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Energy Modeling for Electric Vehicles Based on Real Driving Cycles: An Artificial Intelligence Approach for Microscale Analyses

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Abstract: This paper presents the process of creating a model for electric vehicle (EV) energy consumption, enabling the rapid generation of results and the creation of energy maps. The most robust validation indicators were exhibited by an artificial intelligence method, specifically neural networks. Within this framework, two predictive models for EV energy consumption were developed for winter and summer conditions, based on actual driving cycles. These models hold particular significance for microscale road analyses. The resultant model, for test data in summer conditions, demonstrates validation indicators of an R^2 of 86% and an MSE of 1.4, while, for winter conditions, its values are 89% and 2.8, respectively, confirming its high precision. The paper also presents exemplary applications of the developed models, utilizing both real and simulated microscale data. The results obtained and the presented methodology can be especially advantageous for decision makers in the management of city roads and infrastructure planners, aiding both cognitive understanding and the better planning of charging infrastructure networks.

Keywords: vehicles; EV; modeling; artificial intelligence; microscopic simulation; Poland

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1. Introduction

The transportation sector is the second largest source of CO_2 emissions worldwide, responsible for approximately 34% of their total production [1]. These emissions come from the combustion of fossil fuels, including diesel, petrol, and heavy oils. In addition to CO_2 emissions, the burning of these fuels leads to the release of N_2O, CH_4, CO, and other gases, all of which are considered greenhouse gases (GHG) [2,3]. Without significant change, this situation contributes to climate change, including the global rise in average temperatures [4]. One method to counteract this phenomenon is the adoption of alternative fuels in transportation and the implementation of different vehicle propulsion systems, such as those based on electric platforms [5–7].

The market for EVs is gradually expanding, and, in the near future, it is expected to capture a significant share of the overall vehicle market. Already, in some countries like Norway, the EV market accounts for 83% of new vehicle sales [8]. The increased adoption of EVs onto roads will lead to a considerable reduction in overall fuel consumption and emission levels. This situation underscores the need for the development of precise models for EV energy consumption.

The limited range of EVs is one of the most significant challenges for car manufacturers and simultaneously acts as a key impediment to the widespread adoption of this technology on a global scale [9]. Faced with this challenge, the precise modeling of energy consumption by EVs becomes indispensable, as it enables a better understanding and prediction of their energy behavior. Developing rapid and accurate energy models for electric vehicles, which allow for a more precise estimation of their energy consumption, is particularly crucial. It is worth highlighting that the difficulty in predicting energy consumption arises from the diversity of their operating conditions, such as fluctuating ambient temperatures and varied driving routes. The development of advanced energy models is essential not only for vehicle manufacturers but also for charging infrastructure planners. Effective forecasting of the energy consumption by electric vehicles enables the better planning and deployment of charging stations, contributing to the improvement of the infrastructure supporting electric vehicles. Consequently, the advancement of sophisticated energy models for electric vehicles plays a pivotal role in removing the barriers associated with their limited range, simultaneously accelerating their acceptance on a global scale.

In recent years, there has been a growing number of studies that have focused on various design analyses, such as the design of electric vehicle charging networks. This is significant for balanced infrastructure development, ensuring that new charging points are accessible to a wide range of drivers and strategically located in key road areas with a high demand for charging. One such study is [10], where the authors analyze the energy needs of electric vehicles on roads, considering key parameters such as the number of charging stations, the state of the charge (SoC) of incoming vehicles, and their battery capacities. This work makes a significant contribution to this area and relies on Monte Carlo simulation methods. The same authors have also developed equally interesting models in their subsequent work concerning charging stations in different contexts, such as models based on the charging power distribution of individual charging points [11]. The aim of that paper was to create an algorithm that intelligently controls charging power based on the current state of charge of the vehicle. There are also numerous similar studies, such as [12–16], which also investigate the impact of certain parameters on other selected parameters of electric vehicles, design charging networks, or specify their characteristics.

The number of studies exploring the use of artificial intelligence techniques for various types of modeling and the prediction of different parameters is also increasing. An example of AI utilization in this analysis is the work [17]. The article reviews the applications of artificial intelligence techniques in motor fault detection and diagnosis (FDD). It discusses feature extraction methods and presents traditional machine learning and deep learning algorithms for fault classification in motor drive systems. Another example is the work [18], which reviews AI-based models for forecasting EV charging demand and scheduling, while also highlighting the lack of research on EV discharging scheduling, urging a closer examination of this emerging area. Another example of work that uses machine learning techniques for prediction is [19]. This article explores the potential of lithium-ion-battery-powered vehicles in mitigating climate change and discusses the challenges associated with ensuring the reliability of battery management systems for predicting battery cycles, their state of charge, and knee point. It conducts a comparative analysis of different methods for estimating the state of charge of lithium-ion batteries, including adaptive, data-driven, and hybrid approaches, with a focus on machine learning and artificial intelligence techniques, aiming to identify superior algorithms for battery management systems and address future challenges in electric vehicle technology. Another work addressing the challenges of predicting EV charging using AI is [20]. This article addresses the short-term prediction challenges for EV charging stations due to the unpredictable charging behavior of users. It proposes a model that combines time series and nonlinear features, enhanced through hyperparameter optimization using Bayesian methods, resulting in improved prediction accuracy and enabling the efficient optimization of electric vehicle charging schedules to ensure grid stability.

