

Article

Gaining CO₂ Reduction Insights with SHAP: Analyzing a Shower Heat Exchanger with Artificial Neural Networks

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Abstract: The application of shower heat exchangers (SHEs) allows for a reduction in the amount of energy necessary to heat domestic hot water (DHW). As a result, not only the costs of heating DHW but also the emission of harmful products of fuel combustion is reduced. However, the identification of key areas determining the resulting carbon dioxide emission remains an unexplored issue. For this reason, the main purpose of this paper was to comprehensively analyze the impact of parameters characterizing the operation of a horizontal SHE cooperating with an electric DHW heater on the potential reduction in CO₂ emission. As part of this research study, 16,200 CO₂ emission reduction values corresponding to different conditions of shower installation operation were determined. The analysis was carried out considering the location of the installation in different countries of the European Union. Artificial neural networks and SHAP analysis were used as tools. This research study showed that carbon intensity, corresponding to the location of the installation on the world map, and total daily shower length are of key importance in the prediction of carbon dioxide emission reduction. The efficiency of the DHW heater turned out to be the least important parameter. This research study proved that the greatest environmental benefits of using SHEs will be visible in countries where fossil fuels account for a large share of electricity production, such as Poland, and in buildings with significant water consumption.



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Keywords: carbon emissions; graywater heat recovery; MLP neural networks; Python; SHAP analysis

1. Introduction

In the face of global challenges related to the need to decarbonize the economy and rising energy costs, increasing attention is being paid to ensuring high energy efficiency of buildings. This is particularly relevant for cities, as Fadnes and Assadi [1] emphasized that they account for approximately 70% of global CO₂ emissions. Consequently, urban areas play a key role in efforts to reduce the carbon footprint. These efforts can be based on improving process efficiency [2], thermal modernization [3], or integrating green building technologies [4]. Waste heat recovery [5] is also gaining significance, as achieving climate neutrality requires not only seeking new sources of renewable energy but also optimizing the use of existing resources.

One of the key areas where energy losses occur in buildings is the heating of domestic hot water (DHW). As Hall et al. [6] pointed out, water-related energy consumption constitutes 20–50% of household energy use. The water used in daily activities, after a brief contact with the user, is typically discharged directly into the sewage system, even though it

still carries significant amounts of energy, which is considered thermal pollution of wastewater [7]. However, even partial recovery of the heat carried by wastewater can significantly reduce the energy demand for heating DHW, thereby lowering the CO₂ emissions resulting from fuel combustion. Graywater is particularly noteworthy in this context. Research indicates that it can be utilized both for electrochemical energy generation [8] and as a source of thermal energy in various systems [9,10]. In the latter case, shower heat exchangers (SHEs) are the most commonly used technology. These units operate on the principle of heat transfer between the warm graywater drained from the shower and the cold water supplied to the DHW heater and/or the shower mixing valve. SHEs represent one of the few solutions that enable real energy savings and CO₂ emission reduction without requiring changes in user habits. However, their effectiveness depends on several factors related to both the design of the unit and the operating conditions of the shower installation. Vertical heat exchangers have been found to achieve the highest effectiveness [11]. However, their application in multi-family buildings—prevalent in urban areas—is often challenging, particularly in existing buildings. This is due to the lack of space for SHE installation in service shafts, the need for costly modifications to the plumbing system, and the lack of individual control over internal building installations. Under such conditions, horizontal heat exchangers offer significantly greater application potential. Their use is also justified in high-rise apartment buildings [12]. The literature describes various studies dedicated to these units. For example, Purghel and Teodosiu [13] conducted experimental and numerical research on a prototype of a horizontal SHE designed for integration with a rectangular shower tray. Computational Fluid Dynamics simulations of horizontal heat exchangers have also been studied by Silva et al. [14] and Maciorowski et al. [15]. Bouvenot and Beaudet [16] assessed the impact of fouling on SHE effectiveness. A different approach was taken by Starzec et al. [17], who conducted a comprehensive analysis of the applicability of artificial neural networks (ANNs) for evaluating the effectiveness of horizontal SHEs. On the other hand, Stec and Pochwat [18] employed regression models and machine learning methods.

However, none of the previous studies have conducted a holistic analysis of the impact of shower heat exchangers on CO₂ emission reduction, including the assessment of the factors with the greatest influence on the level of this reduction. This applies to both horizontal SHEs and other types of heat exchangers. While earlier publications provide information on the expected reduction in carbon emissions [11,15], they focus solely on specific scenarios of heat recovery system operation and do not determine the extent to which individual input parameters shape the final CO₂ emission levels. However, the operating conditions of a shower installation significantly influence the amount of recovered energy and, consequently, the reduction in CO₂ emission. Additionally, carbon intensity—a crucial factor in emission calculations—is highly variable. In the case of electricity, it depends on, among others, the share of individual energy sources used for its production, the efficiency of the power plant or the stability of the system. Considering that previous studies on environmental issues related to the application of SHEs have primarily focused on analyzing the expected reduction in CO₂ emission in relation to selected usage scenarios and specific configurations of heat recovery systems, there is an evident lack of research addressing the problem in a comprehensive manner. An approach that would take into account diverse operational conditions and their impact on the final level of CO₂ emission reduction is missing. Identifying the factors of greatest significance in the context of optimizing environmental benefits resulting from the application of SHEs would help fill this research gap.

Therefore, the primary objective of this paper is to conduct a comprehensive analysis of the impact of parameters characterizing the operation of a shower heat exchanger on

potential CO₂ emission reduction, along with the identification of key factors determining the final emission levels. The analysis is based on artificial intelligence methods, specifically artificial neural networks (ANNs), which allow for the modeling of nonlinear relationships among variables. Furthermore, model interpretation and the assessment of the influence of individual input variables on the final CO₂ emissions in relation to the base value were made possible through SHapley Additive Explanations (SHAP) analysis. Previous studies [17,19] confirm that both ANNs and SHAP analysis are effective tools for evaluating the performance and feasibility of shower heat exchangers. They enable the precise modeling of parameter dependencies while providing transparent insights into the impact of individual variables on the final results, making them particularly useful for optimizing SHE operation and predicting their usability under various usage conditions.

The research described in the paper is a continuation and extension of the analyses described in [17], devoted to the assessment of the usefulness of ANNs for predicting the effectiveness of a horizontal shower heat exchanger. The scope of this research study included the following:

- The determination of the potential CO₂ emission reduction under various shower installation operating conditions and considering different carbon intensities corresponding to individual European Union countries.
- The assessment of the usefulness of ANNs for predicting the potential CO₂ emission reduction achieved through the application of a horizontal shower heat exchanger.
- The assessment of the significance of parameters that influence the potential CO₂ emission reduction during the SHE operation period.

2. Materials and Methods

2.1. Research Steps

The first step of this research study (Figure 1) involved collecting experimental data characterizing the operation of a horizontal shower heat exchanger. A detailed description of the heat exchanger and the test stand was presented in a previous publication by the authors [17]. The analysis was conducted under the assumption that all the water used during a shower would be preheated in the shower heat exchanger. This configuration of the heat recovery system was chosen due to its highest effectiveness and the ability to supply preheated water to the DHW heater. The high effectiveness of the heat exchanger ensures maximum energy savings and, consequently, the highest reduction in CO₂ emission. Additionally, the ability to supply preheated water to the DHW heater guarantees protection against Legionella bacteria, which can develop in the installation during prolonged periods of non-use. Based on the experimental results, the CO₂ emissions associated with heating shower water were determined for two scenarios: with and without the heat exchanger. The projected emission reduction (E_{CO_2}) was then calculated under various conditions. A total of 16,200 E_{CO_2} values were obtained and subjected to further analysis.

STAGE 1	STAGE 2	STAGE 3	STAGE 4
Data acquisition and preparation	Development of predictive models	SHAP-based model interpretation	Discussion and future directions
Gathering and preprocessing the data for analysis	ANN models development, training, and validation	Applying SHAP for feature impact assessment	Summary of findings and implications

Figure 1. Research steps.

In the next step, artificial neural network models were developed. The input variables for these models are described in Section 2.2, while the output variable was the projected

reduction in CO₂ emission (E_{CO_2}) resulting from the installation of the horizontal SHE. With the selected ANN model and SHAP analysis, the influence of individual parameters affecting CO₂ emission reduction was identified. The application of machine learning and SHAP analysis was made possible through the Python 3.10.7 programming language. The results of these analyses allowed for an assessment of the impact of variables characterizing the operation of the shower heat exchanger on potential CO₂ emission reduction. Furthermore, key areas determining the usefulness of the horizontal SHE in reducing greenhouse gas emission were identified, enabling the formulation of practical recommendations for the optimal use of SHEs.

During the analysis of potential CO₂ emission reduction (E_{CO_2}) and the development of the ANN model allowing for the assessment of this variable under given operating conditions, certain assumptions were made that may affect the interpretation of the results. It was assumed that the effectiveness of the SHE is constant and does not decrease over the unit's operational period, for instance, due to the accumulation of contaminants. The analysis was conducted under the assumption of constant operating conditions. It was assumed that the temperatures of water and graywater, as well as the total daily shower length, remain constant throughout the entire period of the heat recovery system operation. It should also be emphasized that the analysis only covers the operational period of the shower heat exchanger, and the assumed carbon intensity values remain unchanged throughout the 15-year period of SHE use. Consequently, potential changes in the energy mix over time were not considered in the analysis.

