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Machine-learning-based models for predicting the performance of Ground-source heat pumps using experimental data from a residential Smart Home in California.

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ABSTRACT

Ground-source heat pumps (GSHP) reject (extract) heat to a lower (higher) temperature sink (source) as compared with air-source heat pumps which allows them to operate more efficiently. With the rapid development in the field of artificial intelligence, data-driven based Machine-Learning (ML) models are playing an important role in simulating various building energy systems including GSHP. In this paper, ML models have been applied to predict the performance of a water-water GSHP. The models presented in this paper, require climate data (which is readily available or easily measurable) and the power consumed in the previous time-step for predicting the power consumption for the current time-step. The models were rigorously trained using measured data from a residential technological demonstration home located in Davis, California. Data spanning from October 2018 to April 2019), i.e. heating mode, was used in the study. Eight linear and non-linear ML models were employed and the results show that the linear models namely, multiple linear regression (MLR), elastic net (ELN) and support vector regression (SVR) can predict the power consumption with a very high level of accuracy. Within the linear models, the coefficient of variation of the root mean squared error (CV-RMSE) for the MLR was 4.04062 which was 0.19% and 0.05% less than the ELN and SVR model respectively. Within the five non-linear models, gradient boosting decision tree (GBDT) exhibited the lowest CV-RMSE i.e. 4.26141 (which is 5.46% higher than the MLR model). The CV-RMSE for extreme gradient boosting trees (XGBT) was the highest (i.e. 45.42% higher than the MLR model). Thus MLR model can be used to accurately predict the power consumption of the GSHP system.

INTRODUCTION

Buildings account for around 40% of the total world energy use (Shukla et al., 2022) and Heating Ventilation and Air-Conditioning (HVAC) systems in buildings account for the majority of this energy (Kumar et al., 2018). Thus reducing the energy consumption in buildings is essential in the effort to reduce GHG emissions.

One effective method of reducing the energy consumption of buildings is accurate prediction of the HVAC load profile and performance which allows an effective energy management & control plan to be formulated in advance (Fan et al., 2019). There are two methods for predicting HVAC profile and performance, 1) physical simulation models and 2) Soft computational data-driven models. The latter is rapidly gaining popularity with the development of artificial intelligence and Internet of Things (IoT) (L. Zhang et al., 2021). In this paper, several data driven based Machine Learning (ML) models have been applied for predicting the performance of a high-efficiency GSHP installed in a design house at Davis, California.

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LITERATURE REVIEW

In order to design, optimize and control complex HVAC systems, several ML based models have been presented in the past. Park et al. (2018) presented an hourly GSHP system performance prediction model based on a multiple linear regression (MLR) and an artificial neural network (ANN). Entering source-side temperature, both entering and leaving load-side temperatures, ambient air temperature along with the heating load data was used to predict the system overall Coefficient of Performance (COP). Sun et al. (2015) developed an artificial neural network (ANN) model and an adaptive neuro-fuzzy inference system (ANFIS) model to predict the COP of the heat pump using both entering and leaving source-side and load-side temperatures. Lu et al. (2019) used an ensemble approach using random forest (RF) for hourly performance predictions for GSHP coupled to one hundred vertical type GHEs. In addition to parameters used by previous researchers, models by Lu et al. (2019) also required both load-side and source-side flowrates and pressures along with the cooling to heating load ratio. Although the accuracies of some of these studies is reasonably high, these models can only be used if the load-side and source-side fluid temperatures (and in some cases even the heating loads) are known which is generally not the case. In contrast, the models presented in this paper, after they have been trained, only need climate data (Ambient air temperature, relative humidity, solar insolation and previous time-step power for predicting the power for next time-step).

RESEARCH METHODOLOGY

The overall research architecture of the GSHP performance (power prediction) is shown in Figure 1. The process can be divided into two stages. The first stage is data preprocessing in which data cleaning and feature selection is done to get meaningful dataset. In the next stage training, testing and comparison of various ML model is carried out. Outliers are eliminated from the original data by using the rule of interquartile range i.e. the values outside the specified range are regarded as abnormal data and imputed.

