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MODELING THE RELATIONSHIP BETWEEN OUTDOOR METEOROLOGICAL DATA AND ENERGY CONSUMPTIONS AT HEATING AND COOLING PERIODS: APPLICATION IN A UNIVERSITY BUILDING

Okan Kon*[1], Bedri Yuksel[2]
and Aslan Deniz Karaoglan[3]

[1]Department of Mechanical Engineering
Balıkesir University, Balıkesir,Turkey

[2]Department of Mechatronics Engineering
Gelisim University, Istanbul, Turkey

[3]Department of Industrial Engineering
Balıkesir University, Balıkesir, Turkey

Abstract. In this study regression modeling is proposed for calculating the heating and cooling load of the buildings by considering the outdoor meteorological data. For this pupose, Balikesir University Rectorate Building is selected as the case building. In the winter months, measurements were made in the hot water boiler in the basement of the building for the heating energy load. For the cooling energy load, measurements were made in the chiller groups near the building. As climate data, eight variables were considered: outdoor temperature, solar radiation, relative humidity, wind speed, atmospheric pressure, sunshine duration, steam pressure, and 1 m underground temperature. The Minitab statistical analysis program was used to perform the modeling. 55 samples were used for mathematically modeling the heating load, while 37 samples are used for modeling the cooling load. The R^2 (coefficient of determination) values are calculated as 96.2% and 98.94% for cooling load and heating load, respectively. In addition to these findings, ANOVA results for both models were examined and both models were found to be significant.

1. **Introduction.** Urbanization and the increase in energy use and carbon dioxide emissions due to urbanization have made the climate impacts on energy use in cities more important. This requires research on regional and microclimate effects in the city [2]. Energy consumption for space heating and cooling typically accounts for more than 40% of the energy consumption of residential buildings. Accurate and rapid estimation of space heating and cooling loads sustains energy saving and reduces carbon emissions by using optimization design methods that take into account various building characteristics. Accurate and rapid estimation of space heating and cooling load and optimization methods can provide significant support during both the design and retrofitting processes of pre-built buildings [24].

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*Corresponding author: Okan KON.

When the literature is examined, studies dealing with the relationship between building energy consumption and weather data representing outdoor climate conditions are very rare. Weather data and climate conditions are an essential part of building optimization and simulation tools. These optimization and simulation methods are used to determine the size of HVAC systems as well as to estimate building energy consumption [26]. Building energy consumption is weather dependent. Current studies in the literature only take into account the effects of temperature and ignore other potential climate factors such as humidity, wind speed, and solar radiation [33]. In the studies those are using experimental data, regression analysis is a powerful statistical technique for establishing an adequate functional relationship between response and a set of associated design variables. This method consists of simple linear regression, simple nonlinear regression, multiple linear regression, multiple nonlinear regression, and so on. According to statistical principles of regression analysis, this method investigates the polynomial relationship between the output variable (ie response variable) and the input variables (ie design variables) [47]. Based on influential parameters such as outdoor dry bulb temperature, the regression model can predict baseline or pre-reinforcement energy consumption. The basic regression model can predict the building's energy consumption in the post-retrofit period. This fundamental regression model also enables an analyst to calculate normalized savings under various building operating conditions [40].