2.2. Carbon Dioxide Emission Reduction

The carbon dioxide emission under specific operating conditions of the shower installation (E) was estimated based on the amount of energy used for heating water and the carbon intensity (e_{CO_2}), as described by Equation (1).

$$E = \frac{365 \cdot n \cdot l_s \cdot q_h \cdot \rho \cdot c_p \cdot (T_{hw} - T_{w1})}{\eta \cdot 3.6 \cdot 10^6} \cdot e_{CO_2}, \quad (1)$$

where E is the total projected CO₂ emission over the n -year operational period of the horizontal SHE, kg; l_s is the total daily shower length, min; q_h is the flow rate of water supplied to a DHW heater, determined with the heat balance equation, L/min; T_{hw} is the temperature of DHW, °C; T_{w1} is the temperature of the water supplied to the DHW heater, °C; η is the efficiency of the DHW heater; e_{CO_2} is the carbon intensity, kg/kWh; ρ is the density of water, kg/m³; and c_p is the specific heat capacity of water, kJ/(kg·K).

In the basic configuration, cold water at temperature T_{cw} is supplied to both the shower mixing valve and the DHW heater ($T_{w1} = T_{cw}$). In the configuration with a heat exchanger, both devices receive preheated water at temperature T_{pw} ($T_{w1} = T_{pw}$). The difference in E values determined for these two cases defines the projected reduction in CO₂ emission (E_{CO_2}), which serves as the basis for further analysis.

The E_{CO_2} values were determined for 16,200 different input variable combinations, as presented in Table 1. The values of the variables affecting the effectiveness of the horizontal SHE (cold water and graywater temperatures, mixed water flow rate, and the linear bottom slope of the unit) were adopted based on the results of previous studies conducted by the authors [17]. The assumed total daily shower length corresponds to various usage scenarios (from short individual showers to intensive water consumption in households or collective housing facilities).

Table 1. Values of input variables.

Input Variable	Unit	Values
Operational period of horizontal SHE (n)	years	15
Hot water temperature (T_{hw})	°C	55
Cold water temperature (T_{cw})	°C	8, 14, 20
Graywater temperature (T_{dw})	°C	30, 35, 40
Total daily shower length (l_s)	min	10, 50, 90
DHW heater efficiency (η)	%	90, 95, 100
Carbon intensity (e_{CO2})	kg/kWh	0.040; 0.195; 0.350; 0.505; 0.660
Mixed water flow rate from showerhead (q)	L/min	3, 4.5, 6.5, 8.5, 10
Linear bottom slope of horizontal SHE (i)	%	0, 0.33, 0.66, 1, 2, 2.5, 3.5, 4

The carbon intensity values were based on data regarding electricity generation in European Union (EU) countries in 2023 [20]. According to these data, the lowest e_{CO2} value, around 40 gCO₂/kWh, characterizes Sweden. Conversely, Poland has the highest carbon intensity in the EU (e_{CO2} = 662 gCO₂/kWh) (Figure 2). Analyzing data from other countries [21] reveals that the adopted e_{CO2} range includes values typical for most countries worldwide. Exceptions include countries with extremely high emission, such as Kazakhstan, which heavily relies on cheap coal, and countries with very low emission resulting from the use of clean energy sources, such as Norway and Iceland. Expanding the range to encompass all countries worldwide could lead to a misleading representation, as extreme values are rare and do not reflect the global trend.

**Figure 2.** Carbon intensities in EU countries (based on [20]).

2.3. Artificial Neural Networks and SHAP Analysis

To analyze the impact of parameters characterizing the operation of a shower heat exchanger on potential CO₂ emission reduction, artificial neural networks and SHAP analysis were employed. These methods enabled the effective modeling of the process and provided interpretable insights into key factors influencing E_{CO2} .

Artificial neural networks are advanced computational models inspired by biological neural networks. They consist of layers of neurons that process input data, identifying patterns and relationships that may be difficult to detect by using simpler methods. ANNs are widely used in analyses of complex relationships between input and output variables, including energy efficiency studies. For example, Kaloop et al. [22] used ANNs to predict energy consumption in residential buildings. Vergés et al. [23] performed the predictive modeling of cooling consumption in nursing homes. On the other hand, Li et al. [24] predicted heat transfer characteristics and energy efficiency of a solar collector. Artificial

neural networks are also used in studies devoted to the evaluation of the performance of shower heat exchangers [17,18].

This study employed multilayer perceptron (MLP) neural networks, which can handle both small and large datasets, making them a flexible tool for various applications, including CO₂ emission reduction prediction. Due to their ability to learn from large datasets and model nonlinear relationships, they can achieve higher prediction accuracy than traditional regression methods. By incorporating hidden layers and appropriate activation functions, the model can generalize patterns and adapt to complex processes, such as predicting CO₂ emission reduction resulting from graywater heat recovery. Additionally, MLP ANNs can be analyzed by using interpretability techniques such as SHAP analysis. This approach not only enables CO₂ emission reduction prediction but also helps understand the most influential variables in the modeling process.

The research methodology involved obtaining data reflecting CO₂ emission reduction under specific operating conditions of the horizontal SHE. The next step was constructing and training the ANN models. For this purpose, the dataset was divided into three subsets (training, validation, and testing) in the ratio of 70/15/15. This division ensured proper model tuning and later evaluation using previously unseen data, providing a more objective assessment of model performance. The evaluation of ANN models and the selection of the most effective one was made based on the values of relevant model fitting metrics, such as root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) [25,26]. RMSE measures how much predicted values deviate from actual values. R^2 indicates how much variance in the dependent variable is explained by the model. On the other hand, MAE represents the average absolute difference between actual and predicted values.

SHAP analysis was used to determine how individual input variables (parameters characterizing the operation of the shower installation and carbon intensity) influence the model's predictions. This method is based on Shapley value theory, derived from cooperative game theory. In the context of predictive models, the SHAP value of a given variable represents its average marginal contribution to the model's output across different input combinations. One of the key advantages of SHAP analysis is its ability to provide both global and local interpretations of the model. Global interpretation helps identify general trends, revealing which input variables have the greatest impact on CO₂ emission reduction. Local interpretation explains individual predictions, showing why the model returned a specific value for a given case. SHAP analysis also enables result visualization through techniques such as SHAP value plots and force plots. This allows for a deeper understanding of which variables are most critical to predicting CO₂ emission reduction (E_{CO2}) and how they influence the predicted outcomes. This type of analysis is particularly valuable in the context of heat recovery systems, where the effectiveness of the system and the amount of energy that can be saved depend on a number of parameters.

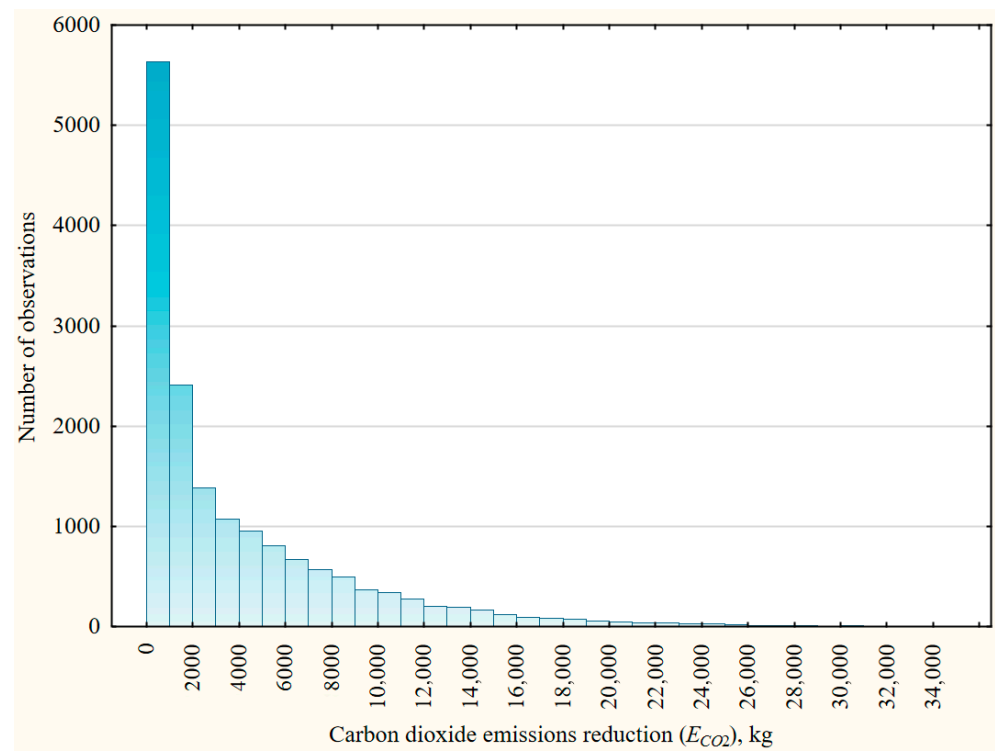
SHAP analysis has been used in numerous studies on CO₂ emission. For example, Han and Lin [27] analyzed long-term CO₂ emission trends. Qiao et al. [28] developed an interpretable model for predicting energy consumption and CO₂ emission in the transportation sector. Zhu et al. [29] examined CO₂ emission reduction in bike-sharing systems. SHAP analysis has also been used to assess shower heat exchanger performance under different operating conditions [19] and evaluate the financial efficiency of SHE implementation [30]. These examples confirm that SHAP is a valuable tool for assessing CO₂ emission reduction potential resulting from the application of the horizontal SHE.