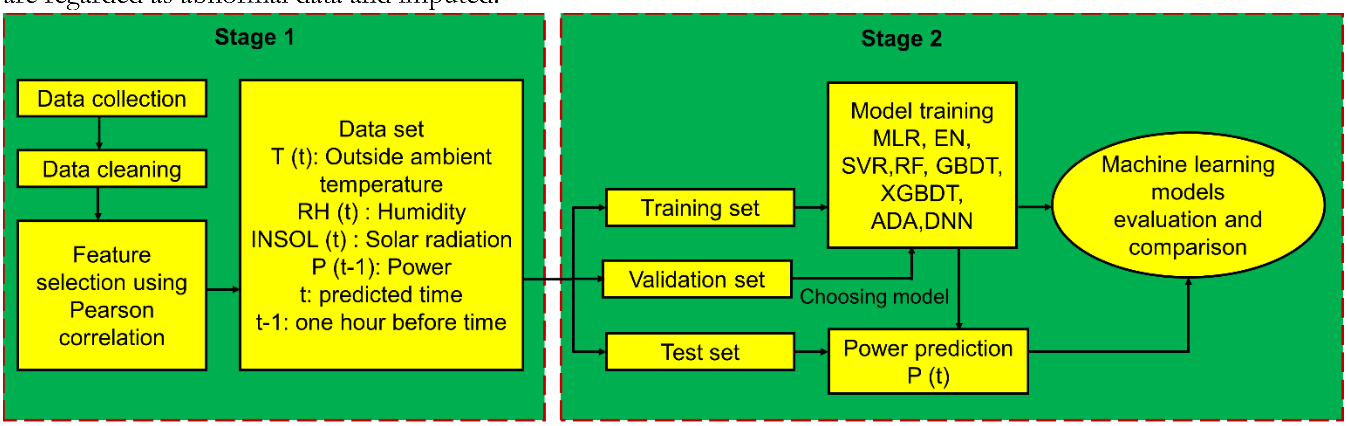

Figure 1 Research Architecture

Selection of model inputs is one of the most important tasks in machine learning. Feature selection is the process of reducing the number of input variables when developing a predictive model. If the number of input variable in model is too high, information redundancy and interference will occur. Therefore, feature selection is effective in reducing the dimensionality, removing irrelevant and redundant feature and thereby, reducing the computational cost. There are several feature selection methods available in the literature (L. Zhang & Wen, 2019), out of which statistical based method (Pearson correlation) is used in this research. Eight prediction algorithms are employed in this study, including multiple linear regression (MLR), elastic net (ELN), support vector regression (SVR), random forests (RF), gradient boosting decision tree (GBDT), extreme gradient boosting trees (XGBT), Adaboost (ADA) and deep neural network (DNN). These prediction techniques are selected due to their popularity in previous studies (L. Zhang et al., 2021). Details of each ML model is widely available in the literature (Ahmad et al., 2014; Lu et al., 2019; L. Zhang & Wen, 2019) and therefore is not repeated here. The entire data-set is randomly divided into training data (50%), testing data (30%) and validation data (20%). The Scikit-learn library in Python is utilized to implement these prediction techniques and the grid search method is used to optimize the parameters. Normalization of the input feature is achieved via z-score normalization.

Case Study

Data measured from Honda Smart Home was used in this study which is a net-zero energy demonstration house located in Davis, California and serves as a pilot home or "living laboratory" for various advance building energy technologies. The building employs eight large diameter shallow-bore vertical helical GHEs connected in parallel and are coupled to a water-to-water heat pump. Space conditioning to the house using radiant floor delivery on the first floor and by using radiant ceiling panels on the second floor by the heat pump only (i.e. no auxiliary systems for peak hours). Table 1 reports various design the characteristics of this site (Davis Energy Group, 2013). Further details have been provided by Najib et al. (2019). The site has an extensive monitoring scheme under which measurements are obtained every minute by in-situ sensors. All climate parameters, temperature and flow-rates at numerous locations for the source-side (ground loop), load-side (hydronic building loop), indoor air etc. Power consumed is also measured for each application. The subsequent section discusses the subset of measured parameters that were used for the ML models.

