Prediction of Cooling Energy Consumption Using Neural Network on the Example of the Hotel Building [†]

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Abstract: The purpose of the work is to determine factors internal and external affecting the cooling energy demand of the building. During the research, the impact of weather conditions and the level of hotel occupancy on cooling energy, which is necessary to obtain indoor comfort conditions, was analyzed. The subject of research is energy consumption in the Turówka hotel located in Wieliczka (Southern Poland). In the article, the designer of neural networks was used in the Statistica statistical package. To design the network, a widely-used multilayer perceptron model with an algorithm with backward error propagation was used. Based on the collected input and output data, various MLP networks were tested to determine the relationship most accurately reflecting actual energy consumption. Based on the results obtained, factors that significantly affect the consumption of thermal energy in the building were determined and a predictive energy demand model for the analyzed object was presented. The result of the work is a forecast of cooling energy demand, which is particularly most important in a hotel facility. The prepared predictive model will enable proper energy management in the facility, which will lead to reduced consumption and thus costs related to facility operation.

Keywords: prediction cooling energy consumption; artificial neural network; energy efficiency; sustainable buildings

1. Introduction

The advancement of civilization and the development of society increase the amount of time that a person spends indoors. Currently, in developed countries people spend up to 80–90% of their lives in buildings, which is why it is so important to ensure proper conditions and high indoor air quality. In new buildings heating, ventilation and air-conditioning systems play a crucial role due to high user comfort requirements. However, air treatment processes are very expensive, while the removal of heated air in winter causes the process itself to be unprofitable. The main task of designers in recent times is to reduce heating and cooling energy consumption, through the use of devices and systems with higher efficiency, reduce energy losses during energy distribution, as well as through proper management of systems. The forecasting of energy consumption in a building is particularly important in terms of planning, managing, and optimizing energy systems. Accurate and reliable heating and cooling energy forecasts for buildings can bring significant benefits to energy savings. The forecasting heating energy consumption is a difficult task due to numerous disturbances and deviations from observed trends. In the case of facilities such as a hotel, the demand for cooling and heating energy, in addition to meteorological factors, is determined by the hotel occupancy and user activity (the use of facilities on the premises, e.g., swimming pool, restaurant, conference room).

Building energy consumption prediction is crucial to appropriate energy management, therefore to improve the energy efficiency of systems and performance of the buildings. In general, methods for estimating and modeling energy consumption could be divided into two groups: engineering and data-driven approaches. The first type, use physical and thermodynamic functions to evaluate the energy consumption of the building or system. A data-driven approach defines the relationship between energy consumption and identified factors based on the historical data [1]. In recent years, artificial intelligence methods have become very popular. This technique is often applied to the prediction of energy consumption due to good accurate prediction results. Among the most popular data-driven prediction models using empirical approach are artificial neural networks (ANNs) and support vector machines (SSM) [2].

Artificial neural networks consist of three types of layers: input (collects data and passes them on), hidden (connections between neurons are searched for here, i.e., learning process takes place) and output (collects conclusions, analysis results). A neural network can consist of any number of layers. Into the first layer, unprocessed input data goes. Each subsequent layer receives data resulting from the processing of data in the previous layer. What the last layer produces is the so-called system output [3]. The simplified artificial neural network was proposed for the first time by McCulloch and Pitts in 1943 [4]. A schematic diagram of the multilayer feedforward neural network architecture is shown in Figure 1.
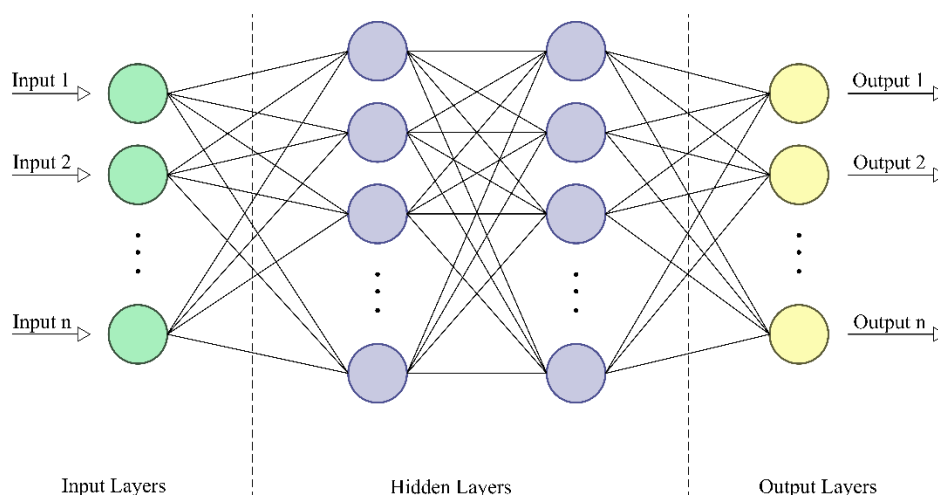