3. Results

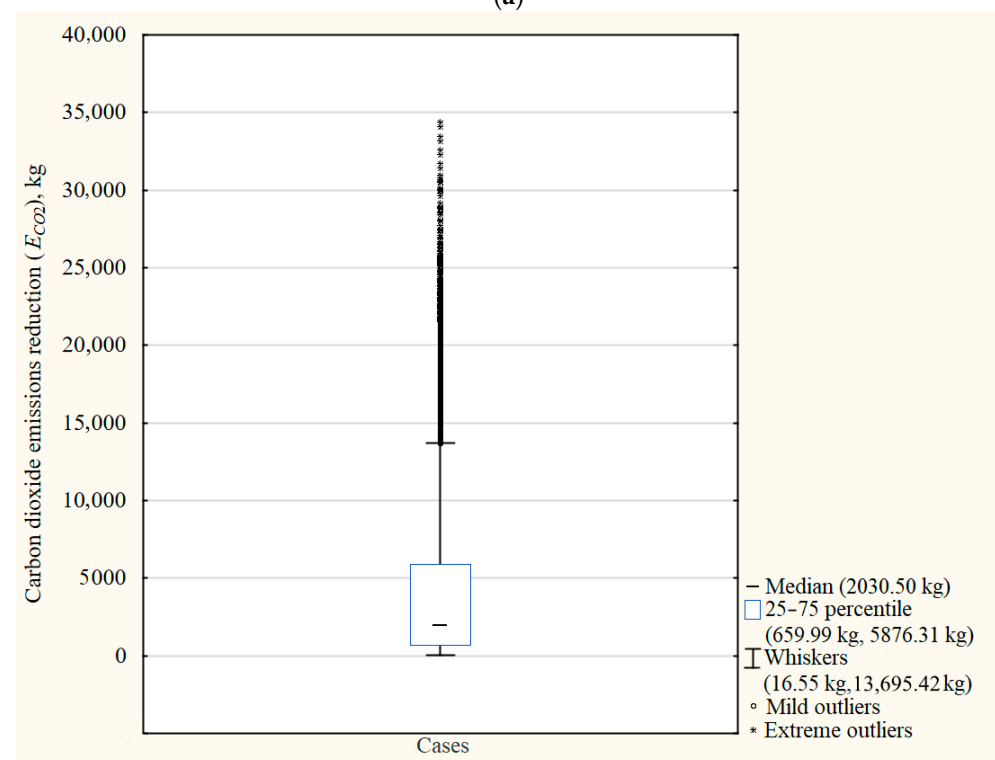
3.1. CO₂ Emission Reduction

Based on the results of experimental studies on the horizontal SHE (Appendix A), 16,200 values of carbon dioxide emission reduction (E_{CO_2}) were determined, ranging from 16.55 kg to 34,415.32 kg (Figure 3). The histogram presented in Figure 3a illustrates the distribution of these values. The horizontal axis represents the ranges of CO₂ emission reduction over the 15-year operational period of the horizontal SHE, while the vertical axis indicates the number of cases in which the results fell within a given range. The distribution of the obtained values is strongly right-skewed. The highest number of observations was recorded in the $E_{CO_2} = 0\text{--}1000$ kg range (5631 cases). In the next three ranges, the numbers of observations were 2406, 1383, and 1075. In the remaining ranges, corresponding to higher CO₂ emission reductions, the number of observations did not exceed 1000 and progressively decreased as the E_{CO_2} values increased. This distribution indicates that the highest reductions in CO₂ emission occur in a relatively small number of cases, usually associated with significant water consumption in buildings, as discussed later in this paper. This observation is further confirmed by Figure 3b, which reveals a considerable number of outliers representing the highest values and substantially exceeding typical E_{CO_2} values. However, it is worth noting that more than half of the analyzed CO₂ emission reduction values exceeded 2000 kg, as indicated by the median value of 2030.50 kg, marked by the horizontal line inside the box. The edges of the box, corresponding to the first and third quartiles, show that 25% of the results were no higher than 659.99 kg, while in 75% of cases, the emission reduction did not exceed 5876.31 kg. Consequently, the interquartile range exceeded 5000 kg, highlighting the significant variability in the achieved results. In some households, the environmental benefits from using the horizontal SHE will be minimal, while under favorable conditions, very high CO₂ emission reductions can be achieved. The observed differences in E_{CO_2} values result from both water consumption characteristics (showerhead type and shower length) and the effectiveness of the heat recovery system under specific operating conditions. Additionally, carbon intensity plays a crucial role, showing significant variation not only across EU countries but also worldwide.

To better understand the influence of individual input variables on the resulting CO₂ emission reduction, Figure 4 presents the distributions of E_{CO_2} values depending on the values of these variables (i , q , e_{CO_2} , T_{cw} , T_{dw} , l_s , and η). Figure 4a illustrates the impact of the linear bottom slope of the horizontal SHE on the obtained analysis results. Each box plot represents 12.5% of all results. Upon examining the figure, it becomes evident that an increase in the value of variable i results in an increase in the predicted 15-year CO₂ emission reduction (E_{CO_2}). In the case of a perfectly horizontal heat exchanger, the median of the obtained results was approximately 1627 kg, with the maximum non-outlier value reaching about 10,741 kg. Increasing the linear bottom slope to 4% resulted in an increase in these values by 687 kg and 4575 kg, respectively. However, it is important to note that the largest differences between adjacent box plots were observed at the lowest i values. This is because the linear bottom slope of the considered SHE is one of the key factors determining its effectiveness [17] and thus also the amount of energy that can be saved. It is also important that the system responds in a scalable manner to the increase in the value of variable i . This means that both in typical cases, where CO₂ emission reduction is close to the median, and in more favorable scenarios, the benefits of increasing the horizontal SHE linear bottom slope will be proportionally similar. However, absolute differences (in kg CO₂) will be more pronounced at higher E_{CO_2} values.



(a)



(b)

Figure 3. Distribution of E_{CO_2} values: (a) histogram; (b) box plot.

