Application of supervised learning methods to better predict building energy performance

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Abstract - Building energy consumption is shaped by a variety of factors which prompts a challenge of accurately predicting the building energy performance. Research findings disclosed a significant gap between the building's predicted and actual energy performance. One of the key factors behind this gap is the occupant's behavior during operation which includes a set of dependent and independent parameters generating a greater level of uncertainties. To accurately estimate the energy performance, we need to quantify the impact of any observed parameters and further detect its correlation with other parameters. Human behaviors are complex and quantifying the impact of all its interconnected parameters can be error prone and costly.

To minimize the performance gap, more scalable and accurate prediction approaches, such as supervised machine learning methods, should be considered.

This paper is devoted to investigate the most commonly used supervised learning methods which, when intertwined with conventional building energy performance prediction model, could potentially provide more accurate and reliable estimates. The paper will pinpoint the best use of each studied method in the relation to energy prediction in general and occupant's behavior in specific and how it can be implemented to better predict building energy performance.

Keywords

Energy performance – Supervised Machine Learning – Energy prediction – Occupants' behavior- Performance gap

Section I: Introduction

Building energy performance has been a central topic among researchers since buildings are one of the main contributors in the energy consumption. There has been a significant increase in building energy consumption during the last decade (Shabani and Zavalani, 2017), in which Buildings account for 40% of total energy consumption (Buratti et al., 2014b) and the electrical consumption of the residential and commercial buildings alone reach a staggering 60% of the total electricity consumption (UNEP, 2016). Reducing the building energy consumption is a global concern that has been researched extensively.

The Energy Performance of Building Directive established a legislation that promotes building energy performance and reduction of CO_2 emissions. The objective is to reduce energy consumption in building in Europe by 20 % by the year 2020 (EPBD, 2010).

There is a weighty potential for the building sector to reduce the energy consumption and perform better by applying more feasible and effective design and operational solutions (UNEP, 2016). Those solutions for buildings can be projected by means of modeling and predicting in order to attain better energy performance and effectively utilize the energy use in buildings. Thus, it is imperative to predict the energy usage in building to achieve energy conservation and to explore different scenarios that can assist in choosing the most effective building use (Huang et al., 2014).

It's agreed on that building energy modeling plays an important role in predicting building energy performance. Modeling tools offers the potential to analyze the energy usage patterns and predict consumption (Huang et al., 2014). Nonetheless, having the model to obtaining reliable results always require time and accuracy (Buratti et al., 2014a).

There's a significant gap between the actual and predicted energy performance defined as the "energy performance gap". De Wilde (2014) noted that one of the obvious causes of mismatch between the prediction and actual measurements is within the modeling and simulation stage, as this stage is a fundamental constituent of prediction. When inadequate tools or methods are used, inaccurate prediction will be obtained, and consequently a performance gap as an end result (CarbonTrust, 2011, Menezes et al., 2012).
Nevertheless, even if the modeling stage was performed correctly, the prediction remains a complex process accompanied by fundamental uncertainties resulting from the various factors that affects the energy consumption (Menezes et al., 2012).

This high obscurity in predicting the energy performance or controlling it, is accounted to a number of variables and parameters that contributes directly and indirectly to the building energy use, such as building design, construction and operation, building technologies, weather conditions, and most importantly occupants and their behaviors (De Wilde, 2014).

Figure 1 provides an overview of the parameters affecting the building energy use, which undoubtedly complicate the energy usage prediction, while Figure 2 provides an overview on the parameters affecting occupant behavior and in return the building energy use.