Such works are very interesting and provide insight into a certain group of vehicle parameters that appear at the station; however, they do not take into account what happens in real time in dynamic road conditions, where driving dynamics are continuously reflected in changing energy consumption and, consequently, range.

Currently, there exists a specific group of models, based on developed algorithms and simulated using macroscale tools, aimed at estimating the overall energy consumption of electric vehicles [21,22]. However, there is a noticeable gap in the availability of models capable of accurately estimating instantaneous energy consumption based on specific input data, such as vehicle speed and acceleration. One of the existing microscale models addressing this issue is [23]. However, it is important to note that despite its presence, this model is characterized by certain limitations that impact its universality and practical application. This model focuses on the microscopic modeling of vehicle traffic and the simulation of instantaneous energy consumption, which is its strength. However, it should be noted that this model has certain limitations, primarily in relation to the fact that it was created and validated based on data from dynamometer test cycles rather than real-world road conditions. These limitations affect its ability to provide comprehensive and accurate results in various road conditions. Consequently, despite the presence of some microscopic models, there is still a need to develop more comprehensive models of instantaneous energy consumption that take into account the various factors influencing energy consumption in real time.

Another approach to modeling EV parameters is the macroscale model, exemplified by [24]. In this study, a simulation-based quasi-statistical approach was used to estimate the energy consumption of electric vehicles (EVs). The developed method is scalable for implementation in regions other than those examined in the study. However, it is important to note that this model has certain limitations, particularly its inability to be used for determining instantaneous energy in vehicles on the road in real time.

Taking the above into consideration, this study was conducted on the creation of an instantaneous energy consumption prediction model for electric vehicles (EVs), using artificial intelligence methods on a microscale. The data utilized in this study consist of road data, containing real driving cycles from various tests. The paper includes a comparison of various artificial intelligence techniques and presents the method that performed the best among the created EV energy models. The selected predictive method for energy is the neural network technique. The prediction models were developed in the Python programming environment. The created models are characterized by simplicity, since only the vehicle speed and acceleration data are needed as input for energy calculations. The source of these data can be versatile, which means that the model can be used for real road data and simulated data.

Given that the energy consumption of electric vehicles mainly depends on road conditions and environmental properties, especially air temperature, the models created cover both warm and cold environmental conditions. This paper includes a description of the method, data collection, and processing, followed by the presentation of the validation results of the created models and their exemplary applications. The work concludes with a discussion section containing a detailed description of the results and a comparison of the results obtained with a review of existing literature.

2. Methods

The work involves developing and presenting a methodology for creating a model of the energy consumption of electric vehicles on the microscale. While there are still relatively few such models, the number of electric vehicles on the roads is increasing, creating a clear need for the development of new models or the expansion of existing ones to include new types of EVs. The developed methodology involves analyzing real data from electric vehicle journeys and creating a microscale model based on this analysis, aiming for maximum universality. The energy models developed are based on predictive artificial intelligence techniques. The universality and potential use of this EV energy model lie in its ability to be applied to various applications for different purposes. Input data, defined as explanatory variables, must also be readily available for each application. For this purpose, vehicle speed and acceleration were chosen as the explanatory variables, serving as attributes for the input data. These data can be easily obtained from real journeys using On-Board Diagnostic (OBD) systems or GPS, from the vehicle movement trajectories captured by cameras, or from road sensors. Such data can also be provided by simulation tools.

The data necessary for creating the model were collected during real-world journeys under various environmental conditions. Considering that the performance and range of electric vehicles depend on external temperatures, data were collected for both summer and winter periods. These data were intentionally separated to create two different models for the energy consumption of electric vehicles. The data were recorded at a frequency of 1 Hz. An illustrative dataset, aggregated into a table, is presented in Table 1.

Table 1. Selected parameters from road tests, categorized into cold and warm environmental conditions.

Ambient Conditions	Battery Temp. Start (Average) (°C)	Battery Temp. End (Average) (°C)	Battery SOC Start (Average)	Battery SOC End (Average)	Ambient Temp. (Average) (°C)	Cabin Temp. (Average) (°C)	Distance Sum (km)	Duration (min)
Cold	6.57	11.14	68.81%	47.93%	2.21	22.00	168.44	195.12
Warm	22.86	24.00	78.91%	69.40%	22.64	24.43	126.35	191.76

Table 1, in addition to the data related to the environmental conditions crucial for electric vehicle (EV) batteries, also includes general technical information such as the battery temperature at the beginning and end of the test, as well as its state of charge. Since the focus of this work is on creating energy consumption models for EVs, the collected data were divided into two models representing the modeling of this attribute, concerning the ambient temperature of the weather conditions classified broadly as cold and warm. The data for warm conditions comprised 11,506 records, while for cold conditions, there were 11,708 records.

In Table 2, the selected operational data of the EVs used to aggregate real-world data from road tests are presented. Works that have used the same vehicle to create models include, for example, [25–27].

Table 2. Selected operational parameters of the EVs.