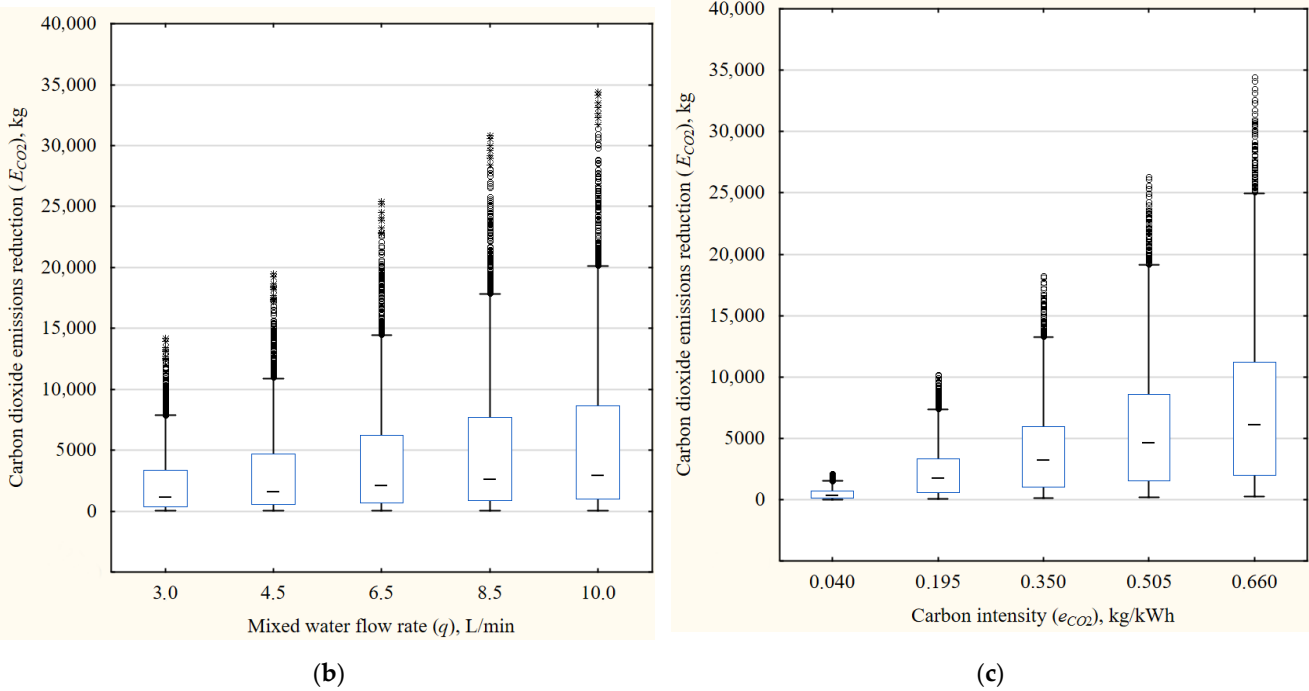
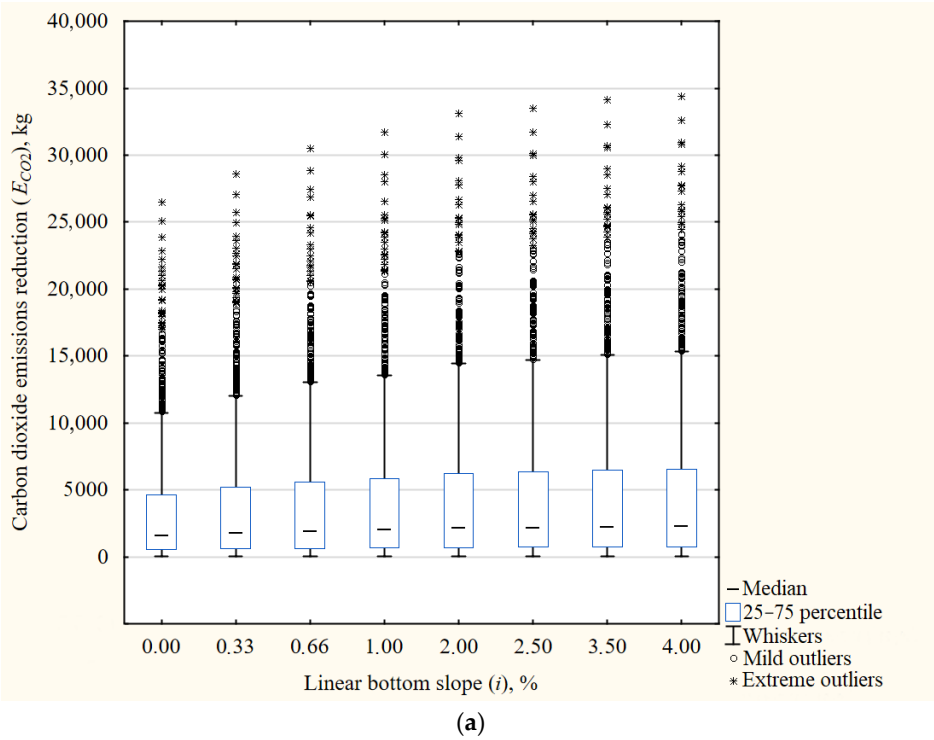


Figure 4. Cont.

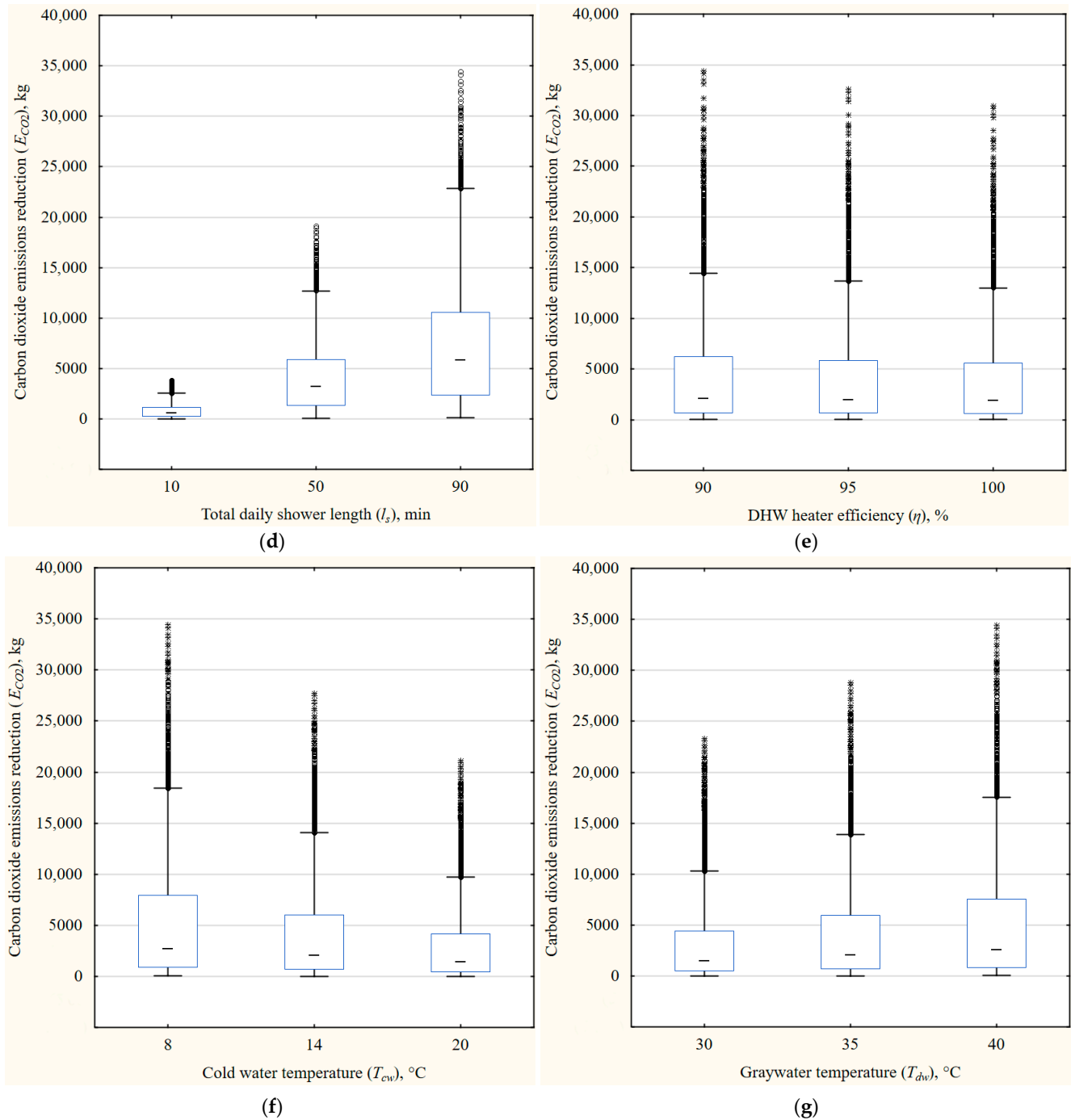


Figure 4. Distribution of E_{CO_2} values against individual input variables: (a) Linear bottom slope. (b) Mixed water flow rate. (c) Carbon intensity. (d) Total daily shower length. (e) DHW heater efficiency. (f) Cold water temperature. (g) Graywater temperature.

Significantly greater differences in E_{CO_2} value ranges were obtained for variables such as mixed water flow rate (q) (Figure 4b) and carbon intensity (e_{CO_2}) (Figure 4c). In these cases, each box plot represents 20% of all observations. The distributions of the obtained results are right-skewed; however, the asymmetry is much more pronounced for mixed water flow rate, whereas for e_{CO_2} , fewer outliers can be observed. Additionally, Figure 4c lacks extreme outliers. Among all considered input variables, such a situation occurs only for e_{CO_2} and l_s (Figure 4d). By analyzing the obtained dependencies, it can be observed that an increase in the q variable results in a higher projected emission reduction (E_{CO_2}). However, under typical shower installation usage conditions, this effect is not as

spectacular as with an increase in e_{CO_2} . An increase in the flow rate by 7 L/min results in an increase in the E_{CO_2} median by approximately 1835 kg, i.e., by over 150% compared with the scenario where $q = 3$ L/min. Meanwhile, the difference in the E_{CO_2} medians obtained for $e_{CO_2} = 0.040$ kg/kWh and $e_{CO_2} = 0.660$ kg/kWh is nearly 5760 kg, representing a difference of around 1550%. Greater differentiation between consecutive box plots is also visible in the first and third quartiles, as well as in the whiskers. This indicates that carbon intensity has a strong impact on typical emission reduction values. This issue has already been noted by other authors [15], who pointed out a significant variation in the projected emission reduction between typical Polish and European families. The E_{CO_2} values increase dynamically and more evenly in these cases, indicating that the impact of the e_{CO_2} variable is independent of individual shower installation usage conditions. As a result, there are no extreme situations, which are present in the case of the mixed water flow rate.

