values of 11.23 and 0.64, shows the best average performance over all of the models. Therefore, it is implemented in the hot water production system to evaluate the potential of energy use reduction;
- Smart hot water system learns the user behavior and provides significant energy saving compared to the conventional systems, from 30 % to 81 % compared to the on-demand system and from 11 % to 38.6 % compared to the with-tank system. However, in house 2 the smart system slightly use more energy than with-tank system, and in house 6 smart system consumes more energy than both conventional systems. This is because of existing long periods of no-demand in these buildings. In this case, the smart hot water system can be integrated with occupancy sensors to identify long periods of non-occupancy and turn-off the system;

Summing up the results, regarding that the hot water use behavior of the occupants is highly stochastic and can change over time, a hot water system that can learn the stochastic use behavior and continuously adapt to the demand will be more efficient than a system with predefined control approach. Further research is required on different methods to better learn highly imbalanced hot water use data and different scenarios to control production system based on the predictions.

Dataset and python codes

To facilitate future research on this topic and reproduction of the results, the Python codes are shared as the supplemental files. The dataset is publicly available at Booysen and Roux (2019).

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgment

We gratefully acknowledge Dr. Thinus Booysen, Associate Professor of Stellenbosch University (South Africa), and his colleagues by kindly sharing their experimental dataset that was used in this study.

References

Bhatia A. Design Considerations for Hot Water Plumbing (Course No: M06-029): Continuing Education and Development, Inc. 9 Greyridge Farm Court, Stony Point, NY 10980.

Booysen, M., Engelbrecht, J., Ritchie, M., Apperley, M., & Cloete, A. (2019). How much energy can optimal control of domestic water heating save? *Energy for Sustainable Development, 51*, 73–85.

Booysen M.J., Roux M. Hot water usage dataset for 98 electric water heaters. https://goo.gl/nswDGF2019.

Brazeau, R. H., & Edwards, M. A. (2011). A review of the sustainability of residential hot water infrastructure: Public health, environmental impacts, and consumer drivers. *College Publishing, 6*(4), 77–95.

Bünning, F., Huber, B., Heer, P., Aboudonia, A., & Lygeros, J. (2020). Experimental demonstration of data predictive control for energy optimization and thermal comfort in buildings. *Energy and Buildings, 211*, Article 109792.

Calvache, M. F., Santos, R., Antunes, P., & Santos-Reis, M. (2018). Long-term monitoring of mediterranean socio-ecological systems. *Agroforestry Systems*, 1–15.

Carvalho, A. D., Moura, P., Vaz, G. C., & de Almeida, A. T. (2015). Ground source heat pumps as high efficient solutions for building space conditioning and for integration in smart grids. *Energy Conversion and Management, 103*, 991–1007.

Forecasting domestic hot water demand in residential house using artificial neural networks. In Delorme-Costil, A., & Bezian, J.-J. (Eds.), *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*, (2017).

Prediction of DHW energy use in a hotel in Norway. In Dmytro, I., Natasa, N., Lekang, SÅ, Igor, S., Wester, P. T. S., et al. (Eds.), *IOP Conference Series: Materials Science and Engineering*, (2019). IOP Publishing.

Dong, J., Munk, J., Cui, B., Boudreaus, P. R., & Kuruganti, T. (2018). *Machine-learning model of electric water heater for electricity consumption prediction*.

Fischer, D., Wolf, T., Scherer, J., & Wille-Haussmann, B. (2016). A stochastic bottom-up model for space heating and domestic hot water load profiles for German households. *Energy and Buildings, 124*, 120–128.

Gelažanskas, L., & Gamage, K. A. (2015a). Forecasting hot water consumption in residential houses. *Energies, 8*(11), 12702–12717.

Forecasting hot water consumption in dwellings using artificial neural networks. In Gelažanskas, L., & Gamage, K. A. (Eds.), *2015 IEEE 5th International Conference on Power Engineering, Energy and Electrical Drives (POWERENG)*, (2015).

Guo, Y., Wang, J., Chen, H., Li, G., Liu, J., Xu, C., et al. (2018). Machine learning-based thermal response time ahead energy demand prediction for building heating systems. *Applied Energy, 221*, 16–27.

Heidari, A., & Khovalyg, D. (2020). Short-term energy use prediction of solar-assisted water heating system: Application case of combined attention-based LSTM and time-series decomposition. *Solar Energy, 207*, 626–639.

Heidari, A., Roshandel, R., & Vakiloroaya, V. (2019). An innovative solar assisted desiccant-based evaporative cooling system for co-production of water and cooling in hot and humid climates. *Energy Conversion and Management, 185*, 396–409.

Heidari, A., Rostamzadeh, H., & Avami, A. (2019). A novel hybrid desiccant-based ejector cooling system for energy and carbon saving in hot and humid climates. *International Journal of Refrigeration, 101*, 196–210.

Combined desiccant-ejector cooling system assisted by Organic Rankine Cycle for zero-power cooling and dehumidification. In Heidari, A., Rostamzadeh, H., & Khovalyg, D. (Eds.), *Journal of Physics: Conference Series*, (2019). IOP Publishing.