Figure 1. Schematic diagram of multilayer feed forward neural network.

There are many types of artificial neural networks (ANN) including backpropagation network (BPNN), general regression neural network (GRNN), and radial basis function network (RBFN) [3]. The most commonly used neural network architecture today is the Multilayer Perceptron (MLP). Each neuron calculates the weighted average of the inputs to it, and calculates the result using the transition function f and gives it to the output. There is also a shift component in each layer of MLP network neurons. Choosing the right number of hidden layers and the number of neurons present in them is an important thing for a perceptron. The choice of activation function and network learning method is also significant.

Numerous interesting methods of prediction building energy consumption have been described in the literature [5–7]. Nowadays, widely used solutions are data-driven models applied to estimate electricity consumption in buildings and to analyze the energy consumption pattern [8–14]. As many studies [15–17] show, artificial neural networks could be useful also in the prediction of heating and cooling energy consumption. Zhao et al. [18] investigated the energy consumption of Variable Refrigerant Volume System in the office building. Authors compared three types of prediction models: ANN, SVM, and ARIMA (Autoregressive integrated moving average). Results showed that ANN model is better than the other two types. In their paper, Biswas et al. [19] proposed a prediction

model of residential building energy consumption. The input variables included the number of days, outdoor temperature, and solar radiation. The output variables are building and heat pump energy consumption. In a paper by Pino-Mejías et al. [20], the authors presented prediction models of the heating and cooling energy demands, energy consumptions, and CO_2 emissions for the office buildings in Chile. The study shows that multilayer perceptron provides a satisfactory degree of accuracy in the determination of demand, consumption, and CO_2 emissions. Annual energy consumption by HVAC systems was also predicted by Nasruddin et al. [21]. Authors used ANN model with the range of decision variables including cooling setpoint, supply airflow rate, window area, supply air temperature, etc. The university building was the subject of the study. The result showed that optimization of HVAC improvement influenced both for thermal comfort, as far as annual energy consumption.

This paper presents an integrated approach to predict energy consumption and develop a predictive model using an artificial neural network. The study includes an analysis of the energy consumption of cooling systems based on the meteorological data and historical cooling energy data during the summer season. The main purpose is to create an accurate ANN model for Turówka hotel to estimate daily cooling energy consumption. The cooling system in the hotel is accountable for about 50–60% of the total building energy consumption, therefore the study focused only on the cooling demand [22].