As previously mentioned, the lack of extreme values is also noticeable in the case of total daily shower length (I_s). In Figure 4d, each box plot covers one-third of all observations. Increasing shower length from 10 to 90 min results in an 800% increase in typical CO_2 emission reduction. This clearly demonstrates that E_{CO_2} growth is directly proportional to the increase in I_s value. This is probably due to the fact that increased hot water consumption results in higher energy demand for heating, which directly translates into the amount of pollutants emitted into the atmosphere. This trend is evident both in conventional DHW heating systems and in systems equipped with a graywater heat recovery installation, as noted by Sayegh et al. [31]. A positive impact on projected emission reduction is also observed with an increase in graywater temperature (T_{dw}), as this allows for greater energy recovery. However, the observed differences are significantly smaller. It should also be noted that increasing the temperature of the mixed water to enhance horizontal SHE effectiveness is not recommended, as this would lead to additional energy consumption and an increase in CO_2 emission. Instead, it is crucial to recover heat relatively quickly, preventing the excessive cooling of graywater.

An opposite trend was observed for cold water temperature (T_{cw}) and DHW heater efficiency (η). In both cases, this is due to the negative impact of the input variable on potential energy savings. An increase in cold water temperature reduces the effectiveness of the horizontal SHE, while an increase in DHW heater efficiency (η) leads to lower energy demand for water heating.

To precisely determine the influence of individual input variables on projected CO_2 emission reduction (E_{CO_2}) and establish the hierarchy of their significance, artificial neural network models were developed in the next step of analysis. The selected model served as the foundation for conducting a SHAP analysis.

3.2. MLP Artificial Neural Networks

In the next phase of the analysis, artificial neural network models were developed. Their performance was evaluated by using three standard model fitting metrics: root mean square error (RMSE), coefficient of determination (R^2), and mean absolute error (MAE). The goal was to minimize RMSE and MAE while ensuring that R^2 remained as close to 1.0 as possible. By considering these three metrics across all data groups (training, validation, and test sets), a comprehensive assessment of the quality and effectiveness of the ANN models was achieved. The network architecture selected for further analysis was 7-14-9-6-1. The performance metrics are presented in Figure 5.

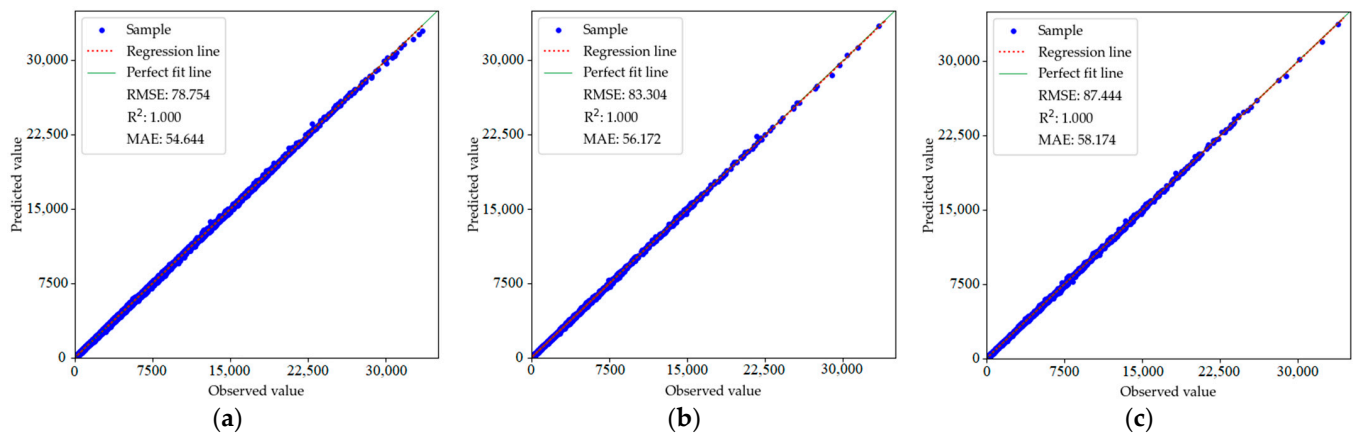


Figure 5. Fit of predicted E_{CO_2} to observed data: (a) Training dataset. (b) Validation dataset. (c) Test dataset.

The obtained results indicate very high predictive accuracy, despite the fact that model has to cope with significant data variability. The R^2 values of 1.000 suggest that the dependencies within the datasets are well described by the model. In addition, the error values (RMSE and MAE) are negligible in the context of the full range of E_{CO_2} values. For instance, the mean absolute error values, ranging from 54.644 to 58.174 kg, represent merely a fraction of a percent of the maximum recorded emission reduction (less than 0.2%). The RMSE values are slightly higher (78.754–87.444 kg), but they remain minimal relative to the E_{CO_2} range. Moreover, comparable values of these metrics were obtained for all three datasets, which proves that the model is not overfitted. This indicates a high generalization ability, making the ANN a reliable tool for estimating CO_2 emission reduction under various operating conditions and serving as a solid foundation for SHAP analysis.

3.3. Global and Local SHAP Analyses

To gain a better understanding of the impact of individual input variables on the predicted CO_2 emission reduction (E_{CO_2}), an interpretability analysis of the model was conducted by using SHAP values (Figure 6). As mentioned in Section 2, this method allowed for an assessment of both the global and local influence of variables related to the operation of the horizontal SHE on the prediction outcomes. In the case of global analysis, it was possible to evaluate their average significance across the entire dataset. Figure 6a provides insights into which variables had the most substantial overall impact on the predicted emission reduction. On the other hand, the local analysis (Figure 6b) illustrated how changes in specific variable values influenced the prediction for individual observations. The points located on the right side of the graph represent a positive impact on the predicted CO_2 emission reduction (E_{CO_2}), while those on the left signify a negative impact.

The global SHAP analysis revealed that carbon intensity (e_{CO_2}) and total daily shower length (l_s) had the most significant average impact on the predicted CO_2 emission reduction. The average SHAP value for both input variables was approximately 2160 kg. Considering the range of the output variable (16.55–34,415.32 kg), it can be concluded that the model is highly sensitive to these two key variables, which is particularly relevant for lower E_{CO_2} values. Therefore, both carbon intensity and total daily shower length should be carefully analyzed in terms of data quality, substantive interpretation, and stability throughout the operational period of the horizontal SHE, as any changes in their values can have a substantial impact on the E_{CO_2} prediction. Additionally, by examining the data in Figure 6b, it is evident that both of these variables are positively correlated with the output variable, meaning that higher values of e_{CO_2} and l_s strongly contribute to an increase in the predicted CO_2 emission reduction. The analysis of individual cases further confirms that omitting

e_{CO_2} and l_s results in the highest SHAP values. The maximum differences between the predicted 15-year CO₂ emission reduction (E_{CO_2}) considering all seven input variables and the values obtained when excluding one of the key variables amounted to over 9000 kg for e_{CO_2} and nearly 7000 kg for l_s .

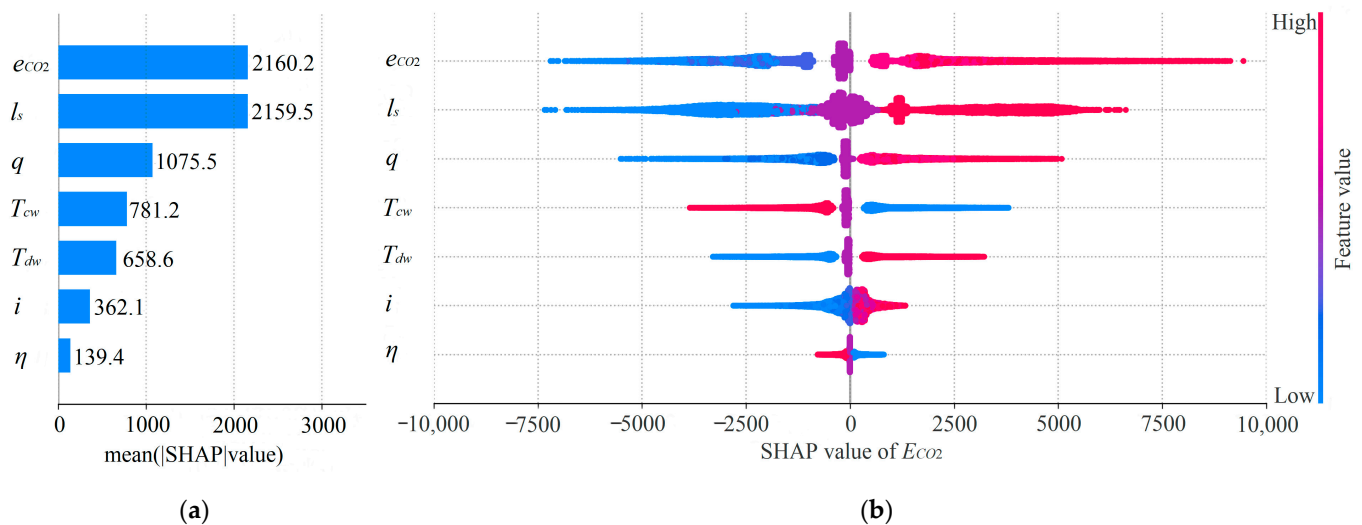


Figure 6. Quantification of variable importance using SHAP values: (a) mean(|SHAP| value); (b) SHAP value of E_{CO_2} .