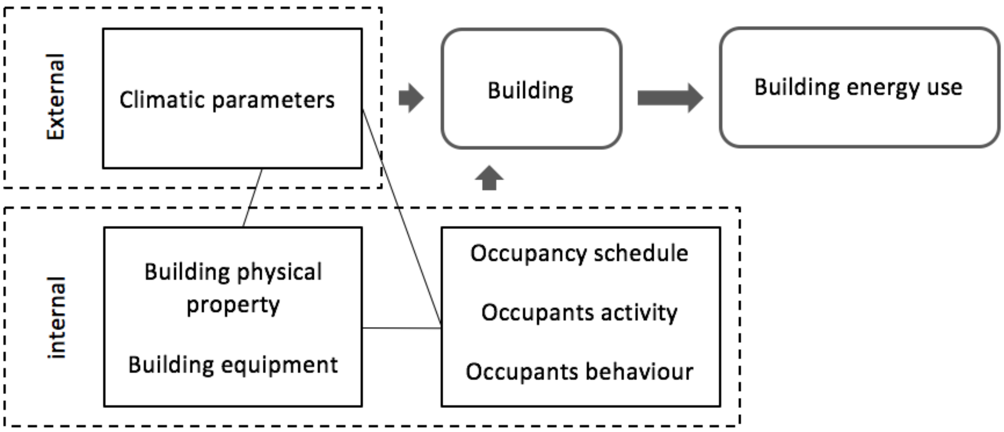

Figure 1 - parameters influencing building energy use

When talking about the factors affecting performance gap, research has disclosed that occupant's behavior is one of the main contributors of this gap (Menezes et al., 2012, Haldi

and Robinson, 2008). Predicting building energy performance whilst comprehending the human behavior is a complicated procedure, as human behavior is stochastic (Yan and Malkawi, 2013). There is a need to find alternative methods to perform such predictions that do not limit the typical occupants' behavior but instead offer suggestions, consent changes and are able to learn from the observation and interaction between the occupants and the building.
As the prediction relates and define patterns of the occupant behavior, the learning will increase, till it is reckoned as truthful. This may be achieved by employing supervised learning techniques.

