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THE IMPACT OF WINDOW CHARACTERISTICS ON GAS AND ELECTRIC COSTS IN EDUCATIONAL BUILDINGS: APPLICATION OF SUPPORT VECTOR MACHINES*

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Abstract– Toward green educational building development, windows are important design elements as the source of natural lighting and heating in classrooms. The amount of natural lighting and net heating received by a classroom in a year depends on the school location, weather conditions, as well as the window orientation and size. Schools in Iran consume a considerable amount of energy which is mostly supplied using nonrenewable fossil fuel resources. This energy consumption can be reduced through a well-designed daylighting approach. In this paper, in order to investigate the effects of window characteristics on construction and operational costs of schools, by varying the Window-to-Wall Ratio (WWR) and window orientation, 288 daylighting scenarios are generated for a typical standard classroom in a warm-dry climatic zone in central Iran. The DOE-2 software is utilized to estimate annual gas and electric consumption, for the generated scenarios over a period of 50 years. Considering the operation and construction cost, the best window facing and optimal range of WWR in each orientation is determined for the studied standard classroom. The results of simulated daylighting scenarios are then used to train regression based Support Vector Machines (SVMs) in order to show the feasibility of applying the Support Vector Regression (SVR) as an artificial intelligent system. The obtained results show that SVR as an architectural assistant performs well and the SVR-based predictor can rapidly, easily and accurately predict the operational and construction cost of a classroom just by determining the window size and installation face.

Keywords– Window characteristics, energy efficient window, daylighting, classrooms, green educational buildings, support vector regression (SVR)

1. INTRODUCTION

Classroom lighting level affects the students' visual comfort and improves educational outcomes. Heschong et al. [1] established a correlation between the presence of daylight and student performance in school classrooms and showed that children in classrooms with better daylighting gain higher end-of-year test scores. Natural light also has a great influence on students' bodies and minds [2]. Since the light source changes depending on time of day, seasonal and weather conditions, combined daylighting and electric lighting is required to set the classroom lighting level. Schools generally are active during sun shine hours and electric lighting is a backup control system during dark periods for poor illumination zones and times.

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Windows are important design elements as the source of natural light in classrooms and have a considerable contribution in reducing the required electric lighting power and saving energy. On the other hand, windows are the main sources of unwanted heat loss in buildings. Singh and Michaelowa [3] showed that about one-fourth of the total energy used for space heating and cooling in 1990 is spent to offset the unwanted heat losses through windows in residential and commercial buildings in the United States. Heating, cooling, and lighting loads of schools can be reduced through a climate-responsive design. Window size and orientation have a great influence on the amount of heat gain in summers and heat loss in winters. Currently, there is not an applied guideline for characterizing windows in classrooms. Even in residential houses, the literature is limited to some general architectural recommendations for determining the window characteristics. For example, to avoid overheating in summer, in northern hemisphere countries architects are recommended to use limited West-facing windows.

Persson et al. [4] investigated the influence of window size on energy balance of low energy houses outside Gothenburg, Sweden. They also estimated the maximum power needed to keep the indoor temperature at a comfort level. Lam et al. ([5] and [6]) simulated and analyzed the interactions between lighting and space heating/cooling loads in office buildings in different climate zones. They showed that lighting and office equipment played a significant role in the overall building energy efficiency and the window solar component can lower the annual building heating load. Wan et al. [7] analyzed the solar heat through the windows for nine major thermal zones in China through an hour-by-hour energy simulation. Perez and Capeluto [8] investigated the influence of window shading, glazing type, infiltration and some other factors on electric consumption of a base-case classroom in hot-humid climatic zone. They showed that the annual electric consumption could be reduced up to 50 percent through a high performance design. The influence of windows on the energy balance of apartment buildings in Amman were investigated by Hassouneh et al. [9] to select the best type of glazing. Li et al. [10] analyzed electricity consumption and indoor illuminance levels for a classroom employing high frequency dimming controls and showed that applying high frequency photoelectric dimming controls is effective in electric energy and lighting performance in schools. Wan et al. [11] carried out some multi-year building energy simulations for generic air-conditioned office buildings in China considering different climates and developed regression models to correlate simulated monthly heating and cooling loads and building energy use.

Heating, cooling, and lighting loads of schools are closely dependent on window orientation and size regarding the amount of heat transmitted through the window and lighting level requirements in classrooms. In the present study, the DOE-2 simulator is used to quantify annual energy consumption in a typical classroom considering numerous window characteristics and daylighting scenarios. Then, perhaps for the first time, the present value of the operational and construction costs of the classroom are estimated over a long-term period of time for each daylighting scenario. By analyzing the results, some recommendations are presented for characterizing windows in classrooms in the study area.