The significant impact of e_{CO_2} , the value of which depends on the geographic location of the installation, indicates that emission reduction through the use of the horizontal SHE is not only a matter of heat recovery effectiveness and operational conditions but also a structural issue, heavily influenced by national energy policies and energy mix. This confirms that implementing systems aimed at reducing CO₂ emission is particularly justified in high-emission countries such as Poland. In contrast, in countries with low carbon intensity, achieving significant reductions is challenging, even when saving large amounts of energy. Therefore, the green transformation of the energy sector plays a crucial role in the potential of SHEs to reduce emissions, whereas the habits of shower installation users have a secondary impact. Regarding the second key variable, total daily shower length (l_s), its effect on the analysis results is directly related to its influence on water consumption, which in turn affects the energy demand for heating DHW. Similarly to the financial efficiency indicators of such investments [30], the longer the total daily shower length, the greater the predicted emission reduction. Therefore, from both an economic and environmental perspective, installing shower heat exchangers is most beneficial in facilities with high-intensity shower usage.

The next most influential variable in the hierarchy of importance is the mixed water flow rate (q), another variable that determines water consumption in the building. However, its average SHAP value is approximately half as high, at 1075.5 kg. The lower SHAP value may result from the fact that while q influences water consumption, it also significantly affects the effectiveness of the horizontal SHE [17]. While increasing water usage leads to higher energy consumption and emission, thereby increasing the potential for CO₂ emission reduction, increasing the water flow rate through the SHE reduces its effectiveness.

Slightly lower average SHAP values were observed for cold water temperature (over 780 kg) and graywater temperature (almost 660 kg). In the latter case, the direction of changes in the input variable aligns with changes in E_{CO_2} , similarly to the most influential variables. Conversely, an increase in cold water temperature (T_{cw}) results in a lower predicted CO₂ emission reduction. The analysis of individual observations confirms that

these variables have a significantly lower impact on the prediction than e_{CO_2} , l_s , and q . The maximum differences between the predicted E_{CO_2} values considering all input variables and those predicted without taking into account the cold water or graywater temperature did not exceed 4000 kg.

The directions of changes in the input variable and the model prediction result are also consistent in the case of the linear bottom slope of the SHE (i). However, its average SHAP value is nearly six times lower than those of e_{CO_2} and l_s , indicating that the model treats this variable as an auxiliary regulator rather than a key parameter, even though it has a significant influence on the effectiveness of the unit [17]. This variable may be important in specific cases, particularly at lower values of i , but its global impact remains limited, largely due to the significant accumulation of individual observation points at values close to 0 kg.

Finally, the variable with the lowest influence on the model's predictions is the efficiency of the DHW heater (η), which is negatively correlated with E_{CO_2} . Its average SHAP value does not exceed 140 kg, making it approximately fifteen times lower than those of the key variables. This is probably because electric water heaters generally exhibit high efficiency, meaning their efficiency does not significantly impact the overall energy consumption for DHW heating.

3.4. Local SHAP Values for the Selected Observations

The analysis of the impact of individual input variables on the prediction results for CO₂ emission reduction is extended to include an examination of three specific cases, which differ significantly in their E_{CO_2} outcomes (Figure 7). Figure 7a presents the SHAP values for the case with the highest E_{CO_2} value. Figure 7b corresponds to the median E_{CO_2} value, while Figure 7c shows the SHAP values for the lowest E_{CO_2} result. In all graphs, red SHAP value bars represent input variables that increased the prediction value, whereas blue bars indicate variables that decreased it. The lengths of the individual bars illustrate the strength of each variable's impact.

In the first case (Figure 7a), the predicted carbon dioxide emission reduction is 34,373.82 kg, which is 41.5 kg lower than the calculated value—representing a difference of just 0.12%. The hierarchy of significance of input variables remained identical to the global analysis. However, the influence of carbon intensity in this case is over 40% greater than that of total daily shower length (l_s). Both variables strongly increased the predicted value, in total by over 16,000 kg, while the sum of SHAP values for all input variables was 30,327.85 kg. It is also worth noting that all analyzed variables contributed to an increase in E_{CO_2} prediction, which is related to the inclusion of their extreme values. The case with the highest carbon dioxide emission reduction assumes the installation of the heat recovery system in the EU country with the maximum carbon intensity, i.e., Poland. Additionally, the most favorable combination of input variables includes the highest mixed water flow rate, the greatest shower length, the highest graywater temperature, and the greatest linear bottom slope of the SHE. At the same time, the lowest cold water temperature and the lowest DHW heater efficiency were considered. This results from the fact that increasing water consumption while simultaneously reducing DHW heater efficiency leads to the highest energy demand, while maximizing the temperature difference between cold water and graywater and increasing the unit linear bottom slope within the studied range enhances the effectiveness of the horizontal SHE.

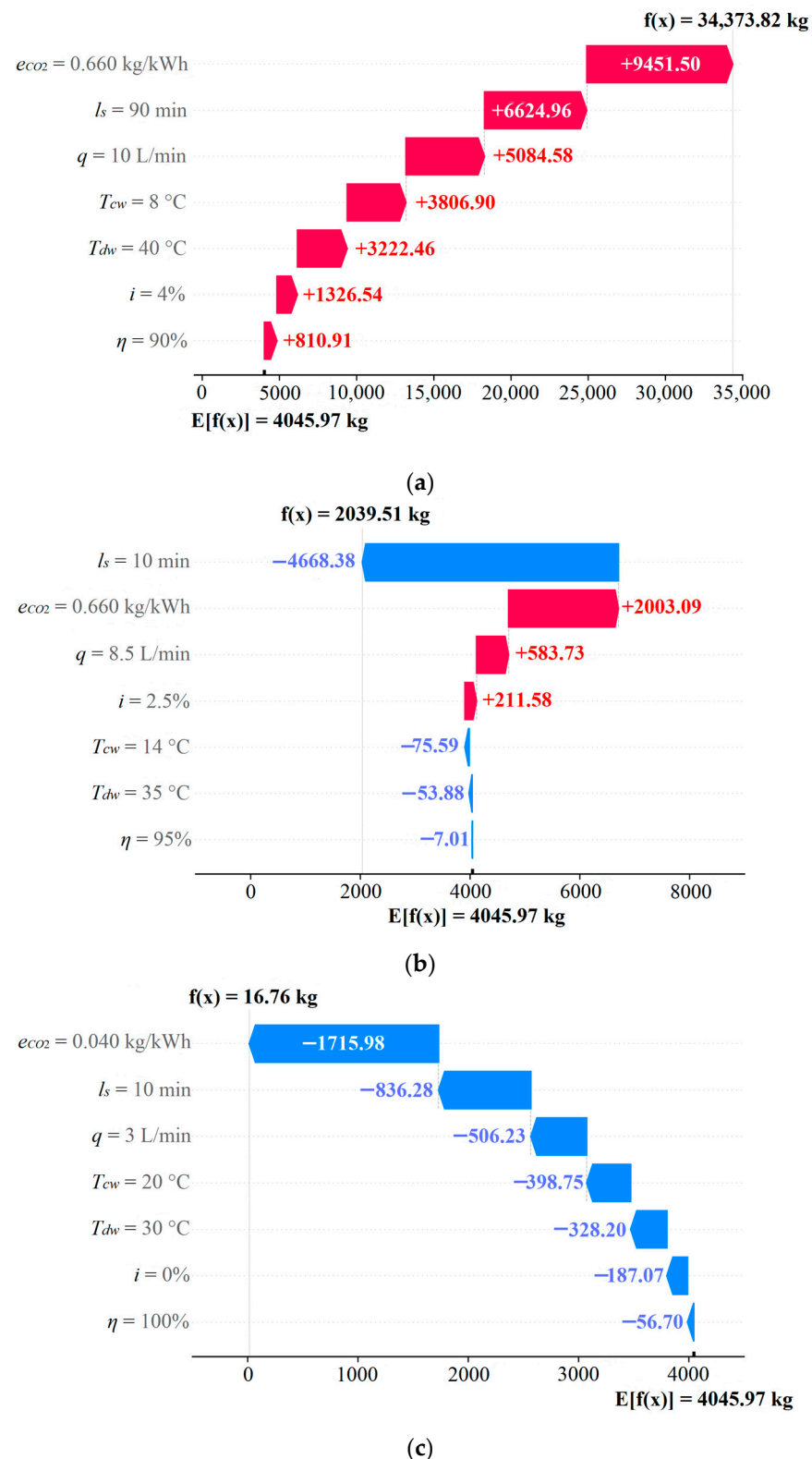


Figure 7. Visualization of the influence of individual input variables on the E_{CO2} prediction: (a) $E_{CO2} = 34,415.32 \text{ kg}$; (b) $E_{CO2} = 2030.50 \text{ kg}$; (c) $E_{CO2} = 16.55 \text{ kg}$.