Parameter	Specification
Number of motor(s)	1
Motor type	Permanent magnet AC synchronous electric motor
Maximum power/at rpm	125/4775 kW/rpm
Maximum regenerative brake power	55 kW
Curb weight (EU)	1390 kg
Transmission type	Single-speed automatic transmission
Battery type	Lithium-ion
Battery configuration	8 modules (96 cells connected in series)
Nominal battery pack capacity	60 Ah
Acceleration (0–100 km/h)	7.9 s
Electric range (NEDC)	170 km
Drivetrain	Rear wheel drive (RWD)

For the development of EV energy models, the Google Colab environment and Python 3 programming language were used. The models were computed using the T4 GPU, which allows for faster calculations compared to standard CPUs and GPUs on regular computers. Google Colab, being a Python runtime environment in the cloud, provides free access to GPU resources, facilitating research into machine learning [28]. The use of the T4 GPU on Turing Tensor Core architecture accelerates tensor operations, which is crucial for the efficient training of deep neural network models [29]. This combination of technologies allows researchers to conduct experiments with the Python language, achieving a significant acceleration of numerical computation, especially in the field of artificial intelligence. The most important parameters needed to create the input model were vehicle speed, vehicle acceleration, battery voltage, and battery current. From the parameters of battery voltage and battery current, the power and then the amount of power consumed were calculated, which will be used as the energy measure (Wh) in the later part of the study.

Our workflow is depicted in Figure 1, which highlights three main fundamental steps: data collection, data processing, and potential use. As previously described, the first stage involves collecting the data required to create the energy model. The collected data were divided into two groups: external conditions for warm temperature and for cold temperature measurements. Warm temperature conditions entail conducting tests during the summer months, where the ambient temperature ranges from 18–26 °C, whereas cold temperature conditions entail the winter months, with ambient temperatures ranging from −3 to 7 °C. The data obtained undergo a qualitative analysis and must be processed appropriately. Data processing in the creation of artificial intelligence models involves collecting, cleaning, and normalizing data to prepare them for machine learning. This process also includes feature engineering, categorical variables, and splitting the data into training, validation, and test sets. The models are then trained on the training data, evaluated on the validation data, and, after their adjusting parameters, if necessary, finally tested on the test set. The processed data can be used to train new models. The selected techniques include linear regression, random forest, gradient boosting, and neural networks. All models were validated based on the analysis of their charts, including residual plots, and the R^2 and MSE were calculated for each. On this basis, the best model was identified. The best model, in this case, the one based on the neural network method, was used to demonstrate its potential use. In this regard, the paper illustrates the use of the energy model to create an energy map in the context of new real-world data from a route driven in Rzeszów (Poland) and simulated data for a roundabout object obtained from PTV Vissim 2024 software.

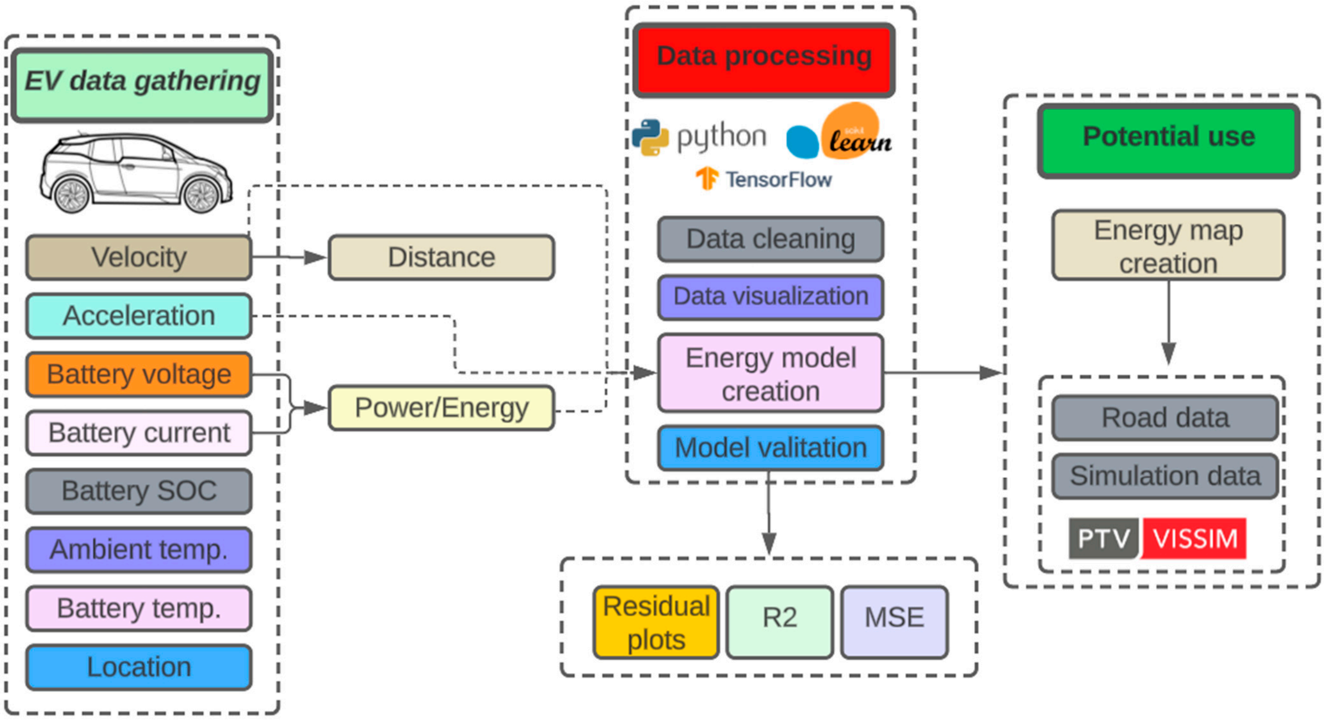

Figure 1. Simplified workflow.