In finding the relations among available data intelligent systems, it is possible to find a hidden law behind the phenomenon. Nowadays, intelligent systems are considered as good predictors regarding their good performance in predictions. Since most architectural engineers are not familiar with the energy simulation codes, the obtained simulation results are utilized to train an artificial intelligence based model for predicting design priority just by determining the window facing and window to wall ratio. Among available several artificial intelligence based models, Support Vector Machine (SVM) as a powerful tool is selected. SVM, first introduced by Vapnik in 1995, [12], is an intelligent system that has been successfully used in different engineering fields. SVM uses the structural risk minimization inductive principle in order to achieve a proper generalization on a limited number of learning patterns. The present paper deals with the application of Support Vector Regression (SVR) as a well-known version of SVM for functional estimation. The SVR is utilized for forecasting the construction and operational cost. Several statistical indices are used to evaluate the trained SVR in forecasts.

2. METHODOLOGY

A flowchart of the proposed methodology is presented in Fig. 1. In general, the methodology includes an energy simulation model, a constructional cost estimator model and a SVM based regression model. In order to investigate the impact of window characteristics on operational cost in a classroom, it is necessary to quantify the gas and electric consumption. Therefore, the first step of the proposed methodology is devoted to selecting a proper simulation model. The simulation model can provide the temporal variations of gas and electric consumption.

Many simulation models have been developed for estimating energy consumption through numerical modeling of heat conduction, convection and radiation processes. Crawley et al. [13] reviewed the main characteristics of some building energy simulation models. In this paper, DOE-2, which is one of the most popular energy simulation models, is selected for energy simulation in classrooms. This model was developed by Lawrence Berkeley Laboratory in 1983, [14], with the financial support of the U.S. Department of Energy [15]. The DOE-2 can be effectively used for determining the impact of daylighting on energy use in buildings [16]. In this paper, the DOE-2 enables us to estimate energy consumption of the classroom. In order to compute the heat transfer by conduction and radiation through the building skin and estimate the heat loss and gain through the building components, the DOE-2 computations are performed on the basis of the thermal properties of used materials, the classroom geometry, the size and position of the window, lighting schedules, ambient conditions, temperature controls, building location, building orientation and the operation of the Heating, Ventilating, and Air-Conditioning (HVAC) system.

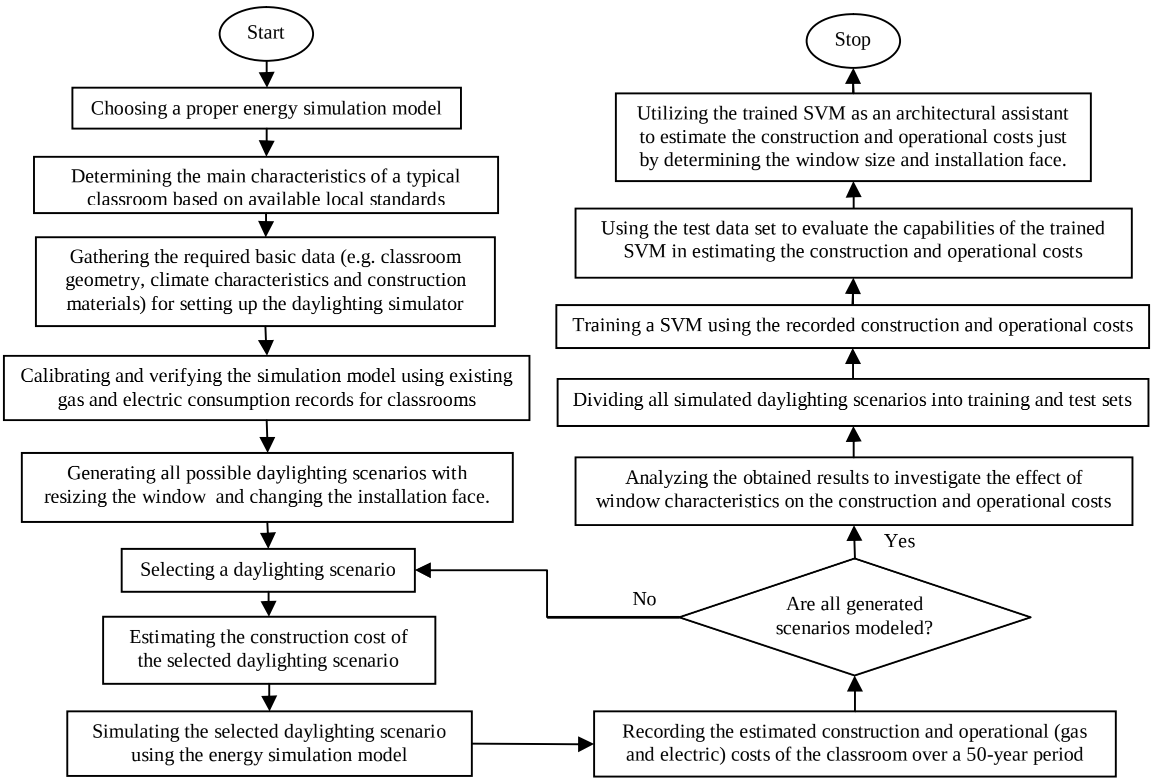


Fig. 1. A flowchart of the proposed methodology for investigating the impact of window characteristics on gas and electric costs in schools