In the case with the lowest predicted E_{CO2} value (Figure 7c), the same input variables acted in the opposite direction, lowering the prediction result (blue SHAP value bars), while their importance ranking remained unchanged. The two most significant input variables, e_{CO2} and l_s , were responsible for lowering the base value by 2552.26 kg, while the remaining five variables collectively decreased the E_{CO2} prediction by an additional

1476.95 kg. However, it should be noted that in this case, the influence of carbon intensity is more than twice as strong as that of total daily shower length.

When considering the observation corresponding to the median E_{CO_2} value (Figure 7b), significant changes in the impact of individual variables can be observed, along with a shift in the importance ranking of key input variables. Total daily shower length (l_s) emerged as the most important variable, while the significance of carbon intensity (e_{CO_2}) was more than twice as low. Notably, unlike in the extreme cases, the first of these variables lowered the prediction value, whereas e_{CO_2} increased it by more than 2000 kg. The predicted E_{CO_2} value, which was 9.01 kg higher than the calculated value, was also increased by the variables q and i (totaling 795.31 kg). Conversely, the variables T_{cw} , T_{dw} , and η collectively reduced the base value by only 136.48 kg. It is also important to highlight that the changes in the ranking of variable importance are not only visible at the top but also among the less significant variables. While DHW heater efficiency remained the least important variable, the impact of the horizontal SHE linear bottom slope turned out to be more significant than that of cold water and graywater temperatures. Additionally, in the observation corresponding to the median of the results, only the two most significant input variables had extreme values.

4. Discussion

Buildings are increasingly incorporating technologies that enhance energy efficiency, many of which rely on renewable energy sources (RESs). This approach not only reduces operational costs but also mitigates the negative environmental impact of the construction sector. However, the availability of RESs is often not synchronized with the energy needs of society [32]. An exception to this is wastewater, which is available year round, allowing the low-grade heat it contains to be harnessed continuously. Various types of wastewater have the potential to reduce CO₂ emission, including urine [33]. However, the greatest potential lies in graywater. By utilizing a seemingly simple device such as a shower heat exchanger, significant reductions in domestic hot water consumption can be achieved, ultimately leading to a decrease in carbon dioxide emission. At the level of an individual household, CO₂ emission reduction may appear minor, particularly if the number of shower users is small or if the installation operates for a limited time. This is because total daily shower length has been identified as one of the key determinant of the predicted CO₂ emission reduction. However, from a broader perspective, assuming that graywater heat recovery technology becomes a standard feature in multi-family buildings, hospitals, dormitories, prisons, sports halls, and hotels, the potential impact of shower heat exchangers in curbing CO₂ emission becomes significantly more pronounced. Deng et al. [34] also highlighted this point, stating that the installation of shower heat exchangers in all households in Amsterdam would allow for a reduction in CO₂ emission by several tens of thousands of tons per year.

This potential is especially evident in countries where the electricity used for water heating is primarily generated from coal- and gas-fired power plants. Poland is a prime example, where as much as 63% of electricity comes from hard and brown coal [35], resulting in a carbon intensity exceeding 0.660 kg/kWh [20]. Given that carbon intensity has been found to be just as influential as total daily shower length, the implementation of shower heat exchangers in Poland is fully justified from an environmental standpoint. Moreover, an analysis of individual observations confirmed that this variable is crucial regardless of the values of other input variables and the expected CO₂ emission reduction. However, it is not only high-emission countries that should consider the wide application of SHEs. Combating carbon dioxide emission is a challenge faced by all nations striving to meet climate targets. While reducing emission in industry is critical, efforts to improve the energy efficiency of buildings and daily energy consumption habits among citizens are

also essential. National and regional strategies in the field of energy policy and climate protection play a major role, enabling initiatives such as financial incentives for SHE installation and regulations mandating their implementation. In many countries, the widespread adoption of SHEs could become standard practice due to supportive energy policies, ultimately contributing to improved air quality. The larger the scale of shower heat exchanger implementation, the more noticeable the CO₂ emission reduction will be. In countries where electricity is primarily generated from renewable sources or nuclear energy, such as Scandinavian countries, the impact of CO₂ emission reduction may not be as significant. However, the prospect of lowering energy consumption and reducing water heating costs should be sufficient incentives, as financial issues are among the key factors determining the success of any eco-friendly installation [36].

Furthermore, the use of shower heat exchangers aligns with the principles of a circular economy, which seeks to address challenges related to resource depletion, ecosystem degradation, and irresponsible consumption patterns [37]. According to this concept, maximizing resource utilization and minimizing energy losses become top priorities. Graywater heat recovery is not only an action that has a clearly positive impact on the environment but also a real saving for users and a step towards decarbonization of the construction sector. The implementation of SHEs reduces the energy demand for DHW heating, cuts CO₂ emission, and fosters a more sustainable future. As a result, their application effectively supports the achievement of the Sustainable Development Goals (SDGs) [38]. In terms of CO₂ emission reduction, particular attention should be given to SDG13, as lowering the carbon footprint of buildings by reducing energy demand for water heating can help mitigate climate change. As already mentioned, these devices hold the greatest potential in multi-family buildings and hotels, where water consumption is the highest, and due to space constraints, horizontal SHEs are an ideal solution. However, this is not the only positive aspect related to the application of shower heat exchangers. Their widespread implementation can also help reduce reliance on fossil fuels, thereby supporting SDG7. Given their applicability in both new and existing buildings of various types, SHEs contribute to sustainable construction and encourage innovation in the design of internal installations and energy saving systems—key aspects of SDG9 and SDG11. Additionally, better resource utilization and reduced energy wastage in the construction sector align with the objectives of SDG12.

Based on this research study, practical recommendations can be made regarding the integration of shower heat exchangers with existing building equipment. These recommendations apply to both individual users of shower installations and professionals such as designers, engineers, and those responsible for developing local support programs and design guidelines. In the latter case, it is crucial to emphasize the need for implementing financial support programs for building owners interested in purchasing SHEs. Additionally, it may be beneficial to develop guidelines that facilitate the selection of an appropriate heat exchanger model, adapted to local operating conditions, including the number of users and the total daily shower length. It is also important to minimize heat losses within the installation, especially in pipes transporting domestic hot water and, if the heat exchanger is located in an unheated utility room, also in preheated water pipes. Moreover, minimizing installation costs is essential, as the prospect of incurring excessively high investment expenses may discourage potential users, ultimately hindering the achievement of the desired environmental benefits. Therefore, it is recommended that in the case of existing buildings, the installation of heat exchangers should coincide with bathroom renovations.

Although the research results clearly indicate the usefulness of SHEs in reducing CO₂ emission, especially in countries with high carbon intensity, certain limitations should be considered, which may affect the results. This research study did not take into account the

full life cycle of the unit, as only the operational phase of the horizontal SHE was analyzed. Potential emissions related to the manufacturing, installation, and disposal of the heat exchanger were not included. This approach stems from the fact that during the operational phase, shower heat exchangers directly reduce energy consumption for DHW heating and, consequently, CO₂ emissions. However, it should be noted that emissions generated during the production of materials, the assembly of individual installation components, and their eventual disposal may partially offset the environmental benefits resulting from the application of SHEs. This is particularly relevant since non-ferrous metallurgy—such as the production of copper, used in domestic water pipes of heat exchangers—is among the most CO₂-intensive industrial sectors [39]. Potential emissions related to transporting the unit to the installation site, assembly processes requiring additional energy (e.g., soldering copper elements), and the recycling of the materials used to build the heat exchanger should also be considered. Considering these aspects, future research should include a life cycle assessment (LCA) of shower heat exchangers under various operational conditions to comprehensively evaluate the impact of using SHEs on expected CO₂ emission reduction. Additionally, the considered scenarios of use of the shower heat exchanger did not consider heat losses in the installation and SHE effectiveness variations over time due to temperature fluctuations or other factors. It should also be noted that only horizontal SHEs were analyzed. While it is reasonable to assume that similar results would be obtained for other SHE models, further research is needed to confirm this hypothesis.

It is also necessary to consider some uncertainties related to the generalizability of the results in different water heating systems. The results presented in this paper pertain to systems where the primary energy source is an electric DHW heater. As previously mentioned, in countries with low CO₂ emission from electricity production, the environmental benefits of using a shower heat exchanger may be less significant compared with countries characterized by high carbon intensity. Similarly, the application of SHEs in buildings where DHW is heated by using low-emission systems, such as heat pumps, may yield smaller environmental benefits. On the other hand, installing a shower heat exchanger in a building where the primary energy source is a coal-fired boiler may result in significantly greater benefits than those described in this paper. Other authors have also noted the variability of environmental effects resulting from the use of shower heat exchangers depending on the primary energy source [40]. It should also be acknowledged that despite the wide range of input data, the model may not fully reflect all real-world scenarios of SHE usage.