3. Results

The first stage of the work involved gathering the data for creating the energy models of electric vehicles (EVs). The aggregated data from real road cycles were saved in the.xls format and then prepared in the .csv format, with individual attributes separated by a semicolon. Below, the data are presented by separating the road cycles into summer and winter conditions. Figure 2 illustrates the dataset used to create the EV energy consumption prediction models.

Based on Figure 2 of the conducted road tests, aggregated data can be observed for speed, acceleration, and other explanatory variables regarding the dependent variable, which is the energy of the EV. At this stage of data analysis, it is already evident that, for winter conditions, the energy consumed during driving is higher, applying to practically every speed interval of the analyzed road cycles.

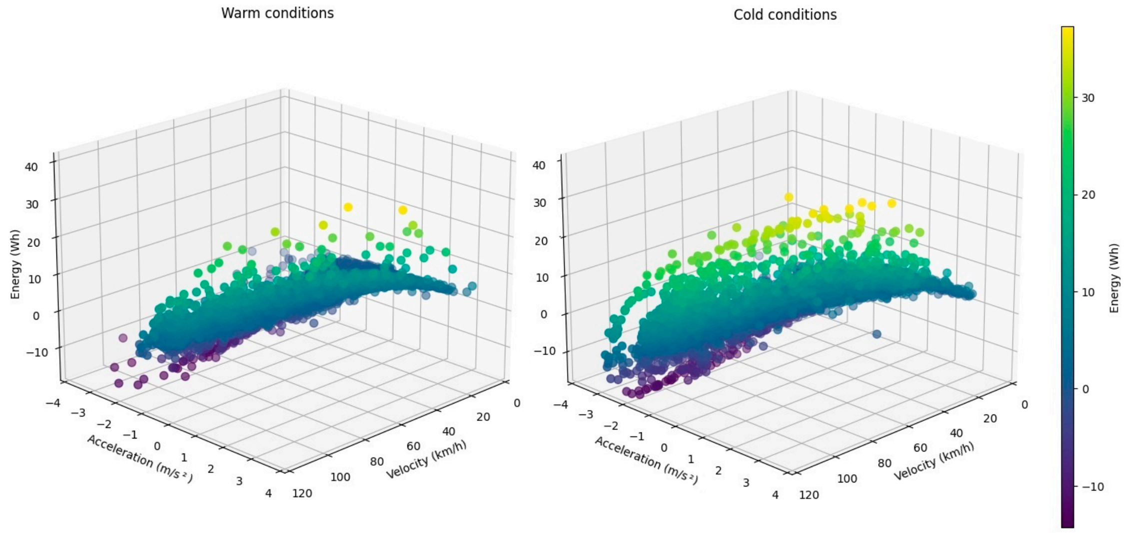

Figure 2. Three-dimensional scatter plots of acceleration vs. velocity vs. energy for both researched ambient conditions.

The data presented for both summer and winter conditions were divided into datasets. To effectively evaluate the performance of the machine learning model, the data were split into two sets: training and testing. The train_test_split function from the scikit learn library was used for this purpose. The test set, comprising 20% of the total data, was separated from the training set, which consisted of the remaining 80%. The random_state = 100 parameter was used to ensure the reproducibility of the results and facilitate comparisons between different models.

The chosen model learning methods include linear regression, random forest, gradient boosting, and a neural network. All results from these methods were validated using the model, based on its R^2 coefficient, MSE, residual plots, and predicted vs. observed charts. The best method was selected to showcase an exemplary use of the EV energy model.

The aim of selecting these methods was to demonstrate, in relation to the advancement of each machine learning technique, the results that can be achieved. Each method has a certain complexity, and its execution of the input data requires a certain time frame. Therefore, it may be appropriate to use the simplest method that provides satisfactory results to limit the time required by the computation algorithms.

3.1. Linear Regression Calculations

Linear regression is a statistical method that is used to model the relationship between an independent variable and a dependent variable, assuming that this relationship is linear [30]. In the case of linear regression analysis, the goal is to fit the best-fitting line (regression) to the data points to minimize the differences between the actual values and those predicted by the model. The linear regression model utilizes an equation of a line, where the dependent variable is a linear combination of independent variables, and the coefficients of this combination are estimated based on the training data [31]. The final model enables the prediction of the values of dependent variables for new data, allowing for trend analysis, forecasting future values, and understanding the strength and direction of the relationship between variables. The validation model coefficients for the winter and summer conditions are presented in Table 3.

The mean square error (MSE) measures the average square difference between the actual and predicted values. A smaller MSE indicates a better fit of the model to the data [32]. On the provided results for both the training and testing data, it can be observed that the model for warm conditions achieves lower MSE values, indicating a better fit to the data in terms of this parameter. However, it is essential to note that this relationship and the statement about which model is better do not necessarily correspond to the R^2

coefficient. In this case, the model has a higher R^2 value for cold conditions, suggesting that it generally predicts future data better.

Table 3. Validation results of the linear regression model of EV energy for different environmental conditions.

Conditions	Training MSE	Training R^2	Test MSE	Test R^2
warm	4.211612	0.621058	3.957043	0.619025
cold	8.83428	0.635986	8.416843	0.627704

Figure 3 presents a comparison of predicted vs. observed data plots and residuals for both temperature conditions.