2. Methods and Building Description

The building studied in this paper is the Turówka hotel, located in Wieliczka, the south-central part of Poland near the Kraków. It is the reconstruction of a historic salt store of 1812, entered into the register of historical monuments. The building is under preservation maintenance, so during hotel refurbishing old saltworks and hotel adaptation, the mass, and dimension if the building should stay the same. The building materials used and window and door frames aim to recreate the structure as faithfully as possible. The building includes four overground floors and the basement with the useful floor area of the hotel section 5525.00 m^2 and a capacity of 19,300 m^3. The hotel has 50 double rooms, a restaurant for 90 people, a hotel bar for 30 people, a drink bar for 30 people, a conference room for 40 people and a pool. The central heating installation is powered by two low-temperature gas boilers with a capacity of 250 and 350 kW. Currently, the hotel uses a two-pipe central heating system with panel radiators and thermostatic valves. The domestic hot water is prepared in the gas boiler house with circulation and with heating circulation pump control. The building is equipped with mechanical supply and exhaust ventilation carried out by seven air handling units with rotary exchangers and air handling units for the kitchen with an exchanger using glycol. The coolers in the air handling unit (AHU) are supplied with chilled water at 8 °C/14 °C temperature parameters. The same cooling installation also supplies fan coil units located in hotel rooms and other rooms intended for guests. The hotel building and its immediate surroundings are shown in Figure 2.
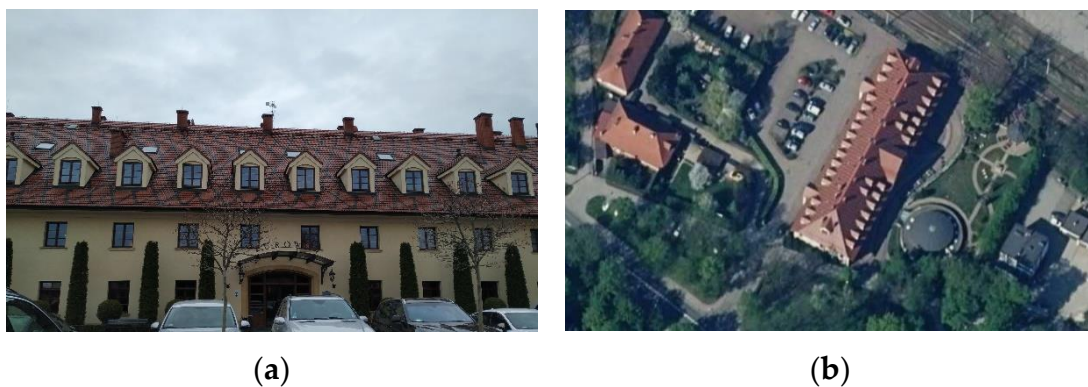

(a) (b)

Figure 2. The Turówka hotel: (**a**) outside of the building; (**b**) localization of the hotel [23].

Cooling energy meters have been installed in main system areas, i.e., feed and return of the high and, depending on demand, low parameter of the refrigerant. Data are transmitted via a serial communications protocol—MODBUS RTU and stored in a recording system. Measurements are made using MULTICAL heat meters by Kamstrup. To ensure measurement stability, flow sensors were submitted to a type approval according to EN 1434 [24], which includes the 2400-h measurement stability test of the flow sensors.

This paper includes an analysis of the cooling energy consumption of the hotel. In the summer season, the main building operating costs are related to the cooling system which ensures thermal comfort for users. Due to the prevailing share of cooling energy demand in total energy consumption in the summer season, the research was focused on providing the most accurate model for the prediction of cooling energy consumption. The data analyzed in this study are a daily time series collected from 15 May to 15 September 2019. This period is a summer season in Poland when the hotel cooling system is working. The data includes cooling energy consumption in the building. The outside temperature was measured directly at the hotel area. Other meteorological data are obtained from the National Research Institute—Polish Institute of Meteorology and Water Management.