The thermal load calculation is performed using the weighting–factor technique. Since the governing differential equations which describe the heat transfer in a classroom are too complex for an analytical solution, both finite difference and finite element calculations have been used in different parts of DOE-2. The governing equations used in the simulation procedure are given in the DOE-2 user's manual. Probably for first time, Gates and Wilcox [17] have made a daylighting study on classrooms in the California region using the old version of DOE-2. Loutzenhiser et al. [18] evaluated the efficiency of building energy simulation models for simulating daylighting in buildings. They concluded that for initial building design applications, the DOE-2 is an efficient practical computational tool for assessing daylighting performance. The capabilities of this simulation model have also been explored by other investigators (e.g. Bodartand De Herde [19], Lam et al. [5], Loutzenhiser and Maxwell [20], Ihm et al. [21]).

Classrooms are generally categorized into four types. Seminar room, small classroom, large classroom and lecture hall are the standard classroom types designing for up to 22, 50, 99 and 100+ students respectively. Determining the classroom type and general features based on available local standards should be done in the second step of the proposed methodology. The third step is devoted to gathering the information needed for simulation. Building orientation and size, external facing characteristics, construction material, characteristics of the HVAC system and operational schedule besides the minimum required lighting level and climate characteristics are the factors required for any energy simulation.

As mentioned before, in the proposed methodology the simulation code is utilized to solve the heat transfer equations to estimate the required annual energy. It is vital to find how well the simulation model predicts building energy usage. Comparing the model monthly energy consumption predictions to the monthly energy bill data of a base case classroom is the approach employed in this paper for calibration and verification of the simulation model. In this regard, as shown in Fig. 1, before investigating the role of window characteristics, simulating a real-world classroom is considered for debugging, verifying, and validating the simulation model.

The methodology used in the present study includes a large number of daylighting scenarios aimed at investigating the impact of window characteristics on gas and electric bills in different daylight conditions. Several possible daylighting scenarios are generated by changing Window Wall Ratio (WWR), which is the ratio of the window area to the gross exterior wall area, and window installation face. The WWR has a considerable influence on the construction cost. To estimate the construction cost of the classroom in each scenario, a construction cost estimation model is developed. This flexible cost estimation tool can easily estimate the construction cost of the classroom based on the size and material of class and window. As shown in Fig. 1, a loop is considered to investigate all generated possible daylighting scenarios by utilizing the verified simulation model and cost estimation tool to estimate corresponding energy consumption and construction cost of each daylighting scenario. The estimated construction and operational cost of all simulated classrooms over a period of 50 years are used to investigate the effect of window characteristics on the present value of the total cost.

Support Vector Regression (SVR) is a powerful tool to predict the operational and construction cost. To this aim, recorded construction and operational costs of all simulated daylighting scenarios should be randomly split into training and test sets. The training set is used to train and set the SVR. The statistical measures are then used to evaluate the capabilities of the trained SVR based model by using the test set. In the case that statistical measures show good dependencies in simulated and forecasted results, the trained SVM based model helps the architects as an assistant capable of estimating the construction and operational cost accurately just by determining the window size and installation faces directly.

3. SUPPORT VECTOR MACHINE

This paper deals with the application of support vector machine (SVM) in forecasting the construction and operational cost of the standard classroom. Since the SVMs have been used successfully by many researchers in optimization and machine learning areas, SVMs have become a very popular method for learning. For example, handwritten digit recognition [22, 23] and face detection using SVMs was proposed. Bashi-Azghadi et al., [24] and Bashi-Azghadi and Kerachian, [25] have successfully applied the SVM in pollution source characterization in ground-water systems. SVM as a soft computing-based method also has the ability of approximating nonlinear wind–wave interaction, the SVM is used by Malekmohamadi et al. [26] for mapping wind data to wave height in Lake Superior, USA. The stock market has high noise, nonlinearity, uncertainty characteristics. Cai et al. [27] used the support vector regression to forecast future stock market. Evaporation estimation is an important task of hydrologists. Lin et al. [28] developed a support vector machine based model for daily pan evaporation estimation. Osareh and Shadgar [29] used the SVMs for automating the identification of blood vessels in color image of the retina to assist in the early detection of diabetic retinopathy disease as a practical, robust and computationally efficient tool. Allahbakhshi and Akbari [30] have applied the SVM for the dissolved gas analysis of insulating oil.

The theory of the SVM algorithm is based on statistical learning theory. Support Vector Regression (SVR) as a well-known version of SVM for functional estimation uses the kernel function for non-linear support vector regression in order to find a function that has minimum deviation from the used training data. Gaussian and Polynomial kernels are the typical examples of kernel functions that are used to define a set of linear functions in a high dimensional space. The kernel function, $\phi(x)$, transforms the nonlinear input space to linear space.