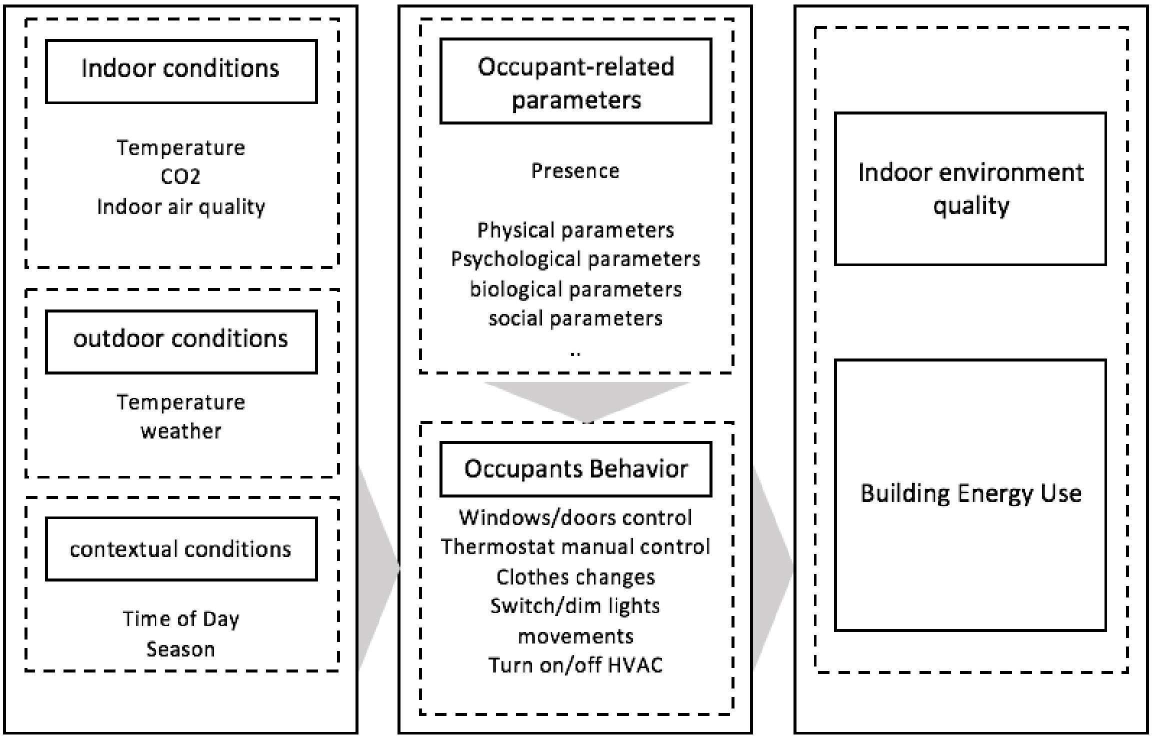

Figure 2 - effect of occupant behavior on building energy performance

For the reliable prediction of building energy performance, various models and modeling techniques were put under investigation showing a discrepancy in the success rates (Zhao and Magoulès, 2012, Crawley et al., 2008, Li et al., 2014, Swan and Ugursal, 2009, Magoulès and Zhao, 2016, Wang and Srinivasan, 2017). Buildings showed that its operation and energy consumption have a nonlinear dependency on exogenous variables (Huang et al., 2014). That being said, supervised machine learning techniques and algorithms have been extensively explored as modeling techniques as they are capable of mapping nonlinear dependencies between variables. Moreover, as evidenced in many research domains, supervised machine learning techniques and algorithms has been an adjunct to many advances related to domains such as criminology, financial trading and fraud detection. Machine learning has the capacity to solve complicated problems and aids in providing more accurate predictions (Najafabadi et al., 2015).

As suggestions on how to bridge the gap is an ongoing concern in the research industry, Literature substantiated occupant behavior must be considered and explored (D'Oca et al., 2015). In this paper, the most common supervised learning methods are reviewed in terms of their capability in predicting building energy performance. By exploring supervised machine learning methods and techniques, new approaches can be employed to predict building energy performance with further consideration of occupant's behavior developed inputs into building energy model.

Section II: Methods

As artificial intelligence based modeling approaches, including supervised machine learning approaches, ought to be known for their scalability, ease of use and adaptability to seek accurate and reliable predictions in an optimal time frame (Wang and Srinivasan, 2017), those modeling techniques have attracted researchers attention to investigate modern solutions for energy performance prediction in general and occupancy behavior prediction in specific. This brings in the necessity to carry out an in-depth literature review for building energy prediction by means of supervised machine learning, and discuss recent development and implication towards incorporating occupant's behavior in the prediction model.

The research at first provides a background about the challenge of modeling occupant's behavior. This is followed by a background of the common used supervised machine learning techniques and algorithms covered in this paper, which are linear regression, Bayesian networks, artificial neural networks, support vector regression and decision trees. Then, a detailed literature review is conducted for recent research development carried in the past decade (2007-2017). Research papers related to our topic are identified, scoped and reviewed paving the road to an elaborated review of the application, benefits and limitations of the studied supervised machine learning techniques.

In short, this paper sets the road for providing better understanding of the use of supervised machine learning techniques for the prediction of building energy use.

The following sections are organized as follows:

Section III provides an overview to the problem which is modeling occupant behavior section IV defines and establishes an understanding of the common supervised machine learning methods and a brief description of their principles; Section V presents a review of the application of supervised machine learning in the field of building energy analysis in which advantages and limitations of each method will be presented. Section VII offers concluding considerations, and covers the future directions of supervised machine learning approaches for predicting energy performance and occupant's behaviors.

Section III: The dilemma of occupant's behavior

Occupants behavior have a significant impact on the building energy use, not only their presence, schedule and number affect the energy use, but also the ability to control lighting, set points, shadings, doors and windows operation, and building equipments (van Dronkelaar et al., 2016).