The study has been divided into four parts. Firstly, the data, including meteorological data and data from the analyzed building, was collected. Another step was to examine the relationship between cooling energy demand and the identified variables in the analyzed period. On this basis, the factors that may affect energy consumption have been selected. Due to the minimal impact of some factors as well as the practical approach to the application of prediction algorithms, only the most significant ones are most often used. Among ten variables: day, month, occupancy level, average outside temperature, minimum temperature, maximum temperature, relative humidity, cloud cover, precipitation, and wind speed, the last two parameters have been rejected. In the paper, a simplified data-driven model for the prediction the energy consumption has been presented. An ANN-based model was used to predict the cooling energy used in a building in the summer season. Figure 3 illustrates the research process.
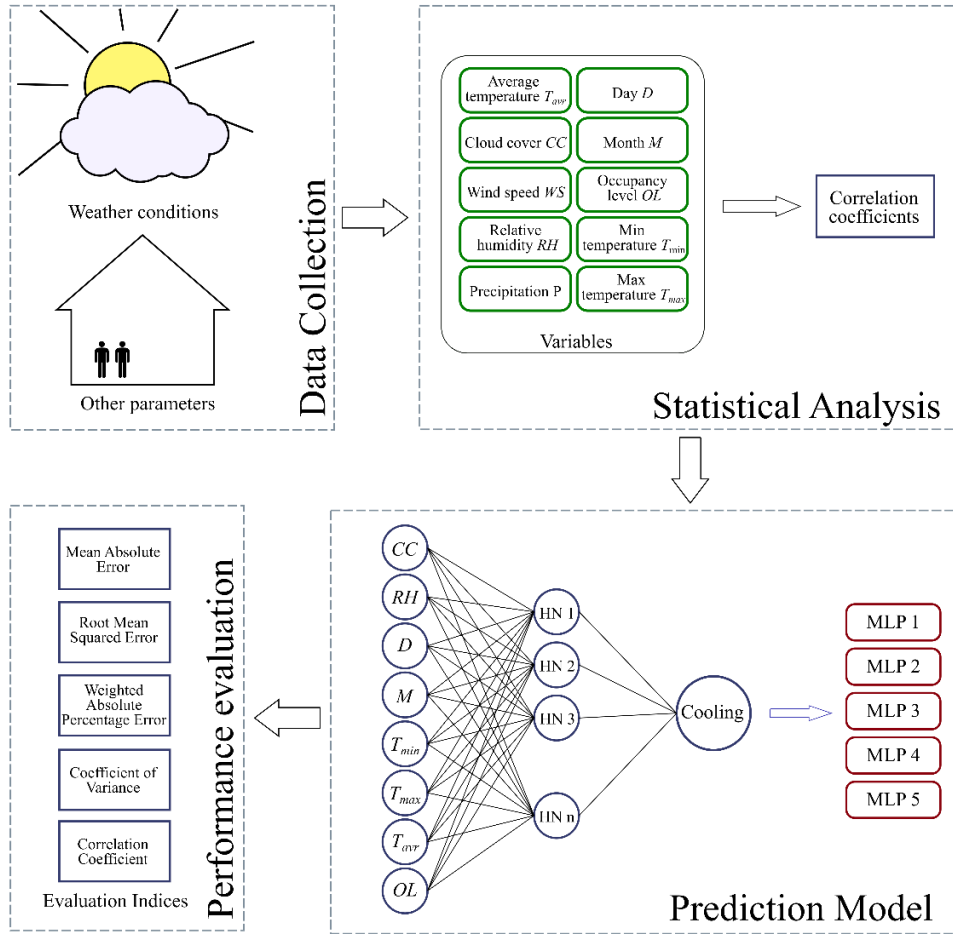
Figure 3. Diagram of energy prediction process.

In this study, three evaluation indices are used to measure the performance of the proposed approach, including the mean absolute error (MAE), root mean squared error (RMSE), and coefficient of variance (CV) [16,18,25]. Additionally, the weighted absolute percentage error (WAPE), proposed by other authors, was used [26]. The mathematical representation of indicates are represented in Equations (1)–(4):

$$MAE \quad = \frac{1}{n} \sum_{i=1}^{n} |E_A - E_P| \tag{1}$$

$$RMSE \quad = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (E_A - E_P)^2} \tag{2}$$

$$CV = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (E_A - E_P)^2}}{\overline{E_A}} \tag{3}$$

$$WAPE \quad = \frac{\sum_{i=1}^{n} |E_A - E_P|}{\sum_{i=1}^{n} E_A} \tag{4}$$

where n denates the entire number of observations, E_A is the actual value, $\overline{E_A}$ denotes the mean of actual values, and E_P represents the predicted value.