Toward minimizing the regression error, minimizing the risk in SVR is the general task. SVR utilize the Vapnik's ε-insensitive loss function in order to estimate the risk. The ε-insensitive loss function exhibits the sparsity of the solution ([11]). The ε-insensitive loss function is defined by

$$L_{\varepsilon}(d,y)=\begin{cases}|d-y| & for\ |d-y|\geq\varepsilon\\ 0 & otherwise\end{cases} \tag{1}$$

where, d is the desired value for a particular input, x, and ε is the approximation accuracy placed on the training data points. A regularization term is also used in SVM for defining a risk function toward estimating the regression function. The regularized risk function is defined by Eq. (2)

$$R(C)=empirical\ error+regularization\ term=C\frac{1}{n}\sum_{i=1}^{n}L_{\varepsilon}(d_i,y_i)+0.5\|w\|^2 \tag{2}$$

where, C is the regularization constant (Tay and Cao, [31]). So the SVM approximation can be represented by Eq. (3)

$$y=w\phi(x)+b \tag{3}$$

Where w and b are determined by minimizing the regularized risk function, $R(C)$. For further details of the basic ideas underlying Support Vector Machines for function estimation readers are referred to Tay and Cao, [31] and Smola and Scholkopf [32]. Since support vector machines have greater generalization ability, in this study, a support vector regression (SVR) is applied for the operational and construction cost prediction and its results are compared to the outputs of the developed simulation model. Training data in SVR can be defined as $[x_i,y_i]$ where x_i is the input vector, $x_i\in R^m$. m is the dimension of input vector and

y_i is the output vector. To have a more accurate forecast, normalizing the input vector in the range that $x_i \in [0,1]$ is recommended. The following is used equation for normalizing the inputs:

$$\bar{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

where $\bar{x}_i$ is the normalized input corresponding to x_i and x_i is the original input variable which varies in the range between $x_{\min}$ and $x_{\max}$.

In order to evaluate the accuracy of the trained SVM in forecasting the construction and operational cost, the well-known statistical measures namely Correlation Coefficient, Mean Square Error (MSE) and Normalized Mean Square Error (NMSE) are used. The correlation coefficient is a measure of how well trends in the predicted costs follow trends in simulation based estimated costs. This factor varies in the range between zero and one. The correlation coefficient for n data in testing data set is defined as:

$$CC = \sum_{i=1}^{n} c_i c_i^* \Bigg/ \left(\sum_{i=1}^{n} c_i^{\,2} \sum_{i=1}^{n} c_i^{*2} \right)^{1/2} \tag{5}$$

where c is the SVM-based predicted construction and operational costs for a daylighting scenario and c^* is the target value. Mean Square Error (MSE) is evaluated by the equation:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(c_i - c_i^* \right)^2 \tag{6}$$

MSE ranges from zero to infinity where the lower bond corresponds to the ideal case. The Normalized Mean Square Error (NMSE) normalizes the MSE by dividing it through the variance of the target values.

4. CASE STUDY

In order to show how the methodology can be applied in investigating the impact of window characteristics on gas and electric costs in educational buildings, a case study in Iran is introduced in this section. Schools in Iran consume considerable amounts of gas and electricity which is mostly supplied using nonrenewable fossil fuel resources. On the other hand, electric lighting load in Iran plays an important role in schools' energy consumption that can be offset through a well-designed daylighting approach. The studied classroom is located in Shiraz City, central Iran. Shiraz City as the capital of Fars province is located at 52.53 East longitude and 29.61 North latitude and about 1530 meters altitude above sea level. Weather data at the nearest weather station to the site is used by the simulation model. The main climatic characteristics of Shiraz City are summarized in Fig. 2.

The classroom modeled in this paper is a typical standard classroom recommended by regulation and design standard published by Iran Organization of School Renovation, Development and Mobilization [33]. The selected classroom is rectangular shaped, with dimensions of 7.40m x 7.40m and a floor to ceiling height of 3m. In the simulation model, the classroom geometry, climate characteristics, daylight parameters and material properties are taken into account. A central packaged single zone air conditioner with combustion furnace is assumed for heating, ventilation and air conditioning. The fans operate one hour before opening time and one hour after closing time.

In our case study, the WWR varies from 1.7% to 65.5%. Besides the geometry of the classroom, climatic variables and material properties, set points for heating and cooling are the main inputs of the simulation model. The main considered parameters in simulating the classrooms in the present study and the one simulated by Perez and Capeluto [8] are summarized in Table 1.

In Table 2 the assumed envelop characteristics of the classroom studied in this paper are summarized.