RSM consists of a set of statistical approaches based on some important variable. The method aims to simplify the model and optimize the response. Accordingly, linear or square polynomial equations are set up to describe the relationship between the response and the independent variables. In the RSM application, an approximation function must first be found, and often a low-order polynomial is estimated. Specifically, if the approximation function gives a linear relationship between input and output, then it is a linear equation model [25, 35, 36]. O. Kon [19] determined how the measured energy, efficiency and COP values during the heating and cooling period changed with meteorological parameters. Also, regression analysis for energy consumption analysis was made depending on meteorological data. Y. Liu et al. [29] examined the energy consumed during the building operating period in order to optimize the relevant design parameters to reduce the total energy consumption. An education building of Huazhong University of Science and Technology was used as a reference model. The building was used to construct an energy consumption model and to validate the model's reliability. Based on this model, it explores the energy-saving perspective to analyze ten factors that can affect the building's energy consumption. These factors are ranked according to their energy-saving potential through design tests. The six factors with the greatest potential for energy savings are selected and the others are separated to perform a different factorial response surface optimization analysis. M. Li et al. [23] examined the impact of climate change on the cooling energy consumption of office buildings in four major architectural climate zones in China. The dominant factors affecting monthly cooling loads are dry bulb temperature and wet bulb temperature. According to the results obtained in the study, the effect of humidity should be taken into account in order to increase the energy efficiency of buildings, especially in hot climate zones. M. R. Allen-Dumas et al. [2] examined the meteorological profiles of each building in a Chicago neighborhood to calculate energy use by building. This review is to measure and analyze the relationships between climate conditions, urban morphology, and energy use. In addition, these relationships have been used to improve energy-efficient urban development and planning. X. Ye et al. [47] investigated the factors affecting the hot jet propagation distance between the design parameters of the building jet ventilation system operated in the heating mode and developed multivariate regression models for the estimation of the propagation distance. With the regression models created for the hot air spreading distance, the optimized combination of the variables to meet the design requirement is determined. N. Mao et al. [31] compared the pros and cons of an (A task/ambient air conditioning) TAC system to save energy and maintain thermal comfort, using two optimization the response surface methodology (RSM) and TOPSIS. In the study, 9 simulation cases were designed and RSM method was applied to create energy consumption estimation models. This method is used to select the best out of 35 simulation situations. The difference was compared and analyzed using the two methods. N. Mao et al. [30] investigated the Task/ambient air conditioning (TAC) system applied in the building and examined the energy efficient performance. A numerical study was conducted on the TAC system applied in five different climate zones. To simplify numerical operation, response surface methodology (RSM) is used to estimate the operating power of TAC based on CFD results. X. Li and R. Yao [24] aim to develop a machine learning-based load prediction model for residential buildings; Five machine learning models (neural networks, polynomial kernel support vector regression (SVR), linear kernel SVR, Gaussian radial basis function kernel SVR, linear regression) were used to predict the space heating and cooling loads of residential buildings. Q. Li et al. [25] presented a simulation-based energy-comfort optimization model to evaluate various design alternatives for retrofitting a pre-built school building in Wuhan, China. The design parameters are the insulation thickness of the external wall, the heat transmission coefficient of the roof, the solar heat gain coefficient of the exterior window, and the window-to-wall ratio. The optimization method RSM (response surface method) was used to determine critical building design parameters and to create many alternative plans for retrofit based on building standards. H. S. Lim and G. Kim [26] developed time-based energy prediction models. To create the prediction models, 4-year (2011–2014) meteorological data in Seoul and mathematical equations used in energy analysis simulations were used. Based on multiple regression analysis, a cooling load estimation per building size, which takes into account the time phenomenon, has been identified as the most important model. Q. Meng and M. Mourshed [32] conducted a building energy analysis using a regression model between four-year (2012–2016) half-hourly measured natural gas consumption and Heating degree-days from 119 non-residential buildings representing seven different building types. Y. Zhou et al. [50] perfomed performance comparison of 15 different machine learning models in building energy consumption prediction. D. D. Kim and H. S. Suh [18] South Korea, developed a prediction model for energy consumption for residential buildings using the statistical method. While developing the model, the relationship between design factors and heating and cooling energy use in residential buildings was determined by using response surface methodology (RSM). The developed model was then compared with data from apartments in two cities in South Korea. S. Dongmei [10] created and tested a multiple regression model of energy consumption benchmarks based on 45 government buildings in Shenzhen, China. The model was applied to estimate energy consumption benchmarks and evaluate energy performance of two government office buildings in Shenzhen. Q. Meng et al. [33] examined how much natural gas consumption for heating different types of buildings, such as education and healthcare, is influenced by air properties. Multivariate regression models were used to determine the effect of air factors on gas consumption. M. Ghaderian and F. Veysi [15] proposed a multi-objective algorithm-based optimization model to simultaneously optimize the building's energy consumption and the thermal comfort of the building occupants. An existing office building in Kermanshah, Iran was selected to implement and evaluate this proposed optimization model. H. S. Lim and G. Kim [27] developed models that can predict thermal loads for heating, taking into account the time phenomenon, using weather data collected by the Korea Meteorological Agency over a three-year period (2011–2014). In addition, different estimation models are developed for different sized buildings in the study. M. T., Paulus [40] proposed a model that gives the best estimates of the coefficients for the three-parameter linear change point model with the sum of the squared errors as the loss function. This model gives accurate and reliable results and is easy to use. The regression model can predict the pre-reinforcement energy consumption of new or old buildings based on influential parameters such as outdoor dry bulb temperature. Ridwana et al. [43] investigate traditional regression modeling in building energy consumption estimation and propose a neural network model and regression models for estimating hourly energy use in the building, with data classifications to improve their performance. The proposed regression models and an ANN model with the proposed classification give very accurate results in predicting the energy demand compared to the traditional regression models. The correlation coefficient and root mean square error values are noticeably improved for the proposed models and can potentially be used for energy conservation and energy conservation purposes in buildings. M. Li et al. [22] examined the effect of climate parameters on building heating energy consumption for different energy types such as coal, natural gas and electricity in Tianjin, a large city in northern China. The energy consumption of the buildings was simulated with a simulation tool (temporary system simulation program (TRNSYS)). The relationships between heating energy consumption and climate parameters on daily, monthly and annual scales were determined by multiple linear regressions. Data for climate variables (dry bulb temperature, solar radiation, wet bulb temperature, wind direction and wind speed. Y. Sun et al. [46] developed statistical models for the energy consumption of buildings using regression-based methods for important microclimate variables such as local temperature, wind speed, wind pressure and solar radiation. In the study, climate parameters were ranked according to their highest effects on building energy consumption. H. Radhi[42] examined the effect of weather data used in building simulations on building energy performance for buildings in Bahrain. Two methods were used for the evaluation of climate variables and building energy consumption. F.Gugliermetti et al. [16] investigated the effect of meteorological data on the evaluation of office building energy performance in the Mediterranean climate. In the study, 20 years of daily direct and diffuse solar radiation, hourly external wind speed and temperature data of the city of Rome, Italy, were used. A. Al-Ghandoor et al. [1] developed two empirical models based on multiple linear regression analysis for savings in electricity and fuel consumption in Jordan's residential sector. Residential electricity and fuel consumption simulations are used in the multivariate regression model. T. Catalina et al. [7] developed a regression model for monthly heating energy estimation for single-family dwellings in warm climates for 16 major cities in France. By using the simplified model, rapid parametric study is provided to optimize the building structure and economic or environmental criteria. The input parameters for the regression model are building heat transfer values, building shape factor, window floor area ratio, building constants, solar air temperature and heating set point. 270 different scenarios were analyzed. Models were made according to multiple regression analysis. Rosa M.D. et al. [44] calculated and compared the heating and cooling degree-day values of hourly temperature profiles for cities such as Rome and Milan in Italy, using the ASHRAE average daily degree-hour method for the period between 1978 to 2013. By using the temperature amplitudes and frequencies, the energy consumption of the buildings can be estimated. Praene J. P. [41] used meteorological values to evaluate the thermal performance of traditional houses in three climate zones corresponding to dry, humid, and mountainous areas in Madagascar. A meteorological clustering technique was used in the calculations. In their study, Lam J. C. [21] investigated the cooling/heating loads and energy uses of buildings in Subtropical Hong Kong depending on parameters such as dry bulb temperature, wet bulb temperature, and global solar radiation. Regression models were developed for simulated monthly building heating/cooling loads and total energy use. By using the developed regression model, it can be used to predict possible changes in building energy use in the coming years. Jovanovic S. et al. [17] analyzed the effect of weather conditions on electricity consumption due to heating in residential and office buildings in the city of Kragujevac, Republic of Serbia, in the seven-year period from 2006 to 2012. The results showed that the average daily air temperature is the most effective parameter among the climate (meteorological) parameters. Chan A.L.S. and Chow T.T. [8] modeled a general office building with a green roof in Hong Kong using EnergyPlus and its energy performance was determined by different future climates for three future periods (2011–2030, 2046–2065 and 2080–2099) and two emission scenarios. Liu Y. et al. [28] developed a method to generate weather data files for a new typical meteorological year for different micro-scale areas in Singapore based on recent years' weather data. In the study, a comparative impact analysis was made between the old air data file and the new air data files in terms of energy consumption in residential buildings. Verichev K. et al. [49] examined the variation of energy consumption for heating single-family dwellings in three regions in southern Chile, according to climate zones, using meteorological data, and analyzed the changes in energy consumption depending on future climate change scenarios. Parhizkar T. et al. [39] used large datasets for energy consumption estimation problems of buildings. Four cases with different climatic zones (cold, temperate, warm-dry and hot-humid) were studied. The big data set consists of five prediction models, including linear regression, support vector regression, regression tree, random forest, and nearest neighbors. The results show that it enables them to obtain an intelligent dataset more efficiently than any large dataset for energy consumption estimation problems. Papakostas K. et al. [37] calculated annual heating and cooling degree-days for two typical base temperatures for heating and cooling for the Greek cities of Athens and Thessaloniki from 1983 to 2002. These calculations evaluated the impact on the energy requirements for heating and cooling a residential building. Cao J. et al. [6] investigated the effect of air inlet height on the vertical distribution of the outdoor atmospheric parameter for mega-scale high-rise buildings constructed in the cold region of China. Cheng R. et al. [9] estimated the cooling load of the air conditioner of the ice storage system in a large public building in northern China; They proposed a short-term hybrid forecasting model based on Mean Effect Value-Improved Gray Wolf Optimizer-Support