Table 1. Design parameters at the case study site

Parameters	Values
Building parameters	
-Total conditioned floor area	189.5 m^2 (2040 ft)
-No. of stories	2
Ground Heat Exchanger	
-Helix pitch & diameter	0.1524 m (6 in.) & 0.5588 m (22 in.)
-GHE center to center distance	4.572 m (15 ft)
-Depth of helical pipe top	0.914 m (3 ft)
-Helical pipe height	5.1816 m (17 ft)
-Nominal pipe diameter	½ in. (nominal size)
-Tube material	High Density Polyethylene (HDPE)
-Backfill	Native soil
-Heat transfer fluid/ heat pump type	Water/ water-water
-Heat Pump nominal capacity	Heating: 6.27 kW (21380 Btu/h) Cooling: 7.33 kW (25000 Btu/h)

Feature Selection and Hyperparameter Optimization

In this study, average hourly data from 1st October, 2018 to 30th April, 2019 is utilized. Although summer and winter season data can be analyzed using similar techniques, only results for winter data are presented for the sake of brevity. In total, the dataset contains 5089 observations. As mentioned in the literature review section, the aim of this paper is to be able to predict the heat pump power consumption using climate data. Therefore, the input feature space was restricted to only climate parameters (Ambient temperature, relative humidity, solar insolation, rainfall, wind direction and wind speed) and power for previous temperatures. Pearson correlation between each feature and the power was calculated which is shown Table 2. The result shows that previous time-step power has the strongest correlation with the predicted time-step power. Solar radiation has a weak correlation, but it is taken as an input feature as it affects both the load side (reduced solar heat gain by the building leads to a higher demand for heating from the heat pump) and the source side (higher solar radiation incident on the ground, allows higher temperatures at the source side). Thus solar radiation is related to various other parameters, which is why it was included in the analysis for completeness. Features such as wind speed, wind direction and rainfall have a very weak correlation and were thus excluded from the analysis.

Table 2. Results for correlation analysis

	T °C (°F)	RH (%)	INSOL Wm^{-2} (BTU ft^{-2} h^{-1})	Rainfall mm (in.)	Wind speed ms^{-1} (mph)	Wind direction °	P (t-1) kW (BTU h^{-1})
Correlation	-0.16	0.18	-0.09	-0.009	-0.039	-0.037	0.98

Table 3 presents the summary of numeric variables in the dataset. Figure 2 shows the power profile in the data set. As it is seen from the figure that power load distribution has different pattern, on some intervals it has significantly larger values, therefore it is important to select the prediction model which has ability to identify the pattern distribution efficiently. The hyperparameter tuning is done by using grid search method with 3 cross fold validation. The optimized parameters are shown in Table 2. In this study the number of neurons at each hidden layer in DNN model is 6 and Mini-Batch training strategy is utilized in the training process to improve the data utilization.

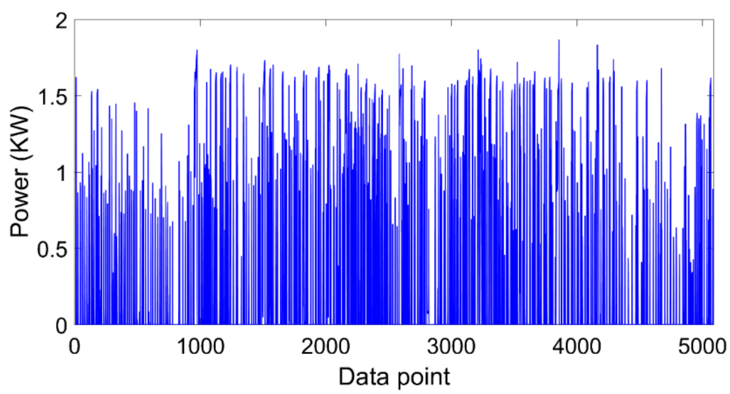

Figure 2 Power data profile in the dataset

Table 3. Summary of numeric variable in the dataset

Variable	Min	Mean	Max
T	-0.74°C (30.67°F)	12.74°C (54.94°F)	26.81°C (80.25°F)
RH (%)	7.06	60.54	88.10
INSOL	0	150.34 Wm^{-2} (47.91 BTU ft^{-2} h^{-1})	641.57 Wm^{-2} (204.46BTU ft^{-2} h^{-1})
P (kW)	0	0.25 kW (853 BTU h^{-1})	1.86 kW (6346 BTU h^{-1})