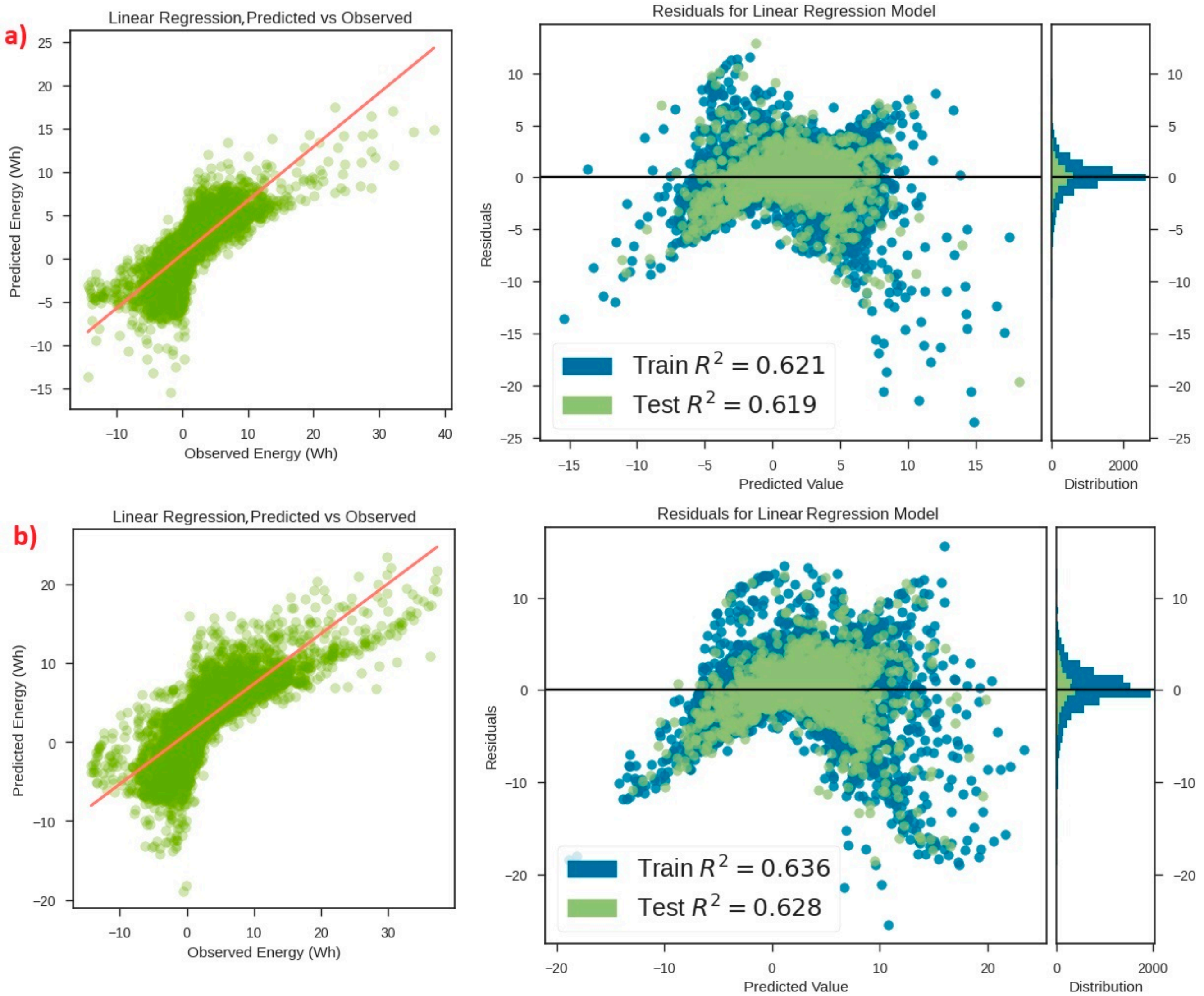

Figure 3. Comparison of graphs of the linear regression method for predicted vs. observed data and residuals for the input data of the two environmental conditions tested: (**a**) warm and (**b**) cold.

Based on Figure 3, we can assess whether the values predicted by the model align closely with the actual values measured. From this, it can be observed that the model, in warm conditions, exhibits a slightly better reflection of reality for practically every examined data range. The cold conditions also oscillate within similar ranges on this graph, but there are some differences in the estimated values for the range of 5–20 Wh.

For the residual plot, it is essential to check whether the values are evenly distributed around the zero axis. Here, for both warm and cold conditions, there are some underestimations and variations in these plots. In summary, while this method provides quick results, it also introduces some inaccuracies in the modeled estimation of the EV's energy.

3.2. Random Forest Calculations

The random forest method is a machine learning tool that is based on the principle of combining multiple decision trees into a single model. By randomly selecting samples and features during the construction of each tree, the model becomes more resistant to overfitting the training data [33]. During prediction, each tree contributes its input, and the final decision is made based on a voting mechanism. Random forest finds applications in various fields, offering high prediction accuracy, flexibility, and the ability to handle diverse data. In addition, it enables the identification of significant features, which is crucial in practical applications. The validation model coefficients for the winter and summer conditions are presented in Table 4.

Table 4. Validation results of the random forest model of EV energy for different environmental conditions.

Conditions	Training MSE	Training R^2	Test MSE	Test R^2
warm	3.293970	0.703623	3.476304	0.665309
cold	6.589128	0.728497	6.528583	0.711226

In terms of the R^2 coefficient, the model performs better with cold conditions, while, with respect to the MSE coefficient, the model of warm conditions produces better results. A comparison of the random forest method for predicted versus observed data and residuals for both temperature conditions is presented in Figure 4.