3. Results

3.1. Preliminary Statistical Analysis

To increase the accuracy of the prediction, the pre-selected meteorological values and data related to the use of the building were subjected to basic statistical analysis. During the initial analysis, ten parameters were identified that may affect the cooling load, including the day of the week, month, the minimal and maximum outside temperature during the day, average daily temperature, occupancy level, average daily cloud cover, wind speed, relative humidity, and precipitation. Statistical analysis was performed for the data presented in Table 1.

Table 1. Identified variables.

Variable	Unit
Day (Monday-1; Tuesday-2; Wednesday-3; Thursday-4; Friday-5; Saturday-6; Sunday-7)	-
Month (May-5; June-6; July-7; August-8; September-9)	-
Minimum temperature T_{min}	°C
Maximum temperature T_{max}	°C
Average temperature T_{avr}	°C
Occupancy level	%
Daily average cloud cover (0 oktas—completely clear sky, 8 oktas—completely overcast)	okta
Daily average wind speed	m/s
Daily average relative humidity	%
Daily average precipitation	mm

Table 2 presents descriptive statistics for each analyzed variable. Day and month are listed but statistics are not provided for them because these parameters represent categorical variables in the model.

Table 2. Descriptive statistics for input and output variables.

Variable	Unit	Minimum	Maximum	Mean	Median	1st Quartile	3rd Quartile
Day	-	1.00	7.00	-	-	-	-
Month	-	5.00	9.00	-	-	-	-
T_{min}	°C	6.24	21.09	14.44	14.68	12.13	16.71
T_{max}	°C	9.92	36.16	26.11	26.39	23.12	29.91
T_{avr}	°C	8.41	29.24	20.23	20.68	17.46	23.05
Occupancy level	%	18.90	100.00	77.64	94.90	65.10	94.30
Cloud cover	octa	0.00	8.00	4.34	4.45	2.95	5.90
Wind speed	m/s	0.90	5.50	2.69	2.50	2.00	3.20
Relative humidity	%	49.00	96.10	72.77	72.10	65.95	79.35
Precipitation	mm	0.00	39.80	2.75	0.00	0.00	1.65
Cooling Energy	kWh/day	0.00	2501.53	1227.32	1170.11	667.91	1704.64

The analysis was based on the Pearson correlation coefficients between the studied variables and the predicted output. The results are summarized in Table 3.

Table 3. Correlation coefficients for numeric variables.

	Day	Month	T_{min}	T_{max}	T_{avr}	Occupancy Level	Cloud Cover	Wind Speed	Relative Humidity	Precipitation
Day	1.00									
Month	0.01	1.00								
T_{min}	−0.11	0.02	1.00							
T_{max}	0.01	0.14	0.76	1.00						
T_{avr}	−0.03	0.05	0.85	0.96	1.00					
Occupancy level	0.47	0.02	−0.06	−0.08	−0.07	1.00				
Cloud cover	−0.15	−0.13	−0.20	−0.60	−0.57	−0.05	1.00			
Wind speed	−0.17	−0.12	0.16	−0.06	0.05	−0.05	−0.03	1.00		
Relative humidity	−0.03	0.09	−0.36	−0.60	−0.65	0.17	0.63	−0.17	1.00	
Precipitation	−0.12	0.04	−0.12	−0.25	−0.28	0.00	0.38	0.07	0.46	1.00
Cooling Energy	−0.07	0.08	0.85	0.84	0.88	−0.01	−0.40	0.08	−0.42	−0.14

Based on the results in the table, it was decided that in further analysis the wind speed and precipitation parameters, which showed the smallest relationships with the searched value, would be rejected. Despite the low correlation coefficient between cooling energy demand and occupancy level, this variable was accepted for further consideration, due to individual cooling control in guest rooms.