A number of researches were dedicated to unveil the substantial effect of occupant's behavior on the energy use. Azar and Menassa (2012) studied the impact of the parameters related to occupant behavior in office building energy simulation. Moreover, a study on housing stock in Mediterranean area, showed that building physical factors and occupant parameters caused 48.7% of variation in electricity consumption (Mora et al., 2015). Parys et al. (2010) demonstrated that energy use differs robustly as occupants' behavior vary with a standard deviation up to 10% on the energy consumption linked with occupant behavior.

Although many research findings have disclosed that occupant's behavior is one of the main contributor of the energy performance gap (Menezes et al., 2012, Haldi and Robinson, 2008, De Wilde, 2014, Azar and Menassa, 2012), it's unfortunate that the occupant's behavior contribution is somehow overlooked and not copiously included in the building energy use prediction. When predicting building energy use, the majority of current used energy simulation tools provides bigger attention for the physical parameters which includes building characteristics, schedules, weather condition(Crawley et al., 2001, Zhang et al., 2008, Yan et al., 2008). On the other hand, the relationship between occupants and the building, and the effect of occupant's behavior on the building energy use are seldom addressed (Jia et al., 2017). In most cases, The occupant behavior is considered deterministic or static and doesn't get full account while simulating energy use (Fabi et al., 2011, D'Oca et al., 2014).

Ahn and Park (2016) mentioned that modeling humans by means of empirical, experimental, and numerical approach is not easy since occupant behavior is accompanied by lots of uncertainties affecting its prediction. Also, There's a necessity to acknowledge the difference in occupant's behavior that are affected by personal, physical, physiological, biological, social and cultural parameters and how these parameters can contribute differently on the energy use (van Dronkelaar et al., 2016). Peng et al. (Peng et al., 2012) has defined the relationship between the occupants and buildings as presented in Figure 3 shedding the light on the main points formulating this relationship which are: behavioral ideologies, occupants feelings, and the influence on occupants behavior on the use of energy.

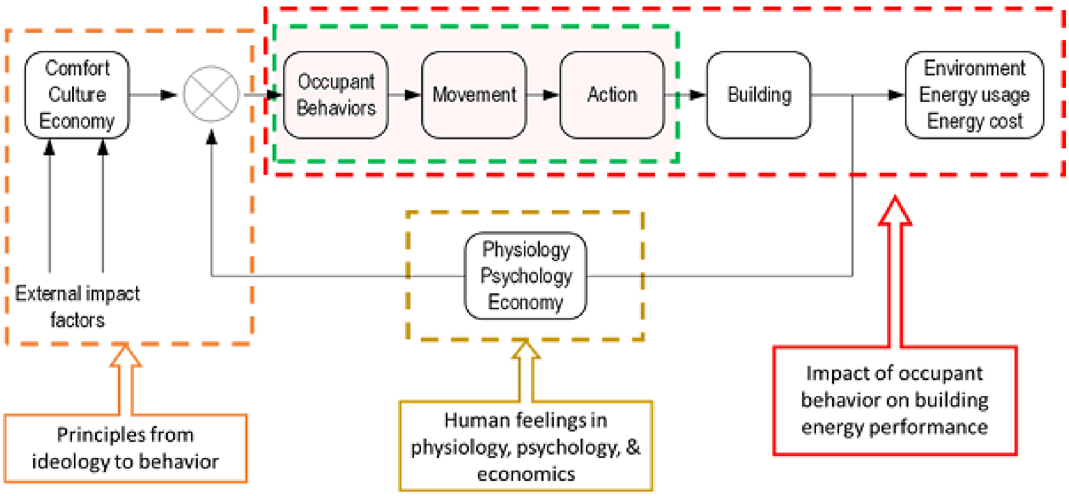

Figure 3 - relationship between occupants and buildings (Peng et al., 2012)

It is imperative to understand that occupant behavior modeling is much more detailed and complex than occupancy detection. It is also important to distinctively differentiate between occupancy (presence of occupants, schedule and number of occupants) and occupants behavior, as more often those two terminologies gets mixed up (Jia et al., 2017).

moreover, it's critical to capture the dynamic and interdependent complexion of occupant behavior when modeling.