Based on data from Table 4 and Figure 4, it can be observed that the model utilizing the random forest technique performs slightly better at predicting energy data from electric vehicles. However, to explore even better computational techniques, the results for gradient boosting and neural networks will be presented in the next part of the study.

3.3. Gradient Boosting Calculations

Gradient boosting is an advanced machine learning method that builds a model by combining weighted decision trees. This algorithm iteratively corrects errors from previous models, focusing on the areas where larger errors were made [34]. It is effective in modeling complex dependencies in data, and, through the iterative process, it can handle diverse types of data. Despite its effectiveness, the careful tuning of parameters such as tree depth is necessary to avoid overfitting the model. The results of the validation model coefficients for the gradient boosting method for both winter and summer conditions are presented in Table 5.

Table 5. Validation results of the gradient boosting model of EV energy for different environmental conditions.

Conditions	Training MSE	Training R^2	Test MSE	Test R^2
warm	1.214071	0.890763	1.506699	0.854938
cold	2.710946	0.888296	3.072594	0.864092

For the gradient boosting method, a clear improvement in the validation results for both the MSE and R^2 coefficients can be observed. Model errors have decreased to the range of 1–3 MSE, and R^2 coefficients oscillate in the range of 0.85–0.89, indicating a high level of model representation with respect to the actual data. In Figure 5, a comparison of the plots of the gradient boosting method's predicted vs. observed data and residuals for both temperature conditions is presented.

For this method, both for the predicted vs. observed data and the residuals plot (Figure 5), it can be observed that the data have a more uniform distribution. The data also fit into patterns to a lesser extent, indicating that the model using this method significantly better represents the actual data.

3.4. Neural Network Calculations

Neural networks are an advanced machine learning method inspired by the structure of the brain. They consist of layers of interconnected artificial neurons, including input, hidden, and output layers [35]. During the learning process, weights are adjusted, minimizing the error between the model's predictions and the actual data. In the case of the utilized code, a sequential model with dense layers was created, where 'relu' activation functions were applied to the hidden layers, and the output layer used a 'linear' function. The input data were normalized to the range [0, 1] using Min–Max scaling. The model was trained on the training dataset and then evaluated on the test dataset. The validation results for the neural network method, under winter and summer conditions, are presented in Table 6.