Table 4. Hyperparameter optimization

S.no	Model	Parameters	Start	Stop	Step	Optimized parameter
1	SVR	C	1	10	1	9
		epsilon	0.001	0.2	0.00995	0.001
2	ELN	L1_ratio	0	1	0.01	0.99
		alpha	1.00E-05	1.00E-01	0.019998	0.0001
3	RF	Max depth	3	11	1	6

		n_estimator	50	200	10	189
4	GBDT	Learning rate	0.01	0.2	0.01	0.0699
		Max depth	3	11	1	3
		n_estimator	50	200	10	150
5	ADA	Learning rate	0.01	0.2	0.01	0.0699
		Max depth	3	11	1	6
		n_estimator	50	200	10	70
6	XGBT	Learning rate	0.01	0.2	0.01	0.19
		Max depth	3	11	1	3
		n _estimator	50	200	10	60
7	DNN	learning_rate_init	0.001	0.01	0.0009	0.009999
		max_iter	100	200	10	100
		hidden layer size	2	6	1	6

RESULT AND DISCUSSION

The prediction performance is evaluated by three metrics, i.e., the squared correlation coefficient (R2), mean absolute error (MAE), and coefficient of variation of the root mean squared error (CV-RMSE).

$$MAE = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{n} \tag{1}$$

$$CV - RMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}}{\frac{\sum_{i=1}^{n}\hat{y}_i}{n}} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{3}$$

Where n represents the total number power values (data points), y_i represents the actual power value, $\hat{y}_i$ represents the predicted value of power from the model, and $\bar{y}_i$ represents the average values of the actual power. CV-RMSE is considered a reasonable statistical evaluation index and if its value is less than 10% then the model is sufficiently close to the physical reality (W. Zhang et al., 2021). The closer the value of R^2 is to 1, the better the prediction accuracy of the model. Table 4 summarizes the resulting RMSE, CV-RMSE, R^2 and MAE. It is shown from the table that the resulting CV-RMSE value of all models are under 10% which shows that all models can be used for the prediction of power.

The prediction performance of ensemble machine learning algorithms i.e. (RF, GBDT, XGBDT, ADA) and DNN which are non-linear models are less than the linear machine learning models i.e., (MLR, ELN, and SVR). This is expected as the output i.e. predicted power consumption of current time-step is highly correlated with the previous time-step power. Out of these eight ML models, XGBDT has the lowest performance and the resulting CV-RMSE value is 5.876, MAE is 0.00450 and R^2 is 0.99916. Comparison within the non-linear ML models (i.e. ensemble and DNN) shows that GBDT has the highest accuracy with CV-RMSE value of 4.261, MAE of 0.00415 and R^2 of 0.99956. Within the linear ML models (MLR, ELN and SVR), MLR has the highest accuracy with CV-RMSE value of 4.04062, MAE is 0.00389 and R^2 is 0.99960.

Table 5. Prediction performance on testing data

Method	MAE	RMSE	R^2	CV-RMSE
MLR	0.00389	0.00992	0.99960	4.04062
ELN	0.00361	0.00994	0.99960	4.04849
SVR	0.00398	0.00993	0.99960	4.04268
RF	0.00425	0.01078	0.99953	4.38983
GBDT	0.00415	0.01046	0.99956	4.26141

ADA	0.00450	0.01085	0.99952	4.42004
XGBT	0.00783	0.01441	0.99916	5.87600
DNN	0.00537	0.01083	0.99952	4.41048

Figure 3 and Figure 4 show the actual power and the error (actual-predicted power) for all the ML models for the entire testing data. Figure 3 depicts the performance of the linear ML models. It can be seen that the power predicted by all three models is very close and the power predicted by MLR and ELN are indistinguishable in the figure. The errors lie within the range of 0.05 kW to -0.05 kW. The lower figure shows the same parameters over a magnified time scale (Jan 1st, midnight to Jan 5th, midnight i.e. 4-day period). It should be noted that only the training data is shown in the figures and the missing points are those that were randomly selected as training data. As expected, most errors are encountered when the models are used to predict non-zero power consumption values.

Figure 4 illustrates the performance of the non-linear ML models. It can be seen that the error band for the non-linear ML models is larger (0.11 kW to -0.09 kW) than that for the linear models. The trend shows that XGBDT and DNN models generally have lower accuracies while the remaining three models shown overall better accuracy.

