Building energy information: demand and consumption prediction with machine learning models for sustainable and smart cities

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Abstract. Building energy consumption plays an essential role in urban sustainability. The prediction of the energy demand is also of particular importance for developing smart cities and urban planning. Machine learning has recently contributed to the advancement of methods and technologies to predict demand and consumption for building energy systems. This paper presents a state of the art of machine learning models and evaluates the performance of these models. Through a systematic review and a comprehensive taxonomy, the advances of machine learning are carefully investigated and promising models are introduced.

Keywords: machine learning, smart cities, IoT, deep learning, big data, soft computing, sustainable urban development, building energy, energy demand, and consumption, sustainable cities

Nomenclatures

Generalized boosted regression	GBR	Feed-forward neural networks	FFNN
Deep learning	DL	Particle swarm optimization	PSO
Artificial neural network	ANN	Random forest	RF
Extreme learning machine	ELM	Non-random two-liquid	NRTL
Machine learning	ML	Recurrent neural network	RNN
Support vector machine	SVM	Partial least squares	PLS
Wavelet neural networks	WNN	Discriminant analysis	DA
Support vector regression	SVR	Principal component analysis	PCA
Genetic algorithm	GA	Linear discriminant analysis	LDA
Multi layered perceptron	MLP	Autoregressive integrated moving average	ARIMA
Long short-term memory	LSTM	Least-squares	LS
Decision tree	DT	Sparse Bayesian	SB
Response surface methodology	RSM	Multi criteria decision making	MCDM
Back propagation neural network	BPNN	Genetic programming	GP
Centroid mean	CM	Multi linear regression	MLR
Adaptive neuro fuzzy inference system	ANFIS	Step-wise Weight Assessment Ratio Analysis	SWARA
Analytic network process	ANP	Multi Objective Optimization by Ratio Analysis	MOORA
Radial basis function	RBF	Nonlinear autoregressive exogenous	NARX

1   Introduction

The energy is one of the essential aspects of smart cities [1]. The sustainability factor of urban development is a direct function of energy production and consumption of every city [2]. The energy consumption of buildings is responsible for a significant amount of energy used in cities [3]. From this perspective, the prediction of demand and consumption is essential in the development of smart cities of the future [4].

Machine learning (ML) has recently well contributed to advancing the accurate and reliable prediction models [5-9]. Literature includes the various application domains and the ML learning methods used in these areas [10-26]. ML methods have shown to outperform most of the conventional modeling techniques considering performance, accuracy, robustness, speed, and computation costs [27-38]. A number of surveys have investigated the usage of ML methods in various application domains [39-43]. However, there is a gap in review studies considering the building energy information for demand and consumption prediction in the era of smart cities, despite the increasing popularity of ML methods. Figure 1 shows the exponential increase in using ML models in this realm within the past decade. Consequently, the contribution of this paper is to investigate the application of novel ML models in shaping the future of smart and sustainable cities in terms of energy.
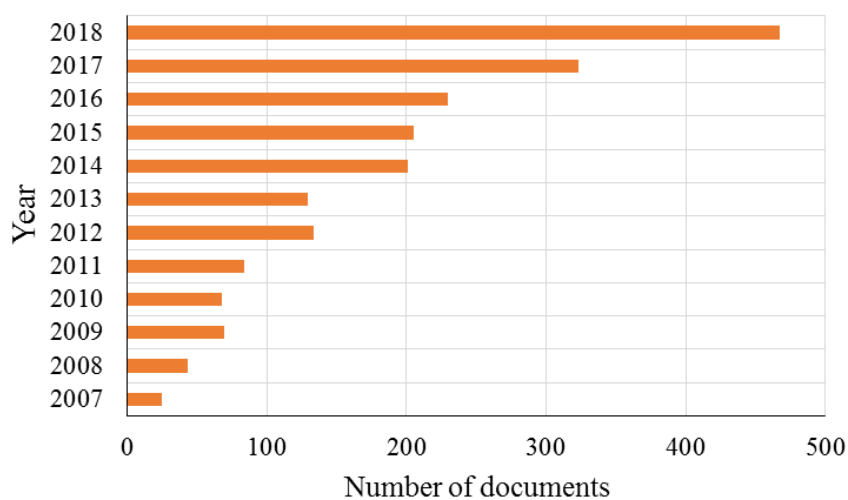

Fig. 1. rapid increase of using ML models in various scientist domains (source: web of science)

2   Building energy demand prediction

Prediction of demand in building energy sector is essential for planning and managing energy systems. Table 1 presents top six studied developed by ML methods in building energy demand prediction.