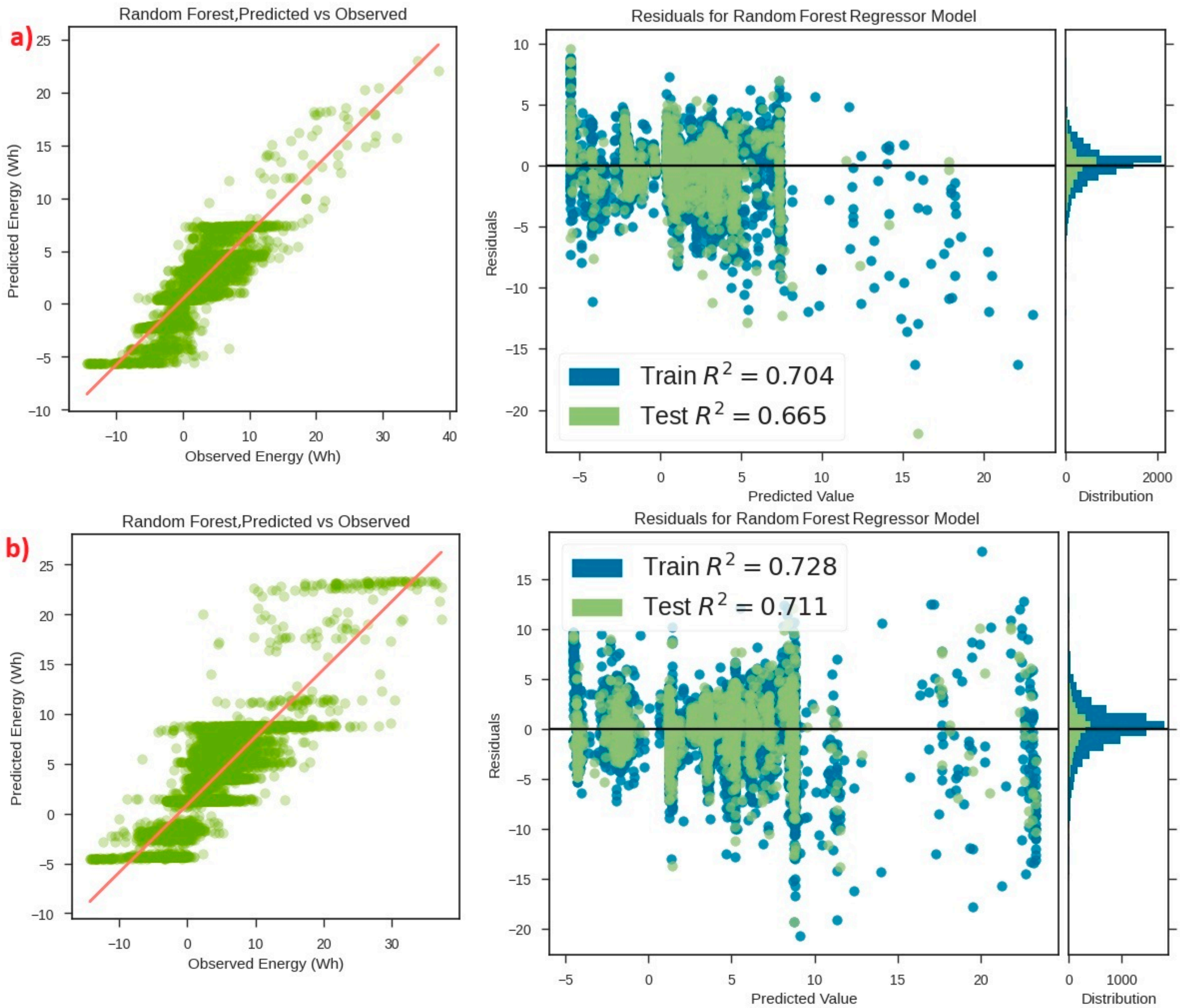

Figure 4. Comparison of graphs of the random forest method for predicted vs. observed data and residuals for the input data for two tested environmental conditions: (**a**) warm and (**b**) cold.

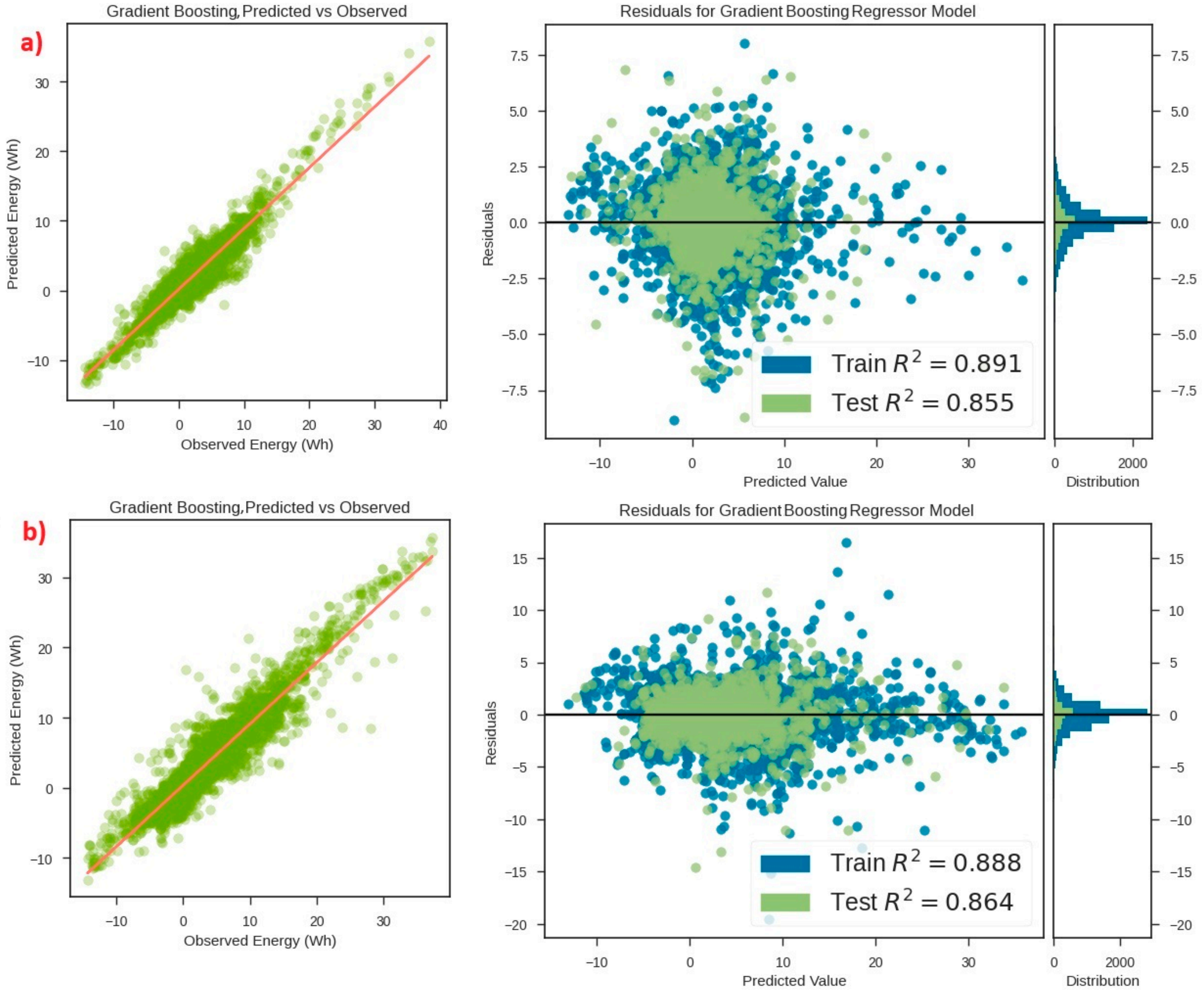

Figure 5. Comparison of the graphs of the gradient boosting method for predicted vs. observed data and residuals for the input data for the two environmental conditions tested: (**a**) warm and (**b**) cold.

Table 6. Neural network model validation results for the EV energy used in different environmental conditions.

Conditions	Training MSE	Training R^2	Test MSE	Test R^2
warm	1.4057	0.8716	1.4727	0.8666
cold	3.0935	0.8694	2.8110	0.8870

The neural network method performs as well as gradient boosting in predicting energy values for the EV model. This method has been recognized as the best method for estimating EV energy. The choice of this method is justified by its superior validation results, especially for the test set. Figure 6 illustrates the comparison of graphs for the neural network method, showing predicted vs. observed data and the residuals for both environmental temperature conditions.