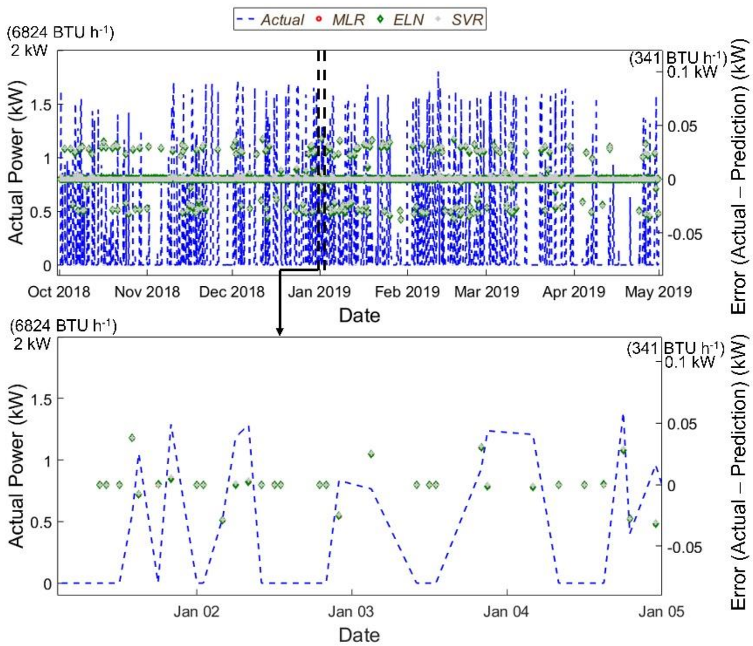

Figure 3 Upper figure shows the actual power consumption (left y-axis) and the error (actual – predicted power) (right y-axis) for each linear ML model for the entire testing data. Lower figure shows the same parameters over a magnified time scale (Jan 1st, midnight to Jan 5th, midnight i.e. 4-day period).

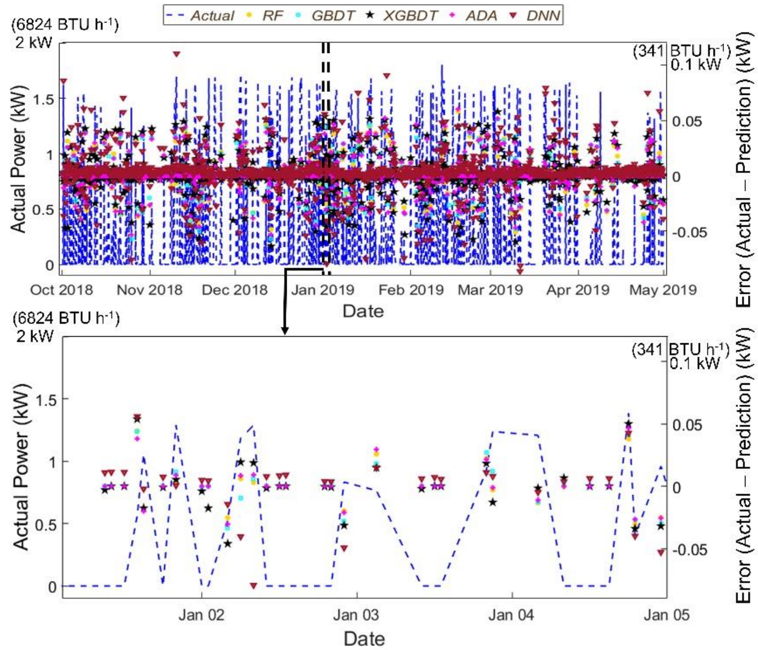

Figure 4 Upper figure shows the actual power consumption (left y-axis) and the error (actual – predicted power) (right y-axis) for each non-linear ML model for the entire testing data. Lower figure shows the same parameters over a magnified time scale (Jan 1st, midnight to Jan 5th, midnight i.e. 4-day period).

CONCLUSION

The results indicate that using only climate data (which is readily available or easily measurable) and the power consumed in the previous time-step, the linear ML models can predict the power consumption to a very high level of accuracy. Within the linear models, the coefficient of variation of the root mean squared error (CV-RMSE) for the MLR was 4.04062 which was 0.19% and 0.05% less than the ELN and SVR model respectively. Within the five non-linear models, gradient boosting decision tree (GBDT) exhibited the lowest CV-RMSE i.e. 4.26141 (which is 5.46% higher than the MLR model). In conclusion, MLR model can be used to accurately predict the power consumption of the GSHP system. Further work on applying these models to cooling data is also underway.

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