Vector Regression (MIV-IGWO-SVR). They analyzed the effect of meteorological data on the cooling load. Amani N.et al. [3] made energy consumption simulations using climate data such as air temperature, sunshine hours, wind, precipitation, and hourly sunlight in northeast Iran for a single-story house in a cold and semi-arid climate. They used DesignBuilder software for thermal simulations and analysis of the building. Elshafei G. et al. [11] investigated the design strategies of different building envelope shapes for green building design with the DesignBuilder program based on meteorological data in Minia City, one of the hot desert climate regions in Egypt. Yoo H. et al. [48] investigated the effects of various selected meteorological parameters such as ambient temperature, solar radiation, relative humidity, and wind speed on the heating and cooling energy loads of office buildings in Seoul, Daejeon, Daegu, Gwangju and Busan, South Korea. They made simulations for energy load calculations. Mean deviation error and root mean square error were determined for heating and cooling loads. Battista G. et al. [5], using the wind speed and relative humidity, monthly average maximum and minimum temperatures, the effect of various meteorological data on the annual heating and cooling energy need of a sample building in Rome was investigated using TRNSYS software. S. Soutullo et al. [45] comparatively examined the impact of climate change on the energy performance of residential buildings to derive potential design strategies. For this purpose, the thermal energy demands of two reference residential buildings in Madrid based on meteorological parameters of the last forty years, twenty years and ten years were investigated. Anjomshoaa A. and Salmanzadeh M. [4] investigated the effects of air psychrometric properties such as temperature, pressure, humidity and relative humidity on the calculation of energy consumption of buildings. Pappaccogli G. et al. [38] simulated the energy consumption of a building in Bolzano, Italy, under various meteorological conditions. Mikulik J. [34] analyzed the energy demand of an office building in the city of Kraków in Southern Poland depending on meteorological parameters such as wind speed, radiation, humidity, and air temperature. The relationship between meteorological parameters and energy loads was also made based on multiple linear regression analysis. A Pearson correlation coefficient was used to estimate the correlation between meteorological parameters. A k-means clustering method was applied to distinguish typical energy load patterns.

We have studied on mathematically modeling the relationship between heating / cooling energy load change and outdoor meteorological data of business and service buildings. For this purpose Balikesir University Rectorate Building was chosen as the business and service building. We used regression modeling for calculating the mathematical relation between the factors (outdoor temperature, relative humidity, solar radiation, wind speed, atmospheric pressure, sunshine duration, steam pressure, 1 m underground temperature) and the responses (the cooling energy load for the summer months, the heating energy load for the winter months). We aimed to effectively predict the the cooling energy load for the summer months and the heating energy load for the winter months. According to the literature review it is indicated that; while estimating the heating and cooling workload, no study was found that uses regression modeling that considers the factors namely outdoor temperature, solar radiation, relative humidity, wind speed, atmospheric pressure, sunshine duration, steam pressure, and 1 m underground temperature together. This was the motivation of this research. Today, energy consumption in buildings and future energy consumption estimations are very important. In this study we propose a method and present the related input variables (factor) for effective prediction of heating / cooling energy load estimation. The most important parameters for energy consumption estimates in buildings are meteorological values. It will be possible to make predictions about the change in energy demand in buildings due to future climate changes. The measures can be determined to be taken in case of difficulties in any energy supply. By determining the capacities of the equipment that provides the energy supply, it will be easier to replace it with the appropriate equipment in case of any failure. Precautions can be taken to ensure that there is no disruption in the energy supply in case of any renovation in the building, the construction of a new additional building, renovation, and repair. In addition, appropriate examination and estimation can be made of energy costs. It will be possible to make predictions by researching the energy consumption and equipment financial values in detail. By providing more efficient energy consumption, important data will be obtained both financially and in terms of reducing energy consumption. By consuming less energy, less negative impact on global warming will be achieved. Indoor comfort temperatures have been determined to a great extent for business and service buildings. But outdoor meteorological conditions are variable. For this reason, the energy consumption of the buildings depending on the outdoor meteorological conditions is among the most effective parameters. In the study, business and service buildings were selected among these building types. Because, such buildings are generally large-volume buildings. It can be an example for making energy consumption estimations of such large-scale buildings in summer and winter periods depending on meteorological parameters. It can be a reference for similar buildings in the equipment capacity required for the heating and cooling load. With this explanation, a new contribution will be made to the literature by using both application and new analysis techniques.