Section IV: Supervised machine learning techniques and algorithms

More reliable modeling techniques should be approached for predicting building energy consumption. Those techniques must ensure consideration of occupancy, occupants behavior (passive and active), and the interaction between occupants themselves as well as the building. When those considerations are met, more accurate and truthful models will provide decision makers with a better approach to conserve energy by revising design consideration through exploring different alternative solutions.

Supervised machine learning is the formulation of algorithms capable to generate patterns and general hypotheses by means of externally supplied input to provide prediction of forthcoming outputs (Singh et al., 2016). In simple terms, supervised machine learning requires a set of input parameter and an output parameter, which with the use of selected algorithm can learn to map function that allows the prediction of the output once a new input data is introduced (Figure 4).

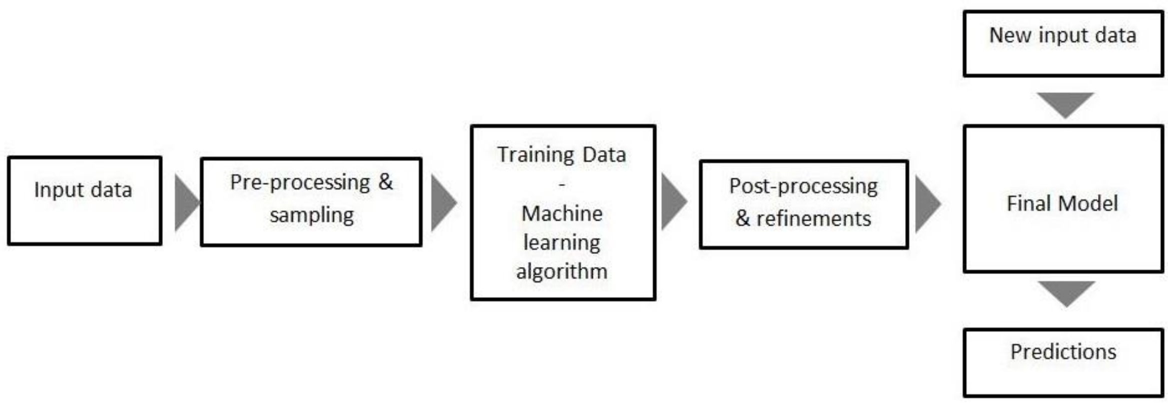

Figure 4 - supervised machine learning process

Overall, Supervised learning approaches have proven to be efficient in the prediction of building energy consumption (Zhao and Magoulès, 2012). When compared to the conventional modeling techniques, the supervised machine learning approaches brought up more advantages in terms of requiring less time and effort, as there's no prerequisite to define explicitly the relationship between input parameters and the output (Huang et al., 2014).

Background on selected supervised machine learning methods

A brief background of the selected supervised machine learning techniques is provided. The studied techniques are: Bayesian network, linear regression, decision tree, support vector machine and artificial neural network.

Linear Regression

Linear regression is a well-known machine learning technique frequently used for prediction and forecasting models. Linear regression tends to be a popular technique because of its easiness of application and understanding of the model parameters. The regression is used to set an equation, derived from the input data, for predicting the value of the output as a linear function (Tso and Yau, 2007).

Bayesian Networks 'BN'

Bayesian networks are graphical models demonstrating probabilistic relationships among set of random variables (Tong and Koller, 2001).
According to Darwiche (2009), Bayesian networks involves the following components:

a) The structure of the network defined as a directed acyclic graph, in which the random variables are presented by nodes, while dependencies among variables are represented by directed edges directed edges.

b) Conditional probability distributions assigned for the variables.