Future studies should also include long-term analyses of the functioning of various shower heat exchanger models under real-world conditions, taking into account a possible decrease in the effectiveness of these devices due to the deposition of impurities or corrosion, especially if the heat exchanger is made of materials susceptible to these processes. Additional validation of the ANN model on independent empirical data from real installations equipped with SHEs would fully confirm the model's reliability. Although this research study was conducted under laboratory conditions similar to actual operational environments, real operating conditions may differ slightly from the assumptions made. Such data could account for the variability of results due to changes in installation usage intensity, the diversity of heating systems, or the impact of contaminants. Incorporating such data would increase the model's predictive accuracy in real-world applications and improve the representation of environmental variables. Additionally, comparing different neural network architectures and exploring alternative model interpretation techniques may prove beneficial. Another interesting research avenue involves expanding the analysis to encompass the full life cycle of SHEs and evaluating the feasibility of integrating them with other energy-saving technologies. It is also worth noting that graywater is not only a

promising renewable energy source but also an alternative water source that, after appropriate treatment, could serve as a valuable substitute for tap water [41]. Therefore, future research should also consider the environmental benefits of combining graywater reuse for both energy recovery and water conservation in buildings.

5. Conclusions

Studies have shown that the application of the horizontal shower heat exchanger not only ensures significant energy savings but also contributes to reducing the carbon footprint of buildings by lowering CO₂ emission. The use of artificial neural networks and SHAP analysis allowed for the identification of key areas determining the extent of this reduction, leading to the formulation of the following conclusions:

1. The analysis of 16,200 scenarios, differing in the conditions of use of shower installation and its location on the map of Europe, revealed substantial variation in CO₂ emission reduction values. In the most favorable case, a 15-year emission reduction could reach 34,415.32 kg, whereas the minimum recorded value was 16.55 kg.
2. This study confirmed that machine learning techniques serve as an effective tool for assessing the performance of shower heat exchangers, as evidenced by the obtained values of the model fitting metrics. Additionally, the application of model explainability methods ensures the identification of key areas influencing the process.
3. One of the most critical variables affecting CO₂ emission reduction during the operation of the horizontal shower heat exchanger is carbon intensity. Consequently, the greatest environmental benefits from using this technology can be achieved in countries where electricity is primarily generated from coal, such as Poland. In countries relying on clean energy sources, the effects will be less pronounced. However, the use of SHEs can still provide energy savings and reduce water heating costs.
4. Another crucial parameter is total daily shower length. Therefore, the highest potential for CO₂ emission reduction is observed in buildings with high shower water consumption, primarily due to a large number of users. This includes multi-family residential buildings, collective housing facilities, hotels, hospitals, etc. Environmental benefits can also be noticeable in individual apartments or detached houses if SHEs become widespread and their application becomes a standard.
5. Other input variables have a significantly lower impact on CO₂ emission reduction predictions, with their importance hierarchy depending on specific parameter values. On a global scale, mixed water flow rate ranks third in importance, followed by cold water temperature, graywater temperature, and linear bottom slope of the horizontal SHE. The least significant variable turned out to be the efficiency of the domestic hot water heater.

The research described in the paper has broad practical, scientific, and environmental value, particularly in the context of improving building energy efficiency and reducing the carbon footprint of buildings. The findings provide data that could serve as a foundation for climate policies and regulations related to building energy efficiency, as well as urban policies promoting energy-saving technologies. The data can also be used to develop guidelines for installing shower heat exchangers in new buildings and for upgrading existing DHW heating systems. Additionally, the research conclusions may prove valuable in the process of building energy certification. They may also be used by developers and individual users, helping them make informed decisions regarding building equipment and the implementation of energy-efficient technologies. This applies to both the design of new buildings and the modernization of existing residential, public utility, or collective housing facilities. The obtained results can support decision makers in selecting the most efficient heat recovery systems, considering operating conditions and local emission parameters.

Further research should explore the impact of input variables on CO₂ emission reduction in the case of other types of shower heat exchangers. It would also be valuable to assess the environmental benefits of integrating shower heat exchangers with installations utilizing other renewable energy sources and graywater recycling systems, allowing for the full exploitation of this resource's potential.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	artificial neural network
DHW	domestic hot water
EU	European Union
LCA	life cycle assessment
MAE	mean absolute error
RES	renewable energy source
RMSE	root mean square error
SDG	Sustainable Development Goal
SHAP	SHapley Additive Explanations
SHE	shower heat exchanger

Appendix A

Figure A1 presents the effectiveness (ϵ) of the horizontal SHE as a function of the mixed water flow rate (q) and the linear bottom slope of the unit (i). The values shown in the graphs were obtained as a result of laboratory tests.

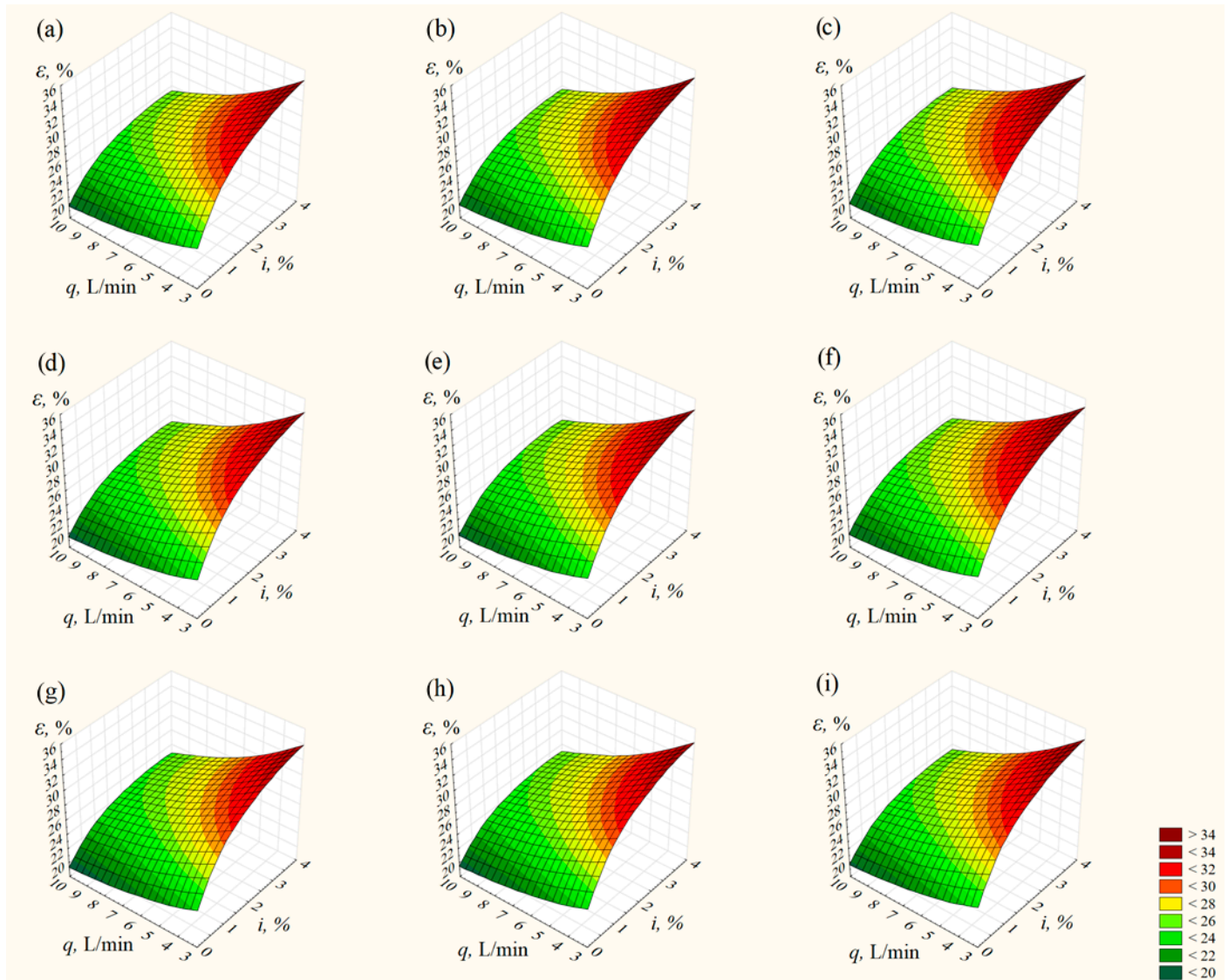


Figure A1. Effectiveness of the horizontal SHE: (a) $T_{cw} = 8^\circ\text{C}$, $T_{dw} = 30^\circ\text{C}$; (b) $T_{cw} = 8^\circ\text{C}$, $T_{dw} = 35^\circ\text{C}$; (c) $T_{cw} = 8^\circ\text{C}$, $T_{dw} = 40^\circ\text{C}$; (d) $T_{cw} = 14^\circ\text{C}$, $T_{dw} = 30^\circ\text{C}$; (e) $T_{cw} = 14^\circ\text{C}$, $T_{dw} = 35^\circ\text{C}$; (f) $T_{cw} = 14^\circ\text{C}$, $T_{dw} = 40^\circ\text{C}$; (g) $T_{cw} = 20^\circ\text{C}$, $T_{dw} = 30^\circ\text{C}$; (h) $T_{cw} = 20^\circ\text{C}$, $T_{dw} = 35^\circ\text{C}$; (i) $T_{cw} = 20^\circ\text{C}$, $T_{dw} = 40^\circ\text{C}$ (designations as in the text).

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