2. **Methodology.** Measurements are performed at Balikesir University Rectorate Building. In the winter months (January, February, March, April November and December), measurements were made in the hot water boiler for the heating energy load. For the cooling energy load, measurements were made in the chiller groups in the summer months (June, July, August and September). Taking the working hours into consideration, the average daily values were determined. Heating and cooling operations are not carried out in May and October. Measuring devices were datalogger and flowmeter. Regression modeling is used for the mathematical modeling. Regression modeling is performed by using MINITAB statistical package.

2.1. **Definition of reference building.** In the study, the building that was taken as a reference is the Rectorate building of Balıkesir University. Balıkesir University is 17 km away from Balıkesir city center, on the road to Bigadic district, in Balıkesir University Cagis Campus (390 39' N - 270 52' E). It is a complex business and service building consisting of the main building and the printing house behind the sample building. The Rectorate building has 13968 m^2 usage area, 4952 m^2 external wall and 2180 m^2 window area. The Printing House, on the other hand, has 1534 m^2 floor area, 645 m^2 external walls and 247 m^2 window area. The view of the building is given in Figure 1. The building envelope areas of the building in different directions are given in Table 1 and the heat transfer coefficient of the building envelope used in the building energy analysis is given in Table 2.

FIGURE 1. A general view of Balikesir University Rectorate Building.

TABLE 1. Total external window and wall areas of the Rectorate and printing house (m^2).

Direction	**NE**	**E**	**SE**	**S**	**SW**	**W**	**NW**	**N**	**Undirection**
Window	978	-	166	11	945	18	156	-	266
Wall	1946	-	980	10	1856	-	851	-	-
Component				**Main Building**			**Printing house**		
Total ground area				13968			1534		
Window to wall ratio				0.440			0.385		

TABLE 2. Heat transfer coefficient values of building construction elements (W/m^2.K).

Parameter	**Main Building**	**Printing house**
Wimdow, door and glass door (12 mm between two glasses, aluminum joinery)	2.908	2.908
External wall	0.494	0.555
Floor (Ground)	0.929	0.929
Roof (Terrace)	0.350	0.350
Concrete curtain wall (interior wall)	1.163	1.163

2.2. **Data Recording System with Measurement in Heating and Cooling System.** The heating and cooling system is located in the basement of the main building. Water temperature and flow measurements were made to use in calculations in the heating center. In the heating system, pipes of different diameters from 40 mm to 150 mm diameter are used in the places where measurements are made in the heating and cooling system. Steel pipes are used in the heating and cooling system. In temperature measurements in both heating and cooling installations, Pt-100 temperature sensors (8 pieces) were used to measure water temperatures. A 100 m cable is used for the Pt-100 temperature sensor and datalogger connections. Computer connections were made with the Datalogger, where the data is stored and recorded. In heating and cooling installation; Pt-100 temperature sensors are

placed before and after the boiler and chiller. A picture of an ultrasonic flowmeter used to measure the amount of flow in the pipe is shown. Ultrasonic flow meter; The pipe-mounted headers are made at the points where the straight pipe length and the distance between the headers are appropriate. In particular, turbulent flow regions were avoided while taking the measurements. Indoor installation pipes and pipes from heating and cooling groups are connected to the same collectors. Pipe valves coming from the boilers are kept closed during the summer months, and the valves of the pipes coming from the cooling groups are kept closed during the winter months. In addition, the electricity consumption of the natural gas and water cooling groups of the boilers was measured and energy calculations were made.
In the study, the system (datalogger) that records the temperature data of the hot water coming to and leaving the boiler from the heating system and the cold water coming to and leaving the cooling system to the chiller is given in Figure 2. Figure 3 shows the views of a) heating system boiler, b) cooling system (Chilller) in the heating center in the sample building. In Figure 4; a) sensor pt-100 installation for water temperature measurement for both boiler and chiller, b) meter for electricity measurement for cooling system, c) ultrasonic flow rate (measurement using Transducers) used to scale the amount of water in both boiler and chiller is given.

FIGURE 2. Datalogger system [19].

FIGURE 3. In the example building, a) Heating system boiler, b) Cooling system (chilller).

2.3. **Formulas Used in Heating Energy Load, Delivered Heat, and Efficiency Calculations for the Heating System.** The heat given to the heating system can be found by multiplying the lower heating value of the natural gas

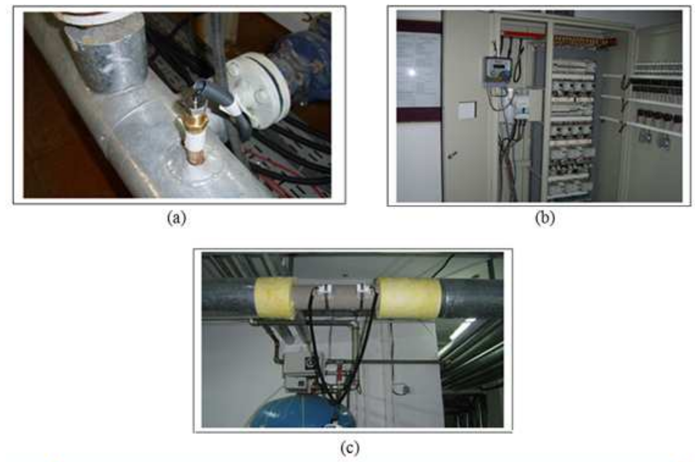

FIGURE 4. a) Pt-100 installation of temperature sensor for water temperature measurement, b) Counter for electricity measurement for cooling system, c) Ultrasonic flow measurement (measurement using transducers).

consumed in the boilers and the average consumption amount of the fuel (average value of the entire heating period). The heat drawn from the heating system can be calculated by multiplying the amount of hot water per unit time circulating in the system and the temperature difference of the water entering and leaving the boiler.

The heating system efficiency value is the ratio of the heat given to the heating system (boiler) to the heating energy load from the system and given in Equation (1) [12, 13, 14, 20].