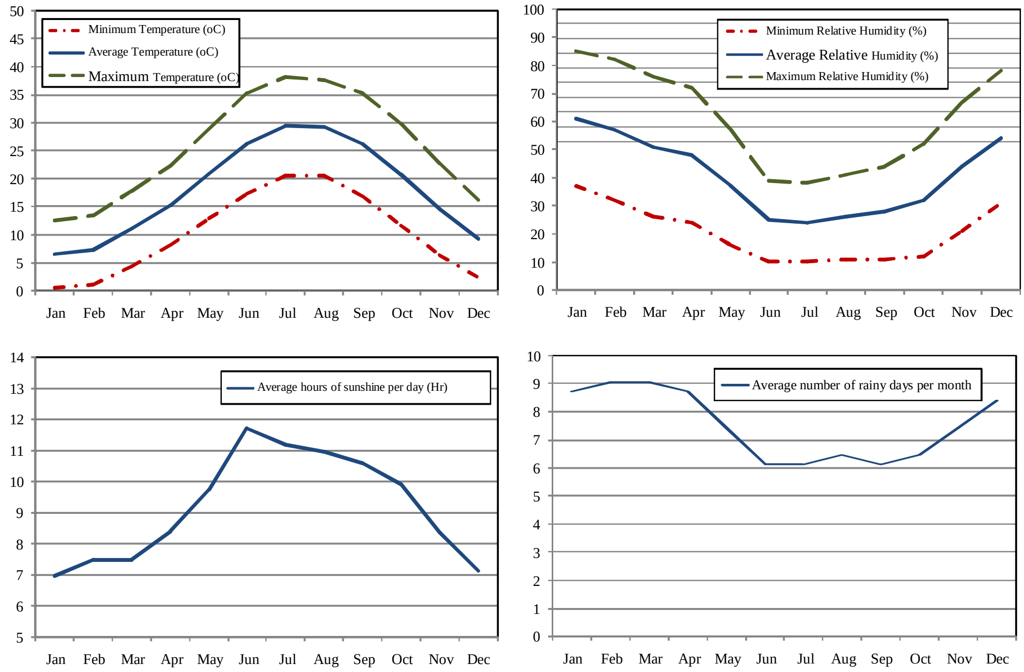


Fig. 2. Monthly average of some climatic variables in Shiraz City (1971-2010)

Table 1. The main considered parameters in simulating the classrooms in the present study and the one simulated by Perez and Capeluto (2009)

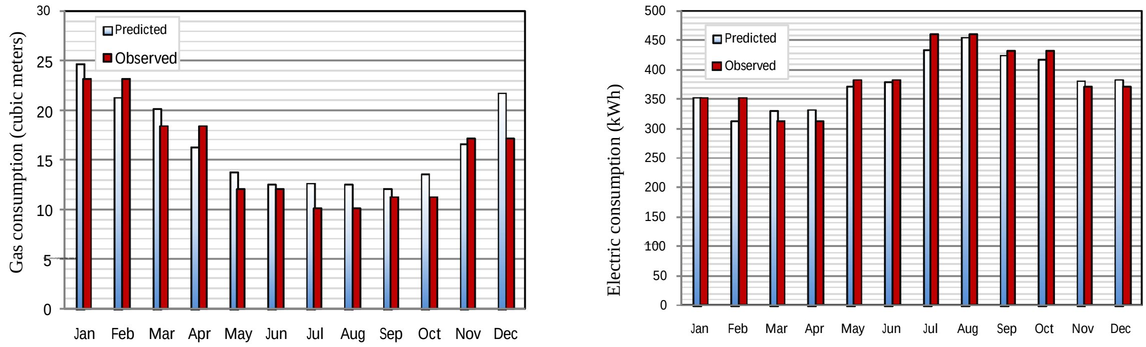
Parameter	Present study	The classroom studied by Perez and Capeluto (2009)
Studied climatic zone	Warm-dry	Hot-humid
Area type	Lecture classroom	Lecture classroom
Classroom area (m^2)	54.76	50
Floor to ceil height (m)	3	2.8
Window glass type	Double clear	Glazing
Lighting control	On/off	On/off
Exterior window shade	None	Shaded by systems installed on it
Schedule information	Classroom is assumed to be active 6 days a week all year round. Opens at 8:00am and closes at 6:00pm	Classroom is assumed to be active 6 days a week from 1st of September to 30th of June. Opens at 8:00am and closes at 6:00pm
Minimum lighting level (lux)	300	300
Cooling design temperature (°C)	23.9	24
Heating design temperature (°C)	22.2	20
Energy simulation model	DOE-2	Energy, shading and radiance

Table 2. The envelop characteristics of the classroom

Parameter	Value
External wall heat transfer coefficient (W/m^2°C)	3.05
Internal wall heat transfer coefficient (W/m^2°C)	2.28
Roof heat transfer coefficient (W/m^2°C)	2.91
Ceiling heat transfer coefficient (W/m^2°C)	2.05
Window heat transfer coefficient (W/m^2°C)	2.68
Solar heat gain coefficient of window	0.81
Window shading coefficient	0.95

5. RESULTS AND DISCUSSION

In order to calibrate and verify the DOE-2 for estimating the gas and electric consumption, a real-world classroom located in the city of Shiraz is modeled. Figure 3 compares the amount of monthly predicted and observed gas and electric consumption in 2010. An error of about 7 percent in estimating annual gas and electric consumption shows the acceptable performance of the DOE-2.