Cooling Energy Consumption

A regression graph with histograms presenting the relationship between energy consumption and the average temperature was plotted (Figure 4a). The data were ordered and divided into groups in specified temperature ranges. Having removed outliers and extremes, linear relationships were plotted in the form of box plots (Figure 4b).
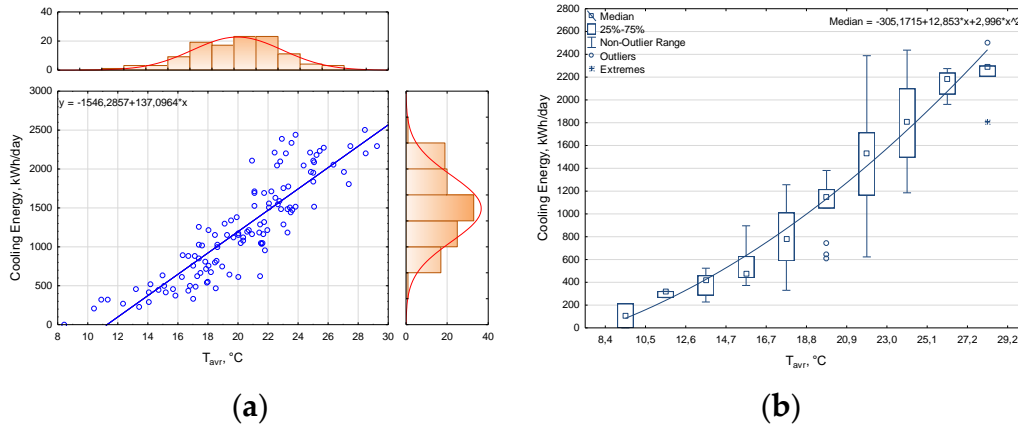
Figure 4. Cooling energy demand depending on the average daily air temperature: (**a**) regression graph with histograms; (**b**) box plot with ten temperature ranges.

The next step was to investigate the relationship between energy consumption for cooling and two variables with the highest correlation coefficients: average temperature and relative humidity. The diagram for the cooling system is shown in Figure 5.
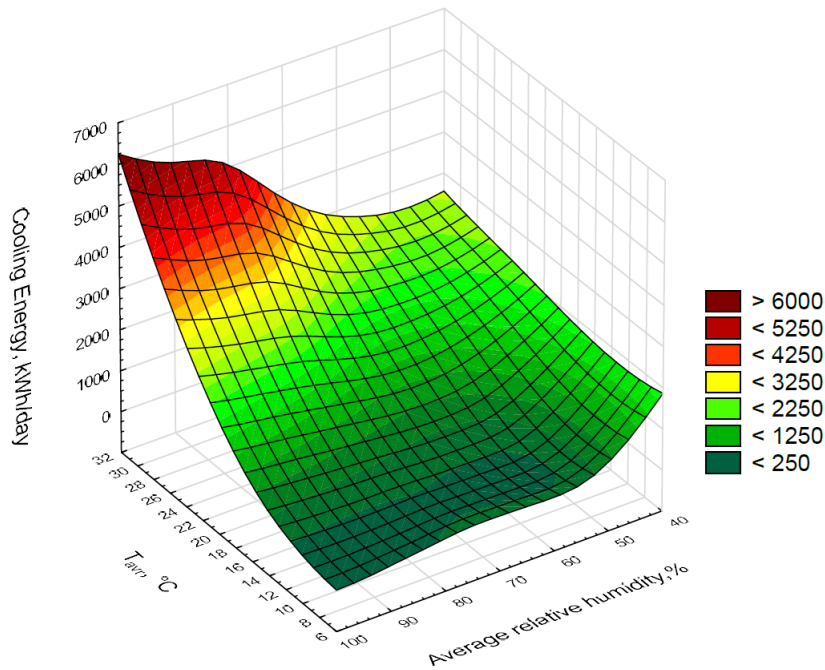

Figure 5. Cooling energy demand depending on the average daily air temperature and relative humidity.

3.2. Neural Networks

The Statistica Artificial Neural Network Package was used to prepare a predictive model. Multilayer perceptrons with backpropagation were performed. The number of hidden neurons, the hidden layer activation-functions, and output layer activation-function are selected using the methodology based on statistical tests and least-squares estimation. Five different networks were created by combining four types of activation functions and a different number of hidden neurons. Training Algorithm BFGS (Broyden-Fletcher-Goldfarb-Shanno) was chosen for this work. Based on the correlation coefficient, five models were selected and described in Table 4.