Decision Trees 'DT'

Decision trees are considered hierarchical model consisting of a set of decision rules that recursively arranges the input parameters into homogeneous zones (Myles et al., 2004). The decision tree can be a regression or classification tree. Its purpose is to provide a prediction by defining a set of decision rules based on the input parameters. Decision trees deals with interaction between parameters and provides high efficiency with low computational effort (Singh et al., 2016).

Support Vector Machine 'SVM'

Support vector machine is one of the latest supervised learning methods. It is established on the basis of statistical learning theory and structural risk minimization principle (Vapnik and Vapnik, 1998). although SVM is considered to be complex, it's highly accurate and can deal with high dimensional data (Singh et al., 2016).

Artificial Neural Networks 'ANN'

Neural networks are nonlinear statistical learning techniques resembling the biological neural configuration; they consist of three layers made up of interconnected neurons: input, hidden and output layer. The ANN is defined by the interconnection between the neurons belonging to different layers, the weight of this interconnection derived from the learning process, and the activation function converting the weighted input of the neuron to the output activation (Wang and Srinivasan, 2017). ANN is employed as a random function approximation tool that can capture complex relationships between inputs and outputs and model dynamic problems. As such, ANN provides ease of use in modeling problems that are difficult to explain (Singh et al., 2016).

Section V: Review of application and discussion

In this section, a review of the application of the selected supervised machine learning approaches in predicting building energy performance is presented. Table 1 presents the reviewed methods, the input needed and their application.

Method	References	Application	Input data
Linear regression	(Li and Huang, 2013) (Yiu and Wang, 2007) (Zhao et al., 2013)	Cooling load prediction HVAC load prediction Occupancy schedule	climatic data, historical data, operation schedule
Support vector regression	(Dong et al., 2005) (Zhao and Magoulès, 2010) (Li et al., 2009)	Prediction of total energy consumption Cooling loads prediction	historical data, monthly utility bills and weather data
Artificial neural network	(Vintan et al., 2006) (Yokoyama et al., 2009, Li et al., 2009, Li and Huang, 2013) (Aydinalp et al., 2004) (Zheng et al., 2008) (Karatasou et al., 2006)	Occupancy movement Cooling load prediction Heating loads prediction Human activity clustering Total energy use	climatic data, time, equipment properties, operational schedule, domestic hot water and heating system properties, historical energy consumption patterns, occupants characteristics
Decision tree	(Nguyen and Aiello, 2013) (Yu et al., 2010) (Tso and Yau, 2007)	Total energy prediction Electricity prediction	Climatic data, building characteristics, utility bills
Bayesian network	(Petzold et al., 2005) (Hawarah et al., 2010) (Tarlow et al., 2009)	Occupants movement Occupants behavioral patterns Energy consumption estimation	climatic data, building characteristics, occupancy schedules, historical data

Table 1 - application of supervised machine learning methods

Bayesian network has been employed to predict building energy performance and occupant related parameters in a number of researches. Petzold et al. (2005) predicted occupants' presence and the amount of time spent at a specific location by means of a dynamic Bayesian network predictor. The research showed that the accuracy for predicting the occupant location reached up to 90 %, while predicting the duration reached 87%. This was compared to the performance of neural network predictor which proven to have same level of accuracy. In Walt Disney World Resort in Florida, a Bayesian network been developed to predict the energy consumption for a food service building and 3 retail shops The input parameters included operation schedule, historical energy data, weather data, building-related data, and other needed inputs were estimated. The results showed that Bayesian network is an applicable network to predict energy consumption on large scale and can deal with missing data (Tarlow et al., 2009).More over Bayesian network used hourly energy consumption in residential property, it was proposed to predict occupant's behavior. The network was trained to learn occupant's preferences and behavior trends to predict their consumption needs such as light intensity, desired temperature, and plug load and to provide system tuning when there is a change in the occupant's behavior(Hawarah et al., 2010).