(a) (b)

Fig. 3. A comparison between the predicted and observed (a) gas and (b) electric consumption in 2010 in the modeled typical classroom

Perez and Capeluto [8] assessed the influence of window size just on annual electric energy consumption of a typical classroom in hot-humid climatic zone by keeping thermal and visual comfort in the classroom. The recommended size of North and South-facing windows by Perez and Capeluto [8] to achieve a high electric performance classroom is 30.6% of the wall area. This percent reduces to 25.5% for West and East orientations. The dimensions of the classroom modeled by Perez and Capeluto [8] are very close to the classroom considered in the present study. However, as shown in Fig. 4, there is a difference between the estimated annual electric consumption per unit area of the classrooms. Though the dimensions of the modeled classrooms are very close, the classroom investigated by Perez and Capeluto [8] is smaller in size, located in a deferent climate zone, is not active in July and August, and the exterior window is assumed to be shaded by systems installed on it (see Table 1 for details). Therefore, more annual electric consumption per unit area of the classrooms considered in this paper is expected. As shown in Fig. 4, general similar trends in behavior of annual electric consumption with the variation of WWR in the present study and those reported by Perez and Capeluto [8] for all window installation faces are seen. In this regard, such modeling is reliably justified for energy consumption approximation.

To find the optimal value for WWR considering the total construction and operational cost, 288 daylighting scenarios are generated for the standard classroom by varying window orientation and size. Each window is assumed to be located in the wall center and is characterized by its size and orientation. The DOE-2 is used to estimate the energy needed for heating, cooling and lighting. External shading due to surrounding building is not considered in this study. In all simulations, the time series of annual gas and electric consumption are estimated for a 50-year planning horizon. In Iran, the Ministry of Energy charges the educational customers 0.0294 US Dollars per kilowatt-hour (kWh) and schools buy natural gas at 0.0816 US Dollars per cubic meter. Figure 5 shows the present value of the estimated electric and gas consumption for operation of the selected classroom over a period of 50 years. As shown in Fig. 5a, for WWR greater than 0.2, electric costs of North-facing windows are very low. However, the gas cost in North-facing windows is generally the worst case for any particular WWR. Figure 5a shows that for East, West and South-facing windows, the optimum WWR is in the range of 0.1 to 0.25 from the electric cost point of view. Figure 5b demonstrates that for WWR less than 0.15, there is a small range of variations of 50-year gas cost per unit area in different daylighting scenarios. As shown in this figure, for WWR greater than 0.15 there is a significant drop in 50-year gas cost per unit area in East-facing windows. However, increasing trends in gas cost versus the WWR can be seen in North and West-facing windows. It can also be seen that 50-year gas cost for East-facing windows in the range of studied WWR is considerably lower than other window orientations.