Table 4. Network configurations tested.

Network Name	Hidden Layer Activation-Function	Number of Hidden Units	Output Layer Activation-Function
MLP 1	Hyperbolic tangent	9	Logistic
MLP 2	Logistic	33	Logistic
MLP 3	Hyperbolic tangent	9	Logistic
MLP 4	Linear	13	Logistic
MLP 5	Hyperbolic tangent	6	Logistic

3.3. Performance of the Model

Based on the above-mentioned indicators: MAE, RMSE, WAPE, CV, and correlation coefficient (R^2), selected models were compared. The results for cooling consumption, are presented in Table 5.

Table 5. Performance evaluation of different forecast models for cooling energy consumption.

Indicators	MLP 1	MLP 2	MLP 3	MLP 4	MLP 5
MAE	191.18	195.78	190.82	190.11	189.00
RMSE	242.28	242.84	243.98	239.91	239.78
WAPE	15.58%	16.49%	15.70%	16.02%	15.53%
CV	19.74%	19.79%	19.88%	19.55%	19.54%
R^2	0.926	0.924	0.925	0.925	0.925

For each of the analyzed outputs, the MLP 5 model was the most accurate in modeling energy consumption for the full dataset. Further analysis was therefore carried out only for this model. Figure 6 shows the comparison between actual consumptions and forecasts for the cooling system.
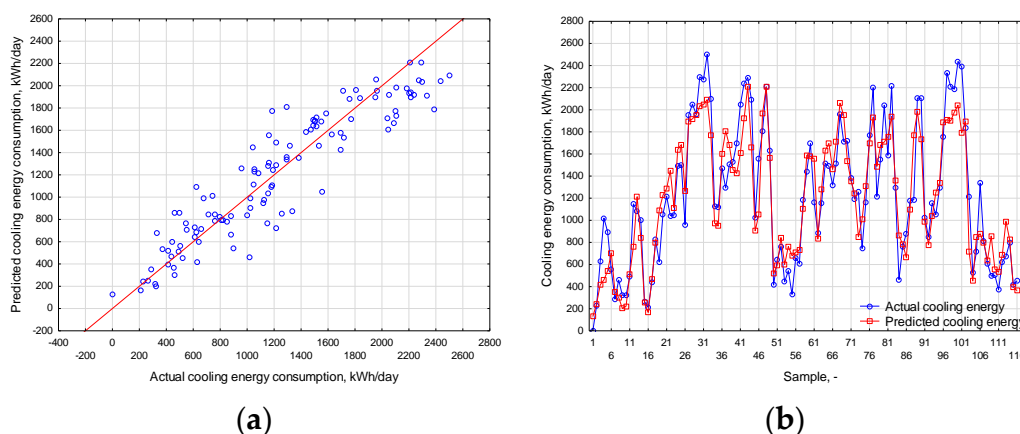
(**a**)

(**b**)

Figure 6. Results of the prediction model MLP 5 for cooling energy consumption: (**a**) Comparison of observed values and predicted values; (**b**) Comparison of measured and predicted energy consumption.

4. Discussion

In this paper, the ANN predictive model for hotel Turówka is presented. CV rate for the proposed models varies from 19.55% to 19.88%. Similarly, the weighted absolute percentage error for models ranged from 15.53% to 16.49%, and the correlation coefficient in range 0.924–0.926. Based on these indicators investigated for each of the analyzed systems, MLP 5 model was selected. The differences between the proposed models are not large, and the choice was conditioned mainly by lower values of the coefficients describing the prediction error. For model 5, mean absolute error was 189 kWh/day, and weighted absolute percentage error 15.53%. The predicted results are found to be very close to the experimental values. For maximum and minimum values of energy consumption, the largest differences between the actual value and predicted value are visible.