Table 1. Notable ML methods for 2 building energy demand prediction

Reference	Contribution	ML method	Keywords
[44]	To employ machine learning for Quantifying the effect of landscape composition and configuration on urban land surface temperatures	Generalized boosted regression (GBR)	-Land surface temperature -Machine learning
[45]	To present a comprehensive review about the application of machine learning as a solution in smart buildings	ANN, DL, SVM, GA and SVR	-Internet of Things -Machine learning
[46]	To compare different forecasting models for estimating the natural gas demand	empirical models, RNN and LR	-Machine learning -Deep learning

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[47]	To employ different machine learning methods for Building Performance Simulation	ANN, LSTM	-Deep learning -Machine learning
[48]	To present a comprehensive state of the art of machine leaning methods for the prediction of building energy demand	ANN and SVM based machine learning methods	-Machine leaning -Building energy demand
[49]	To present a hybrid ensemble method to increase the accuracy of load demand estimation of PV for building energy sector	Single and hybrid machine learning methods	-Machine learning -Ensemble method

Osborne and Alvares-Sanches [44] developed an innovative approach in the presence of machine learning technique (GBR) for Quantifying the effect of landscape composition and configuration on urban land surface temperatures. Based on findings of the study, GBR could successfully predict land surface temperatures with a high correlation coefficient (0.956) using 102,935 data.

Djenouri et al. [45] presented a comprehensive state of the art about the application of ML methods in buildings. ML has been employed as solution for occupants and energy or devices. ML can be used as a multi-disciplinary solution for building purposes but in general the type and the size of the building are main factors for considering

the effectiveness of ML method. But the use of ML methods can be more successful in energy demand purposes in buildings by developing innovative approaches. Hribar et al. [46] developed a study for evaluating the forecasting capabilities of different methods including empirical, deep learning and LR models for the prediction of natural gas demand in the presence of daily and hourly datasets. All the methods have been employed in their single form. Evaluations have been performed by the use of MAE and MAPE factors. Based on results deep learning method have the best performance (with MAE 1.06 and 18.3 for hourly and daily datasets, respectively) compared with that of the other techniques.

Singaravel et al. [47] employed ANN while comparing with single, two and three layer LSTM method for the estimation of building sustainability. Machine learning methods can play an important role in reducing the processing time and increasing the sustainability by increasing the model accuracy. Comparing the accuracy values of models for the prediction have been performed by employing determination coefficient values. Based on results all of methods could successfully cope with the prediction task but two layered LSTM method have the best performance compared with others. Ahmad et al. [48] provided a comprehensive state of the art of the machine learning based prediction models for the estimation of building energy demand sector. In general methods have been divided into two main categories including ANN and SVM based machine learning methods as the most frequently used methods in this field of science. This paper also indicated the importance of machine learning methods in the sustainability of buildings energy demand. SVM based methods provided a higher accuracy compared with that of the ANN based methods.

Reza et al. [49] developed a novel hybrid ensemble method including neural ensemble, Bayesian model and wavelet transform method for the prediction of PV performance in the building energy demand sector. This method has been developed by comparing different single and hybrid machine learning techniques in the term of the normalized root mean square error. This study wants to emphasize on the importance of

the hybrid methods over the single methods. The proposed hybrid method could successfully estimate the demand forecasting factors and increased the accuracy of the model significantly.

Table 2 present a brief comparison about the accuracy, reliability and sustainability of methods developed for forecasting the energy demand in building sector. Accuracy factor has been generated from the performance factors related to the training step and reliability has been generated from the performance factors related to the testing step. But, sustainability was a little difference and has been generated by comparing reliability, accuracy, processing time and other factors which have been considered by results of the reviewed articles.

Table 2. the comparison results of methods for energy demand in building sector

Method	Application	Accuracy	Reliability	Sustainability	Reference
GBR	Regression	++	+	+++	[44]
ANN	Classification Regression	+	+	+	[45]
SVM	Classification Regression	++	++	+	[45]

DL	Classification Regression	+++	+++	+++	[45]
Hybrid ML	Classification Regression	+++	++	++	[45]
RNN	Regression	+++	+++	+++	[46]
LR	Regression	+	+	+	[46]
LSTM	Simulation	+++	++	++	[47]
ANN	Simulation	++	+	+	[47]
ANN-based	Regression	+	+	+	[48]
SVM-based	Regression	++	++	++	[48]
BPNN	Regression	-	-	-	[49]
ARIMA	Regression	+	+	+	[49]

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RBF-PSO	Regression	+	+	+	[49]
FNN-PSO	Regression	++	+	+	[49]
WT-BPNN	Regression	+	-	-	[49]
WT-ARIMA	Regression	+	+	+	[49]
WT-FNN-PSO	Regression	++	++	++	[49]

3   Building energy consumption prediction

Building energy consumption is important as much as the importance of building energy demand. Prediction of energy consumption in building energy sector can be one of the main steps for reaching the sustainable buildings and is essential for planning and managing of energy systems. Table 3 presents top six studied developed by ML methods in building energy consumption prediction.