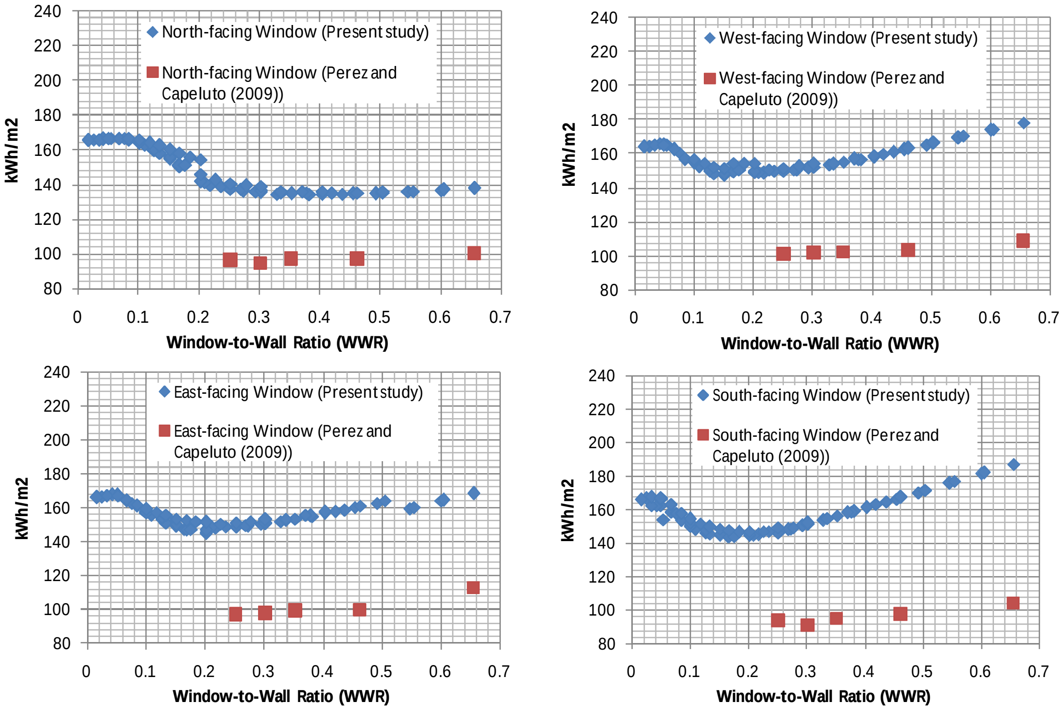
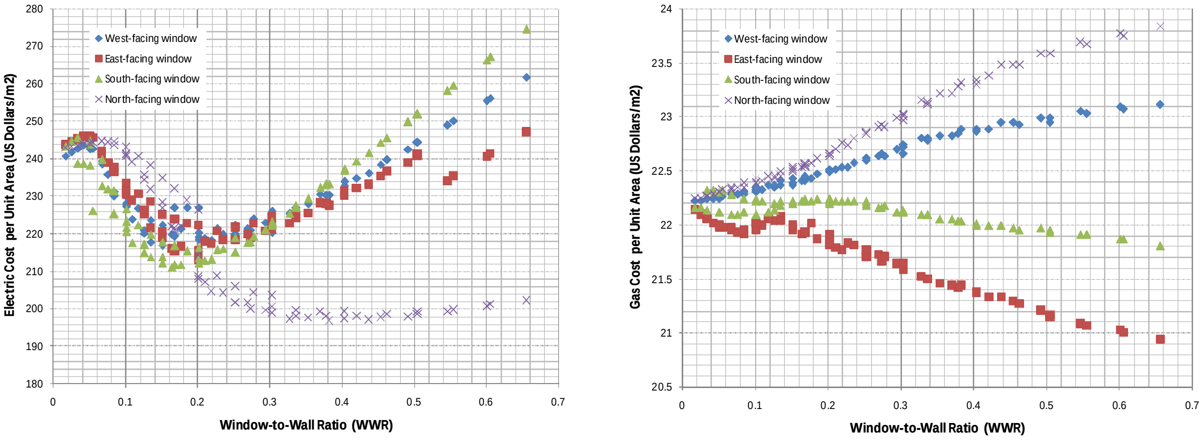


Fig. 4. A comparison between the estimated annual electric consumption per unit area of the classroom modeled in this paper and the one considered by Perez and Capeluto (2009)



(a) (b)

Fig. 5. The present value of the estimated (a) electric and (b) gas consumption per unit area of the selected classroom over a period of 50 years

A simple model is developed to estimate the construction cost of each classroom in different daylighting scenarios. Results of estimating the construction cost of simulated daylighting scenarios show that increasing the WWR leads to an increase in construction cost in a linear manner. The influence of size and orientation of the window on the present value of total cost of the classroom, which is the summation of gas, electric and construction costs is shown in Fig. 6.

As shown in Fig. 5 the electric costs of North-facing windows are very low. However, the gas cost in North-facing windows is generally the worst case for any particular WWR. Since in computing the total cost the contribution of gas cost per unit area is much less than electric cost, in the case that the construction cost is the same for all window orientations, the construction and operational cost of North-facing windows still have the lowest value.

According to this figure, large facing windows will generally increase the total cost, while for WWR greater than 0.2, a North-facing window performs much better in comparison with other window facings. Therefore, we can recommend the school designers to use the North-facing windows as much as possible. As it can be seen in Fig. 7, the orientation of the South, East and West-facing windows does not influence the total cost noticeably. The optimum value for the WWR in East, West and South-facing windows is in the range of 0.1 to 0.25. Therefore, the WWR of North-facing windows should be large (up to 0.5), but it should be kept reasonably small, less than 0.25, in other window orientation.

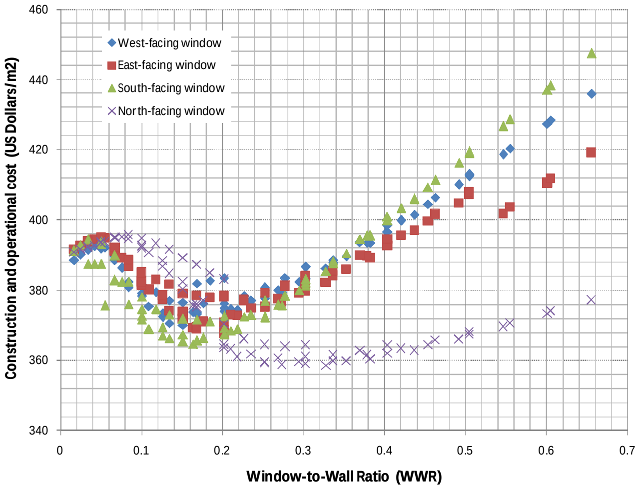


Fig. 6. The variation of the present value of the total cost of the classroom versus the WWR over a 50-year period