Table 6 presents sensitivity coefficients, which describe the change in the system's outputs due to variations in the parameters that affect the system. For each of the analyzed models, the ratio of network error without a given variable to the error with a set of inputs was given. A quotient of less than 1 means that the network works even better without a given variable, which is an obvious signal to remove a given independent variable from the analysis.

Table 6. Sensitivity analysis of inputs.

Variable	MLP 1	MLP 2	MLP 3	MLP 4	MLP 5
Day	1.00	1.02	1.02	1.05	1.02
Month	1.09	1.01	1.01	1.02	1.01
T_{min}	2.21	1.66	1.65	2.41	1.69
T_{max}	1.16	1.18	1.18	1.25	1.18
T_{avr}	1.17	2.05	2.06	1.32	1.72
Occupancy level	0.99	1.02	1.02	1.00	1.00
Cloud cover	1.01	1.02	1.02	1.06	1.02
Relative humidity	0.98	1.05	1.05	1.00	1.05

As Table 6 shows, the impact of variables on predicted value varies depending on the analyzed model. As mentioned before, the MLP 5 model was chosen for further analysis, for which the most important parameters are the minimum and maximum temperatures during the day. The occupancy level does not affect the values obtained. During the initial analysis, attention was paid to the relationship between the consumption of cooling energy and relative humidity. As the analysis shows, humidity is included in the model, but it is not a determining factor. The sensitivity factor smaller than 1 in model MLP 1, suggests that this parameter is not important in analysis. This is also due to the significant correlation between temperature and humidity (Table 3).

5. Conclusions

The HVAC system consumes a large amount of energy, especially in commercial buildings. Energy consumption prediction is an interesting solution for energy management building, and hence for saving energy and reducing operational cost. The cooling load is affected by many factors, including weather conditions, building operation, thermal performance, and users' behavior. In the paper, a simplified data driven-model for predicting energy consumption has been presented. The methodology is based on the use of Artificial Neural Networks. A sensitivity analysis demonstrated that part of the proposed input variables initially selected offer limited contribution to the model. Among the ten identified parameters, eight input features were used in the proposed models. Based on the mentioned variables, fife ANN models were created and compared using the evaluation coefficients discussed above. Model MLP 5, with six hidden neurons, was chosen as the most appropriate and effective. External minimum, average, and maximum temperature as well as relative humidity were considered the most important variables in this selected model. Cloud cover, day, and month have less impact on the predicted values. Based on the sensitivity analysis, it was found that the occupancy level has no significant effect on the prediction model. For each of the output parameters, the predictions were good, especially in terms of average values. The biggest errors were noticeable for extreme values that are not completely reproduced by the model. The largest observed difference in the analyzed period was 596 kWh/day, which was 25% of the actual value. The best mapping was obtained for cooling energy. This is particularly important due to the prevailing share of cooling energy in the total energy load of the building during the summer period. The prediction task performed for the whole day is difficult due to changing conditions. To increase the accuracy of predictive models, the analysis could be performed based on hourly energy consumption.

Nomenclature

CC	Cloud cover, -
D	Day of the week, -
E_A	Actual value of the energy consumption, kWh/day
E_P	Predicted value of the energy consumption, kWh/day
M	Month, -
n	Number of observations, -
OL	Occupancy level, %
P	Precipitation, mm
R^2	Correlation coefficient
RH	Daily average relative humidity, %
T_{min}	Daily minimum temperature, °C
T_{max}	Daily maximum temperature, °C
T_{avr}	Daily average temperature, °C
AHU	Air Handling Unit
ANN	Artificial Neural Network
ARIMA	Autoregressive, Integrated and Moving Average
BFGS	Broyden-Fletcher-Goldfarb-Shanno
BPNN	Back Propagation Neural Network
CV	Coefficient of Variance
GRNN	General Regression Neural Network
HVAC	Heating, Ventilation, Air Conditioning
MAE	Mean Absolute Error
MLP	Multilayer Perceptron
RBFN	Radial Basis Function Network
RMSE	Root Mean Squared Error
SSM	Support Vector Machine
WAPE	Weighted Absolute Percentage Error

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