Table 3. Notable ML methods for 2 building energy consumption prediction

Reference	Contribution	ML method	keywords

[50]	To present a robust artificial neural network to explore complex building energy consumption data which have been generated from the simulation-Based Multi-Objective Optimization model	ANN	-Energy consumption -Machine learning
[51]	To develop an accurate machine learning method for energy prediction in buildings using data generated from internet of things technology	MLP, LR,RF, SVM and GBM	-Internet of things -Machine learning
[52]	To develop a long short term memory (LSTM) network to predict the energy consumers' behaviour based on their recent energy consumptions	LSTM	-Machine learning; -Smart grid
[53]	To develop an innovative hybrid deep learning method for the prediction of energy consumption in buildings	Hybrid LSTM-GA	-Deep learning -Machine learning
[54]	To develop a comprehensive survey about different machine learning methods developed for the prediction of energy consumption in buildings	Single, hybrid and ensemble machine learning methods	-Data mining -Machine learning

[55]	In order to develop machine learning methods for the prediction of energy load in building sectors.	SVM and NARX-RNN	-Machine learning -Deep learning

Sharif and Hammad [50] developed a robust ANN method to explore complex building energy consumption data which have been generated from the simulation-Based Multi-Objective Optimization model. In fact, this study focuses on developing an accurate prediction method for the energy consumption of buildings. Evaluating of results indicated that the developed ANN method benefits less time consuming as well as high accuracy, which increases the sustainability of the developed method.

Chammas et al. [51] developed a study for the prediction of the energy consumption in buildings using data generated from the IoT technology embedded in buildings. The proposed method is a prediction model based on MLP while comparing with LR, SVM, GBM, and random forest. Methods have been compared in terms of determination coefficient, MAPE, and RMSE. Dataset for the training process was separated into three categories (no light, no date, and weather only) for finding the effective variables on the modelling process. Based on the results, eliminating lights data have an essential effect on increasing the accuracy of the target model. The developed MLP model has a higher determination coefficient and a lower RMSE and MAPE compared with that for other methods.

Fenza et al. [52] developed a LSTM method for the prediction of consumers' behaviors in the term of energy consumption. Time series data have been employed in order to develop the target network. Results have been evaluated using RMSE factor. Based on the results, the proposed method has successfully cop with the task as well as providing the required sustainability for the prediction phase. Almalaq and Zhang [53] developed an innovative prediction model for the estimation of energy consumption in build-

ings using LSTM and optimizing its parameters by GA methodology to take an evolutionary DL method. The evaluation phase for this study has been performed by the use of datasets related to residential and commercial buildings. Results indicated that the hybrid methods which take an evolutionary DL method present an accurate and sustainable method for the prediction of energy consumption in buildings over the DL methods.

Chou and Tran [54] developed a comprehensive survey for studying different machine learning techniques developed for the prediction of energy consumption in building sectors. Methods have been categorized into three main categories, including single, hybrid, and ensemble machine learning methods. Methods have been compared in terms of performance factors and sustainability index. Results indicated that in the case of using single and ensemble methods, ANN-based methods have the best prediction performance, but in the case of using hybrid methods, SVM based methods could present the best performance. In general, hybrid methods is the proposed method from the viewpoint of accuracy and sustainability.

Koschwitz et al. [55] developed predictive models in order to estimate the building energy load. The target models include the RBF based SVM and Nonlinear Autoregressive Exogenous Recurrent Neural Networks which have been developed by the historical data from residential buildings in Germany. Based on the results, NARX-RNN provided higher performance and sustainability in comparison with those for the SVM method. Table 4 present a brief comparison of the accuracy, reliability, and sustainability of methods developed for forecasting the energy consumption in the building sector.

Table 4. the comparison results of methods for energy consumption in the building sector

method	Application	Accuracy	Reliability	Sustainability	Reference
ANN	Regression	++	++	++	[50]
MLP	Regression	++	++	++	[51]
LR	Regression	--	--	--	[51]
SVM	Regression	+	+	+	[51]
GBM	Regression	+	+	+	[51]
RF	Regression	+	+	+	[51]
LSTM	Regression	+++	+++	+++	[52]
LSTM-GA	Regression	+++	+++	+++	[53]

Single-ANN based	Regression	++	++	++	[54]
Hybrid-ANN based	Regression	+++	++	++	[54]
Ensemble-ANN based	Regression	++	++	++	[54]
Single-SVM based	Regression	++	++	++	[54]
Hybrid-SVM based	Regression	+++	+++	+++	[54]
Ensemble-SVM based	Regression	+++	++	++	[54]
SVM	Regression	++	+	+	[55]
NARX-RNN	Regression	+++	+++	+++	[55]

4   Conclusion

This paper concludes that the usage of machine learning in building energy information applications is growing at a higher rate than we have seen during the last decade. The ensemble and hybrid models have emerged and continue to advance for higher accuracy and better performance. Deep learning models also will bring a tremendous amount of intelligence for better prediction models. This trend has been also reported in other research domains, e.g. biofuels, agriculture, hydrology, and production [56-64].

Acknowledgments

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