Development of standardized domestic hot water event schedules for residential buildings. In Hendron, R., & Burch, J. (Eds.), *ASME 2007 Energy Sustainability Conference*, (2007). American Society of Mechanical Engineers Digital Collection.

Hohne, P., Kusakana, K., & Numbi, B. (2019). A review of water heating technologies: An application to the South African context. *Energy Reports, 5*, 1–19.

Smartphone-based human activity recognition using CNN in frequency domain. In Jiang, X., Lu, Y., Lu, Z., & Zhou, H. (Eds.), *Asia-Pacific Web (APWeb) and Web-Age Information Management (WAIM) Joint International Conference on Web and Big Data*, (2018). Springer.

Ju, F., Fan, X., Chen, Y., Wang, T., Tang, X., Kuang, A., et al. (2018). Experimental investigation on a heat pump water heater using R744/R290 mixture for domestic hot water. *International Journal of Thermal Sciences, 132*, 1–13.

Kapsalis, V., & Hadellis, L. (2017). Optimal operation scheduling of electric water heaters under dynamic pricing. *Sustainable Cities and Society, 31*, 109–121.

Kazmi, H., Mehmood, F., Lodeweyckx, S., & Driesen, J. (2018). Gigawatt-hour scale savings on a budget of zero: Deep reinforcement learning based optimal control of hot water systems. *Energy, 144*, 159–168.

Kenway, S. J., Binks, A., Scheidegger, R., Bader, H.-P., Pamminger, F., Lant, P., et al. (2016). Household analysis identifies water-related energy efficiency opportunities. *Energy and Buildings, 131*, 21–34.

Laaroussi, Y., Bahrar, M., El Mankibi, M., Draoui, A., & Si-Larbi, A. (2020). Occupant presence and behavior: A major issue for building energy performance simulation and assessment. *Sustainable Cities and Society*, Article 102420.

Li, J., Yu, Z. J., Haghighat, F., & Zhang, G. (2019). Development and improvement of occupant behavior models towards realistic building performance simulation: A review. *Sustainable Cities and Society, 50*, Article 101685.

Luo, J. T., Joybari, M. M., Panchabikesan, K., Sun, Y., Haghighat, F., Moreau, A., et al. (2020). Performance of a self-learning predictive controller for peak shifting in a building integrated with energy storage. *Sustainable Cities and Society*, Article 102285.

Predicting domestic hot water demand using machine learning for predictive control purposes. In Maltais, L.-G., & Gosselin, L. (Eds.), *Multidisciplinary Digital Publishing Institute Proceedings*, (2019).

Marszal-Pomianowska, A., Zhang, C., Pomianowski, M., Heiselberg, P., Gram-Hanssen, K., & Hansen, A. R. (2019). Simple methodology to estimate the mean hourly and the daily profiles of domestic hot water demand from hourly total heating readings. *Energy and Buildings, 184*, 53–64.

Ngo, N.-T. (2019). Early predicting cooling loads for energy-efficient design in office buildings by machine learning. *Energy and Buildings, 182*, 264–273.

Rahman, A., Srikumar, V., & Smith, A. D. (2018). Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. *Applied Energy, 212*, 372–385.

Ritchie, M., Engelbrecht, J., & Booysen, M. (2020). *A probabilistic hot water usage model and simulator for use in residential energy management*.

Roux, M., Naude, N., Booysen, M., & Barnard, A. (2017). Electric water heaters in smartgrids: Individual savings versus network peak load management. *SAUPEC In Stampa*.

Roy, S. S., Roy, R., & Balas, V. E. (2018). Estimating heating load in buildings using multivariate adaptive regression splines, extreme learning machine, a hybrid model of MARS and ELM. *Renewable and Sustainable Energy Reviews, 82*, 4256–4268.

Ruelens, F., Claessens, B. J., Quaiyum, S., De Schutter, B., Babuška, R., & Belmans, R. (2016). Reinforcement learning applied to an electric water heater: From theory to practice. *IEEE Transactions on Smart Grid, 9*(4), 3792–3800.

Sanchis-Cano, A., Romero, J., Sacoto-Cabrera, E. J., & Guijarro, L. (2017). Economic feasibility of wireless sensor network-based service provision in a duopoly setting with a monopolist operator. *Sensors, 17*(12), 2727.

Sernhed, K., Johansson Kallioniemi, P.-O., Wollerstrand, J., Ottosson, K., & Karlsson, L. (2018). *Cool ways of using low grade Heat Sources from Cooling and Surplus Heat for heating of Energy Efficient Buildings with new Low Temperature District Heating (LTDH) Solutions: Report on solutions for avoiding risk of legionella*.

SIA.381/1. (2011). *Plants for domestic hot water in buildings - basics and requirements*. Available from: http://shop.sia.ch/normenwerk/architekt/385-1_2011_d/D/Product.

Suisse Energie. (2016). *Production efficace de l'eau chaude sanitaire*. Suisse Energie.

Thinsz, D. (2019). *A comparative study of machine learning algorithms for short-term building cooling load predictions*.

Zhou, Z., Wang, C., Sun, X., Gao, F., Feng, W., & Zillante, G. (2018). Heating energy saving potential from building envelope design and operation optimization in residential buildings: A case study in northern China. *Journal of Cleaner Production, 174*, 413–423.