The recorded construction and operational costs of simulated 288 daylighting scenarios were randomly split into training and test sets. In this regard, for each considered installation face, 15 daylighting scenarios are randomly used for testing. In order to find the proper kernel function, kernel functions in this investigation were studied empirically and the polynomial kernel that provides the best results is selected. Besides setting the kernel function for SVR, it is necessary to set up the optimal values of error size, ε, and regularization factors, C, a toolbox in MATLAB, namely LIBSVM (Chang and Lin, [34]), is able to find the optimal values toward a unique, optimal and global solution through an automatic trial error process. The LIBSVM toolbox is used here for predicting the total construction and operational costs.

Correlation Coefficient (CC), Mean Square Error (MSE) and Normalized Mean Square Error (NMSE) were used to evaluate the performance of SVR. The best answer corresponds to polynomial kernel function with CC=0.988, MSE=12.02 and NMSE=0.042. These values confirm that SVR works well in predicting the total cost of a class room. Figure 7 provides a plot between the actual and predicted construction and operational cost.

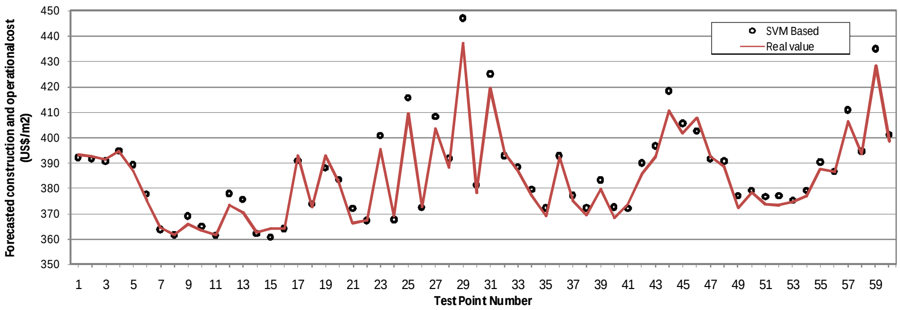


Fig. 7. Comparison between the observed and forecasted construction and operational costs using the trained SVM

6. SUMMARY AND CONCLUSION

Heating, cooling, and lighting costs of a classroom can be reduced through a climate-responsive design. In an integrated design, construction, gas and electric costs as well as climatic conditions are the main factors which should be considered by an architect in configuring classrooms' windows. Currently, there is no applied guideline to help architects in characterizing classrooms' windows. Even in residential houses, the literature is generally limited to some general architectural recommendations for determining the window characteristics.

The methodology of combining an energy simulation model with an artificial intelligence based model is proposed to investigate the effects of window characteristics on the present value of the total construction and operational cost of a classroom. The proposed model was applied to a standard classroom in a warm-dry climatic zone, Shiraz City in Iran. All possible daylighting scenarios were generated for the considered standard classroom and in the classroom. By keeping thermal and visual comfort at the standard level, the DOE-2 was utilized to estimate annual gas and electric consumption for the generated scenarios over a period of 50 years. A simple model was also developed to estimate the construction cost of the classroom in different daylighting scenarios.

Considering the operational and construction cost of the classroom, the results of simulations show that large facing windows will generally increase the total cost, while for WWR greater than 0.2, a North-facing window performs much better in comparison to other window facings. The optimum value for the WWR in East, West and South-facing windows is in the range of 0.1 to 0.25. Therefore, the WWR of North-facing windows should be large (up to 0.5) but it should be kept reasonably small, less than 0.25, in other window orientations. In finding the relations among available data, intelligent systems are able to find the hidden law behind the phenomenon. In this paper the feasibility of applying the Support Vector Regression (SVR) as a well-known version of SVM for functional estimation of the construction and operational cost is also examined. Appropriate statistical measures of the test results on several daylighting scenarios prove that the trained SVM-based model provides an excellent performance and the SVR is applicable and performs well for estimating the total cost of a classroom with respect to outputs of simulation model. Regarding the good performance of SVR in predictions, the trained SVR as an architectural assistant can rapidly, easily and accurately predict the operational and construction costs of a classroom just by determining the window size and installation face. The output of this study is useful to architectural designers of educational buildings to examine the energy behavior of various window characteristics. It should be noted that energy in Iran, especially for educational buildings, is offered at less than the actual price. By considering the actual energy price the benefits of using optimal window characteristics will become clearer. Further investigations are necessary to find out how classroom size affects the optimal window size and orientation. As the methodology is general, by increasing the training data set, the trained SVM can be utilized for simulating various classroom sizes in different climatic zones. In future works, classrooms with two or more windows in different directions can also be taken into account to find the optimal size of each window.

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