Heating system efficiency value is the ratio of the heat given to the heating system (boiler) to the heating energy load from the system and given in Equation (1).

$$\eta=\frac{\mathrm{Q_H}}{\mathrm{Q_V}} \tag{1}$$

where Q_H is the heating load from the system (kW) and Q_V is the heating that is given to the system (kW). The formula for Q_H is given in Equation (2):

$$\mathrm{Q_H}=\dot{\mathrm{m}}\ \mathrm{C_p}\ \Delta\mathrm{t} \tag{2}$$

where m (kg/s) is flow rate, C_p is specific heat (kJ/kg.K), Δt is the temperature difference between entry and exit of the heating system (^{0}C). The formula for Q_V is given in Equation (3):

$$\mathrm{Q_V}=\dot{\mathrm{Y}}\ \mathrm{H_u} \tag{3}$$

where; Y is fuel flow (m^3/s), H_u is lower heating value (kJ/m^3).

2.4. **Formulas Used for The Cooling Energy Load, Power And COP (Cooling Performance Coefficient) Calculations for the Cooling System.** Water chillers (Chiller) used in the cooling system consume electricity. The daily average energy consumption in kW is calculated with the help of the daily electricity consumption values and daily operating times of the water chillers. The energy drawn from the cooling system can be calculated by multiplying the amount of cold water per unit time circulating in the cooling system and the temperature difference of the water leaving and entering the cooling group. The performance value of the cooling system is the ratio of the energy taken from the system to the supplied (consumed) energy as in Equation (4) [12, 13, 14, 20].

$$\mathrm{W} = \frac{\mathrm{E}}{\mathrm{S}} \tag{4}$$

where E (kWh) is average daily consumption of electricity, and S (hour) is the daily average operating time of chillers.

$$\mathrm{Q_C}{=}\dot{\mathrm{m}}\ \mathrm{C_p}\ \Delta\mathrm{t} \tag{5}$$

where Q_C is the energy is the cooling energy load from the system (kW) and W is the electricity energy is given to the system (kW). In the equation above; (kg/s) is flow rate, C_p is specific heat (kJ/kg.K), Δt is the temperature difference between entry and exit of the cooling system (^{0}C).

$$\mathrm{COP} = \frac{\mathrm{Q_C}}{\mathrm{W}}. \tag{6}$$

2.5. **The parameters used in the calculations.** In the study, the values used in energy load calculations in both heating (boiler) and cooling (chiller) systems are given in Table 3 and Table 4. These values are used in the energy load calculations for the heating and cooling period of the sample building.

Table 3. The values used in the calculations for the heating system [19].

Flow (m^3/h)	14.7
Specific heat (kJ/kg.K)	4.183
Usage period (hour/day)	7.63
Lower heating value (kJ/m^3)	34645
Average delivered heat (kW/day)	415.12

Table 4. The values used in the calculations for the cooling system [19].

Flow (m^3/h)	93
Specific heat (kJ/kg.K)	4.199
Average usage period (hour/day)	7.62

3. Mathematical Modeling by the aid of Regression.

3.1. **The cooling energy load for the summer months.** In this study, cooling energy load for summer months and heating energy load for the winter months are mathematically modeled in terms of the climate data (factors). In the first stage, mathematical modeling is performed for the cooling energy load (first response) and in the second stage, the same calculations are performed for the heating energy load (second response). The same factors are valid for both responses. As climate data, 8 factors such as outdoor temperature, relative humidity, solar radiation, wind speed, atmospheric pressure, sunshine duration, steam pressure and 1 m underground temperature were considered. The factors which have effect on the cooling energy load is listed in Table 5.

Table 5. Factor levels.

Factor	Symbol	Unit of measure
Outdoor temperature	X_1	^{0}C
Relative humidity	X_2	%
Solar radiation	X_3	kWh/m^2
Wind speed	X_4	m/s
Atmospheric pressure	X_5	mbar
Sunshine duration	X_6	hour
Steam pressure	X_7	hPa
1 m underground temperature	X_8	^{0}C

The observed cooling load values are presented in Table 6. In the following parts of the text, Y_i is used to represent the observed values.

A regression equation with linear and quadratic terms is used to model the relationship between summer cooling load (kW) and the factors influencing this load. The Minitab statistical analysis program was used to perform the modeling, and 37 samples were used for this purpose.The full quadratic regression model for summer months cooling load (kW) is given in Equation (7) [35, 36]:

$$\begin{aligned} \hat{Y}_i \quad = \quad & -192554.14296686 - 69.05173048X_1 + 16.18029972X_2 \\ & -17.83732959X_3 + 8.55787804X_4 + 396.15302875X_5 - 11.30228472X_6 \\ & +11.35626881X_7 - 34.18566697X_8 + 1.23106366X_1^2 - 0.21075906X_2^2 \\ & +0.37131604X_3^2 - 0.49666035X_4^2 - 0.20243446X_5^2 - 1.45058397X_6^2 \\ & +0.00831456X_7^2 + 1.12069057X_8^2 \end{aligned} \tag{7}$$

R^2 for the model is calculated as 96.20%. R^2 is close to 100% which means These values indicate that the eight factors included in the model during the modeling phase are adequate to explain the change in cooling load. The ANOVA results are presented in Table 7 [35, 36]:

When the analysis of variance (ANOVA) was examined, it was seen that the model was significant. Prediction performance of this model is presented in Table 8. In this table, $\hat{Y}_i$ is used to represent the expected value (predicted (fitted) value from the mathematical model) and PE (%) is the prediction error percentage.

The regression equation was tested with samples belonging to the relevant period but not used in the modeling phase, and allowed to make high-accuracy predictions for the related days with very low estimation errors. The confirmations results are given in Table 9.

According to the results presented in Table 9, it can be clearly indicated that the predicted results are very close to the observed results and the overall prediction error is less than 11%.

Similarly, the relationship between the winter heating load (kW) and the factors affecting this load is modeled with a regression equation containing linear terms and interaction terms. 55 samples were used. The data used for mathematical modeling of winter months heating load (kW) is presented in Table 10.