Linear regression, which is known for its ease of use, has been successfully employed to predict building energy performance. Electrical consumption, HVAC performance and total building energy use is predicted (Li and Huang, 2013, Yiu and Wang, 2007). Moreover, Zhao et al. (2013) used linear regression to predict occupancy schedule in an office building. The results disclosed practicability for the model in predicting occupancy schedule.

SVM is considered to be a modern supervised machine learning methods (Shabani and Zavalani, 2017). SVM have been used extensively for predicting building energy performance, as it is capable to deal with nonlinear regression problems. Dong et al. (2005) used support vector regression for the prediction of energy consumption for four commercial buildings in Singapore. The input parameters included historical data, monthly utility bills and weather data. The prediction reached accuracy within 4%. Li et al. (2009) compared SVM to other modeling approaches in terms of predicting cooling energy loads for an office building in china. The results proved that SVM predictions are accurate when compared to back propagation neural network and radial basis function neural network. Also, by means of large energy consumption data sets, an SVM model is developed to predict energy consumption. Findings emphasized on the benefits of SVM modeling for large datasets (Zhao and Magoulès, 2010). SVM predictions showed higher accuracy when compared to many supervised machine learning approaches such as ANN, decision trees and statistical approaches (Shabani and Zavalani, 2017).

Artificial neural networks have been employed in many researchers to predict building energy performance due to its ability to handle complex and nonlinear problems. ANN managed to predict occupancy movements (Vintan et al., 2006), cooling loads (Yokoyama et al., 2009, Li et al., 2009, Li and Huang, 2013), heating loads (Aydinalp et al., 2004), daily human activity clustering (Zheng et al., 2008), total energy use (Karatasou et al., 2006). Overall the performance of ANN was satisfactory as the results show that ANN has noteworthy accuracy in prediction.

Decision trees has been applied in the recent years for prediction energy consumption in buildings (Nguyen and Aiello, 2013). A decision tree model was used to predict the annual energy demand level (Yu et al., 2010). By using decision tree, a classification of the factors influencing the energy consumption were derived. Moreover, Decision tree model was used in different buildings to predict electricity consumption(Tso and Yau, 2007). The decision tree model proved to require less input data and have better performance when compared to neural networks.

The table below compares the selected methods in terms of input and training quantity requirements and states the benefits and limitations of each studied method.

Method	input data requirement	training data requirement	Benefits	Limitations
Linear regression	Low	High	Wide application opportunity as output is interpreted as probability. Capable of dealing with nonlinearity.	Entails large sample size.
Support vector regression	Low	High	Capable of dealing with nonlinearity. High accuracy and flexibility.	Complex process dependent on the selection of parameters.
Artificial neural network	Low	High	Ability to handle complex and dynamic relationships as well as irrelevant input data and parameter independencies.	Complications in terms of interpretation of the output.
Decision tree	Low	High	Deals with interactions among variables. Provides high quality performance.	Incapable of managing complex interactions. Difficulty in processing high dimensional data.
Bayesian network	Medium	Medium	Deals with relationships between various input parameters.	Performance dependent on data. Difficulty in processing high dimensional data.

Table 2 - comparison of the reviewed methods

Section VI: Conclusion and future scope

The means presented in the research industry to model building energy performance are diverse. Current research presents a wide range of complex models in an attempt to model the occupants' stochastic behavior. However, there's a narrow employment of such models in building energy simulation software. According to Gaetani et al. (2016), up till now, research has not offered recommendations to support the choice of a modeling technique with respect to occupant behavior in terms of simulation and prediction. This paper reviewed the most commonly used supervised machine learning methods for energy performance predictions and their use in predicting occupant's behavior in an attempt to identify the variations between the discussed models, as well as their benefits and limitations. The paper concludes that each supervised machine learning method has its own constraints and conditional requirements. Also the selection of method differs according to the input data available and application needs. The research deduces machine learning approaches, when selected properly, could provide more accurate predictions and eventually support the simulation phase by providing more accurate predictions with an intent to minimize the energy performance gap.

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