TABLE 6. Observed cooling energy load for summer months (kW)

Observation No	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	Y_i
1	29.45	51	43.5	3.2	999.6	8.9	20	20.2	215.0
2	31.6	40	44.4	2.0	1001.7	8.9	17.5	20.4	214.2
3	30.35	48	40.3	3.8	999.1	7.9	20.7	20.9	226.4
4	30.2	31	43.8	4.5	994.5	8.4	13.2	21.8	243.5
5	21.7	66	23.8	2.8	991.7	1.8	15.1	22.0	204.3
6	24.15	60	37.7	2.2	998.6	6.3	18.6	21.5	179.8
7	28.925	52	43.5	4.0	999.7	8.9	20.3	21.6	247.2
8	27.8	58	37.1	5.5	999.9	5.4	20.6	22.0	234.6
9	28.4	41	43.5	4.2	1000.1	8.4	15.8	22.3	239.6
10	24.2	60	23.5	5.5	999.6	2.9	18.7	22.4	207.0
11	22.775	60	27.0	3.2	1001.3	2.3	16	22.6	198.9
12	28.975	50	44.3	3.4	998.5	8.6	19.8	22.7	290.6
13	30.175	47	42.9	4.9	996.6	8.8	19.4	22.9	291.1
14	29.55	53	40.5	5.6	996.5	8	21.6	23.1	273.0
15	29.8	49	39.8	9.7	999.1	7.6	20.8	23.3	300.2
16	30.125	55	42.3	7.7	997.9	8.1	22.6	23.8	294.4
17	29.55	54	41.5	5.5	998.1	7.8	21.3	24.0	291.4
18	29.35	57	35.1	5.9	996.8	6.4	22.8	24.3	312.5
19	30.9	48	40.1	9.2	997.2	8.2	21.1	24.4	304.9
20	31.125	41	35.6	3.3	989.9	7.1	19.2	24.8	341.4
21	27.675	49	43.9	9.0	998.7	7.9	18.2	25.0	352.0
22	28.1	65	25.0	1.9	993.5	2.9	25.5	25.4	300.7
23	30.875	60	34.5	4.8	996.6	5.9	26.5	25.6	359.4
24	32	61	39.3	6.0	996.9	8.2	27.1	25.7	330.8
25	32.675	53	41.3	4.5	998.0	8.7	24.6	25.8	369.2
26	33.125	42	40.8	3.8	999.2	8.8	20.1	25.8	334.9
27	32.3	50	39.5	3.8	1000.0	8.8	23	25.9	320.1
28	32.125	50	39.2	7.7	999.4	8.8	22.8	26.1	356.7
29	32.375	52	37.9	2.0	996.9	8.8	24	26.2	327.8
30	31.175	51	38.5	6.1	996.1	8.8	22	26.3	340.9
31	31.675	46	38.8	5.5	998.8	8.8	20.4	26.4	334.0
32	28.575	52	39.0	4.4	998.9	8.8	19	26.4	241.1
33	29.275	44	38.5	6.3	999.9	8.8	16.9	26.4	238.6
34	30.45	34	35.9	3.2	990.5	8.7	15	26.3	291.2
35	23.95	37	40.4	4.6	1004.7	8.8	10.7	26.1	172.3
36	25.425	59	25.1	6.3	1002.3	3.8	16.8	25.3	216.7
37	25.55	42	30.4	3.6	998.8	7.6	14.3	23.8	168.0

TABLE 7. ANOVA results for the mathematical model of summer months cooling load (kW).

Source of the Variation	Degrees of Freedom(df)	Sum of Squares (SS)	Mean Squares (MS=SS/df)	$F_0 = \frac{MStr}{MSE}$,	F-Critical = $F_{0.05.\ 16.\ 20}$	Result
Regression	16	SS_{Tr}= 119302	MS_{Tr}= 7456.37	31.61	$F_0 > 2.1840$	Model Significant
Residual Error	20	$SS_E = 4718$	$MS_E = 235.91$			

TABLE 8. Performance of the regression model of summer months cooling load (kW).

Observation No	Y_i	$\hat{Y}_i$	PE_i (%)
1	215.0	209.5434	2.621
2	214.2	215.8918	0.781
3	226.4	247.6857	8.583
4	243.5	242.6024	0.362
5	204.3	204.8480	0.273
6	179.8	182.5927	1.533
7	247.2	227.5941	8.617
8	234.6	230.8839	1.602
9	239.6	236.7435	1.222
10	207.0	215.8362	4.088
11	198.9	191.6143	3.826
12	290.6	278.7376	4.263
13	291.1	289.1346	0.663
14	273.0	285.4407	4.343
15	300.2	291.8697	2.863
16	294.4	311.8819	5.598
17	291.4	298.9131	2.523
18	312.5	291.3290	7.270
19	304.9	324.6703	6.074
20	341.4	350.4664	2.588
21	352.0	341.0928	3.189
22	300.7	309.2216	2.758
23	359.4	352.5373	1.954
24	330.8	334.3784	1.064
25	369.2	371.2435	0.554
26	334.9	342.6600	2.277
27	320.1	319.9383	0.052
28	356.7	336.0115	6.150
29	327.8	325.1083	0.832
30	340.9	333.3041	2.284
31	334.0	322.9598	3.410
32	241.1	257.8842	6.495
33	238.6	260.9476	8.547
34	291.2	276.2196	5.429
35	172.3	178.8187	3.673
36	216.7	210.0973	3.123
37	168.0	163.7964	2.540

TABLE 9. Confirmation tests.

X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	Y_i	$\hat{Y}_i$	PE_i (%)
25.325	55	23.0	4.4	991.9	3.3	16.5	21.9	250.1	257.4703	2.845
21.25	75	15.1	2.9	996.7	0.7	17.7	22.2	135.1	136.4706	0.985
28.725	55	43.5	4.5	1000.8	8.5	20.3	22.6	240.7	232.6609	3.472
28.575	55	34.8	3.8	998.3	5.4	20.8	24.2	312.3	283.5535	10.153

The relationship between the winter heating load (kW) and the factors affecting this load is modeled with a regression equation that includes linear terms and interaction terms. The Minitab statistical analysis program was used to perform the

TABLE 10. Observed cooling energy load for winter months (kW).

Observation No	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	Y_i
1	2.47	82	5.7	3.2	1010.8	0.1	5.9	11.7	217.5
2	1.67	74	16.2	0.5	1010.4	4.6	6.4	11.6	216.3
3	11.57	50	9.0	4.8	1004.0	0.2	9.1	11.3	210.5
4	16.27	52	6.3	4.1	1005.2	0.1	10.1	11.0	166.2
5	11.17	65	15.4	2.9	1002.8	4.8	9.0	11.1	169.0
6	10.60	83	4.0	2.0	995.7	0.0	10.3	11.3	188.6
7	8.18	96	6.4	4.0	998.6	0.0	9.9	11.3	207.1
8	8.03	99	5.8	0.5	1002.9	0.0	10.0	11.1	200.9
9	3.38	91	5.7	4.0	1002.5	0.0	6.7	10.9	201.4
10	2.55	99	1.1	6.4	998.6	0.0	6.2	10.6	203.3
11	-2.80	97	8.2	7.2	1020.1	0.4	4.6	9.8	293.9
12	-1.88	74	19.6	4.4	1021.3	7.2	3.7	9.6	320.0
13	5.88	78	4.2	0.5	988.7	0.1	10.7	8.6	214.1
14	12.52	63	14.9	6.4	997.6	4.0	9.4	8.1	188.8
15	7.05	79	15.7	0.8	998.4	3.5	9.4	7.7	177.9
16	15.85	61	12.9	7.5	988.5	2.4	11.2	8.4	191.3
17	9.40	68	17.7	0.3	1002.3	3.9	9.5	8.7	173.7
18	12.95	66	4.7	0.8	994.7	0.0	10.9	8.8	168.1
19	9.32	64	19.6	0.3	1005.3	4.3	8.1	9.8	175.0
20	14.75	64	12.3	0.9	994.7	1.2	11.3	10.1	166.6
21	11.70	75	17.0	0.3	989.1	2.9	11.2	10.2	151.8
22	9.63	98	3.6	3.6	997.1	0.0	11.2	10.3	179.5
23	15.07	55	18.0	3.5	997.6	4.1	11.0	10.6	160.1
24	8.90	55	12.5	1.0	1000.8	0.1	7.3	10.8	147.5
25	12.95	87	8.0	0.5	993.2	0.0	13.4	10.8	169.7
26	6.33	99	7.3	2.8	998.9	0.0	8.6	10.8	189.6
27	7.87	59	25.0	4.3	1000.2	5.5	6.4	10.7	166.1
28	8.18	45	29.4	1.8	1011.2	7.1	5.1	10.7	145.1
29	7.42	46	31.5	2.7	1019.4	7.6	4.6	10.7	166.5
30	7.57	45	35.7	2.0	1020.5	8.5	5.3	10.6	156.6
31	14.53	35	31.9	0.3	1010.6	8.3	7.2	10.3	135.6
32	19.00	56	37.1	3.6	1005.2	7.4	11.6	10.3	166.3
33	12.03	64	33.5	7.2	1009.6	8.6	9.0	10.8	196.5
34	15.30	50	37.1	2.5	1006.6	8.0	8.8	11.2	188.1
35	11.25	97	5.3	1.6	1000.8	0.0	11.3	12.5	195.9
36	11.73	85	12.4	2.9	1007.6	0.8	10.8	12.6	209.1
37	13.07	62	34.6	8.1	1001.8	6.5	9.2	12.5	193.0
38	12.17	71	45.6	1.0	1005.9	8.8	9.2	12.5	231.0
39	16.87	54	18.2	1.0	1003.4	0.7	9.7	12.6	168.8
40	12.75	72	17.4	7.1	1007.8	1.5	10.1	14.5	175.4
41	14.97	66	47.2	4.6	1004.1	8.8	10.3	14.5	146.5
42	11.25	84	17.6	0.0	1013.9	5.8	13.6	16.5	165.1
43	16.08	38	12.8	1.3	999.9	1.3	9.5	16.1	91.5
44	21.98	44	17.9	7.2	1003.5	6.0	12.1	15.9	122.8
45	19.80	35	17.7	3.3	1005.3	5.9	9.7	16.0	85.8
46	8.70	71	11.0	0.0	1004.2	1.0	10.3	16.0	209.2
47	14.55	66	9.4	2.8	996.0	1.0	12.1	15.7	238.4
48	8.07	74	12.3	0.5	1007.8	4.3	10.7	15.5	286.2
49	12.65	72	5.7	1.5	1000.7	0.9	12.9	15.2	263.2
50	6.45	99	2.5	4.1	993.8	0.0	8.1	15.0	303.4
51	3.13	99	7.0	0.4	999.9	0.0	7.2	13.3	178.9
52	5.13	99	4.2	0.9	993.3	0.0	7.9	12.5	182.2
53	8.03	80	3.4	0.9	991.1	0.0	8.8	12.3	202.3
54	12.43	69	9.2	0.6	1008.3	0.7	11.9	11.8	188.6
55	12.55	87	1.2	1.1	1004.0	0.0	13.6	11.9	198.5

modeling, and 55 samples were used for this purpose. The full quadratic regression model for summer months cooling load (kW) is given in Equation (8) [35, 36]

$$\begin{aligned}\hat{Y}_i = & -14682.378466 + 794.224483X_1 - 2.090533X_2 - 282.645950X_3 \\ & +259.779595X_4 + 14.957958X_5 + 1089.985609X_6 - 59.821875X_7 \\ & +685.217329X_8 - 0.028387X_1X_2 + 2.277754X_1X_3 + 1.385693X_1X_4 \\ & -0.801453X_1X_5 - 4.631985X_1X_6 - 3.148900X_1X_7 + 0.900811X_1X_8 \\ & +0.370872X_2X_3 + 0.081150X_2X_4 - 0.004368X_2X_5 - 0.642246X_2X_6 \\ & -0.286225X_2X_7 + 0.505321X_2X_8 - 1.034765X_3X_4 + 0.276715X_3X_5 \\ & +0.230631X_3X_6 - 2.017779X_3X_7 - 2.204987X_3X_8 - 0.249737X_4X_5 \\ & +2.966932X_4X_6 - 2.999157X_4X_7 + 1.135007X_4X_8 - 1.079128X_5X_6 \\ & +0.141094X_5X_7 - 0.721311X_5X_8 + 0.598379X_6X_7 + 5.918684X_6X_8 \\ & +0.886180X_7X_8\end{aligned} \tag{8}$$

R^2 for the model is calculated as 98.94%. R^2 value indicate that the factors used in the model are sufficient (there is no need to add additional factors to the model). The ANOVA result for the regression model given in Equation (8) is presented in Table 11 [35, 36].

TABLE 11. ANOVA results for the mathematical model of winter months heating load (kW).

Source of the Variation	Degrees of Freedom (df)	Sum of Squares (SS)	Mean Squares $MS = \frac{SS}{df}$	$F_0 = \frac{MStr}{MSE}$	$F-Critical = F_{0.05.\ 36.\ 18}$	Result
Regression	36	SS_{Tr}= 105801	MS_{Tr}= 2938.91	46.69	$F_0 > 2.0778$	Model Significant
Residual Error	18	SS_E= 1133	MS_E= 62.94			

According to the given results, it can be clearly observed that the calculated F_0 value is greater than the F-Critical value (which can be referred from the F-table) which means the regression model is significant and it can be used for predictions. Prediction performance of this model is presented in Table 12.

According to the results presented in Table 13, it can be clearly indicated that the predicted results are very close to the observed results and the overall prediction error is less than 9%.

The regression equations created for both periods were tested with samples belonging to the relevant periods but not used in the modeling phase, and allowed to make high-accuracy predictions for the related days with very low estimation errors.

4. **Conclusions.**

We have studied on mathematically modeling the relationship between heating/cooling energy load change and outdoor meteorological data of

Table 12. Performance of the regression model of winter months heating load (kW).

Observation No	Y_i	$\hat{Y}_i$	PE_i (%)
1	217.5	220.2425	1.262
2	216.3	222.8993	2.975
3	210.5	210.1218	0.157
4	166.2	167.5518	0.797
5	169.0	178.1366	5.150
6	188.6	195.7938	3.683
7	207.1	216.9125	4.508
8	200.9	202.1976	0.653
9	201.4	194.8478	3.365
10	203.3	202.0938	0.598
11	293.9	294.3949	0.168
12	320.0	317.7057	0.730
13	214.1	216.0205	0.867
14	188.8	185.4679	1.785
15	177.9	167.9116	5.956
16	191.3	192.4553	0.604
17	173.7	178.4649	2.684
18	168.1	164.8426	1.956
19	175.0	173.842	0.667
20	166.6	164.1457	1.506
21	151.8	154.4695	1.736
22	179.5	177.4386	1.168
23	160.1	156.0207	2.605
24	147.5	143.687	2.671
25	169.7	172.6706	1.711
26	189.6	192.0509	1.283
27	166.1	172.659	3.775
28	145.1	143.81	0.873
29	166.5	165.0346	0.914
30	156.6	157.5415	0.599
31	135.6	133.5612	1.539
32	166.3	165.7186	0.353
33	196.5	199.1031	1.318
34	188.1	193.6068	2.864
35	195.9	194.7535	0.584
36	209.1	202.1079	3.484
37	193.0	187.6846	2.849
38	231.0	226.8434	1.849
39	168.8	170.1388	0.775
40	175.4	176.4463	0.621
41	146.5	148.4599	1.336
42	165.1	168.5969	2.066
43	91.5	95.13215	3.793
44	122.8	122.7778	0.040
45	85.8	83.37705	2.874
46	209.2	201.9263	3.583
47	238.4	233.5918	2.054
48	286.2	277.6922	3.067
49	263.2	271.9211	3.224
50	303.4	302.4892	0.296
51	178.9	183.6906	2.614
52	182.2	177.3421	2.727
53	202.3	200.8026	0.739
54	188.6	194.2589	2.923
55	198.5	191.3545	3.726

Table 13. Confirmation tests.

X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	Y_i	$\hat{Y}_i$	PE_i (%)
7.63	99	3.9	2.7	996.9	0	10	10.7	180.7	193.6789	6.714
9.25	97	10.4	0.6	1000.6	0.1	10.7	10.5	225.5	206.8667	9.000
10.78	98	6.6	2.8	1003.9	0	11.9	10.5	195.1	181.3946	7.563
10.80	99	19.8	0.0	1010.4	6.1	10.8	17.4	218.7	219.3612	0.313
5.73	82	13.2	0.1	1006.4	5.2	8.9	15.7	308.9	295.7905	4.444
6.00	99	1.9	6.4	1008.5	0	8.8	12.1	290.6	289.7942	0.280

business and service university buildings. Regression modeling is used for calculating the mathematical models those represents the relation between the factors (outdoor temperature, relative humidity, solar radiation, wind speed, atmospheric pressure, sunshine duration, steam pressure, 1 m underground temperature) and the responses (the cooling energy load for the summer months, the heating energy load for the winter months). These selected response and the factors did not investigate together previously for mathematical modeling and this is the novelty aspect of this research. The R^2 values are calculated as 96.2% and 98.94% for the mathematical models of summer and winter months respectively, which indicates that the selected outdoor parameters are sufficient for modeling. Also the ANOVA results indicate that both models are significant. Confirmations are performed for and it is observed that the calculated mathematical models good fit the observations. Overall prediction performance is acceptable. The PE values are calculated as less then 11% for the summer months cooling load and less then 9% for the winter months heating load according to the confirmation test results. In future researches, energy consumption cost values can be found with the help of the energy consumption estimation for the sample building. It will be an exemplary study for similar public buildings. In addition, detailed information will be given about the characteristics of the mechanical equipment used in the heating and cooling systems, such as energy load and efficiency. Much easier and more reliable estimations will be made for parameters such as energy load, efficiency, maintenance, repair, and other labor of heating and cooling systems (installations) in different meteorological conditions going forward.

In the future, studies will be made using different modeling analysis techniques for energy efficiency analyses of complex buildings such as hospitals and airports during heating and cooling periods. Thermal comfort properties are the most important criteria in energy efficiency studies of complex buildings. For this reason, different programs and software will be used in energy consumption analyses for parameters such as indoor temperature, humidity, and air velocity, apart from external meteorological parameters of complex buildings. In addition, the usability of the Response Surface Methodology, Taguchi, and Factorial Design methods, which are commonly used design of experiments methods, suitable for the structure of the problem will be investigated.

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