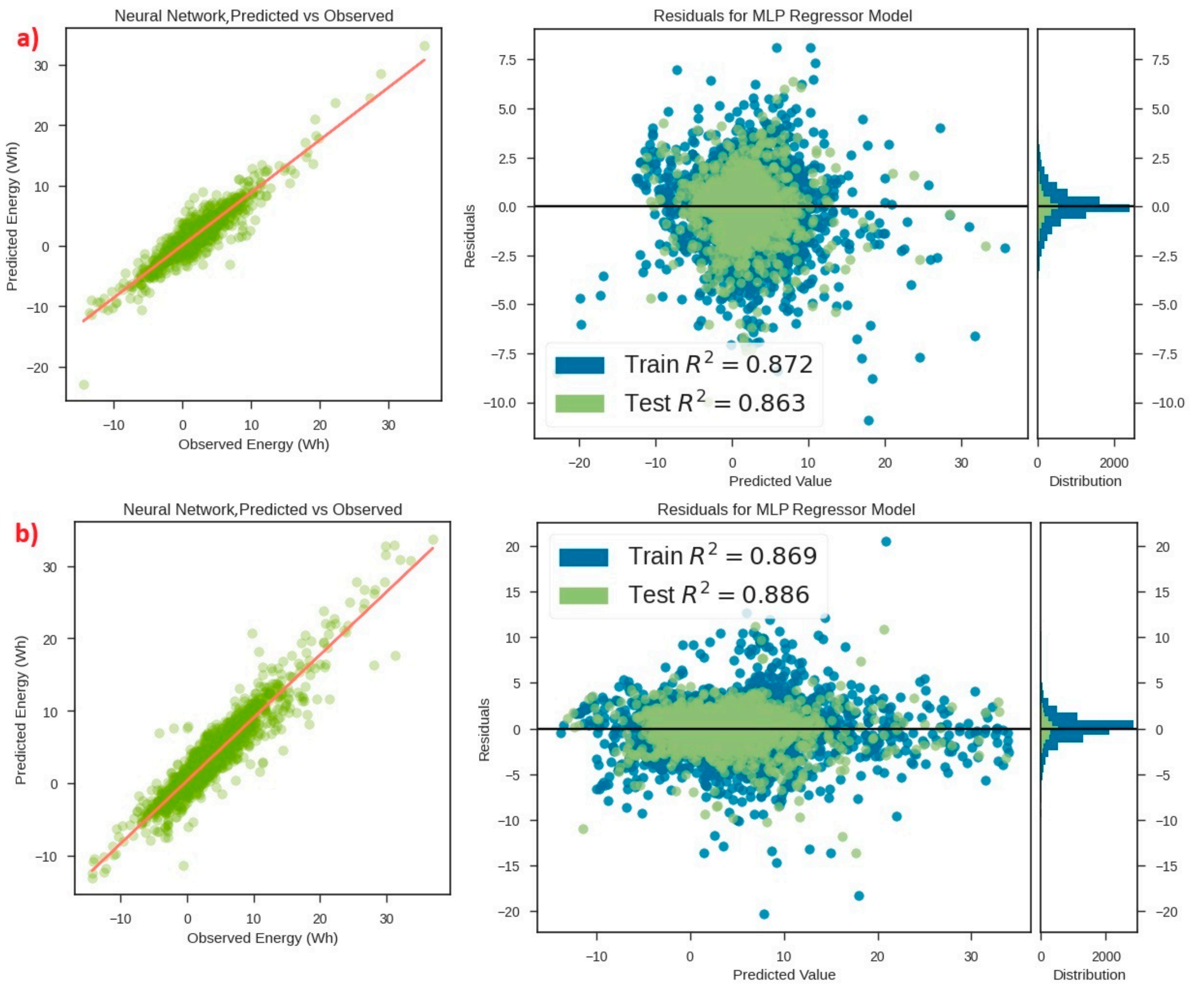

Figure 6. Comparison of the graphs of the neural network method for predicted vs. observed data and residuals for the input data for the two environmental conditions tested: (**a**) warm and (**b**) cold.

The results presented in Figure 6 are qualitatively similar to the gradient boosting method. However, differences can be observed in that the results are less scattered from the axis 0, indicating that this method has smaller errors compared to the gradient boosting method. Therefore, in the next part of this work, when presenting the potential use of the EV energy model, the results will be presented by taking into account this particular model.

4. Utilizing the Obtained EV Energy Model for Microscopic Analyses

The obtained EV energy model, based on the neural network technique, will be used to predict the energy consumption of different vehicle traffic scenarios. The first scenario will be based on a new, real road trip. The second scenario involves the use of the obtained energy model for simulation analysis on a microscopic scale. The scheme that illustrates the procedure carried out to utilize the model is presented in Figure 7.

The model operates based on input data, ideally at a frequency of 1 Hz for the speed and acceleration of the EV. Using the results generated, we obtain the EV's energy consumption in Wh. With these data, we can generate, for example, energy maps for EVs to better tailor infrastructure, such as charging points, to the needs of electric vehicles. A microscale model can be used, for instance, to determine the average energy consumption rates for aggregated vehicle speeds, providing a macroscale model. In addition to energy maps, further data analysis is possible for average energy values or, for example, calculating the energy used based on the duration of the trip.

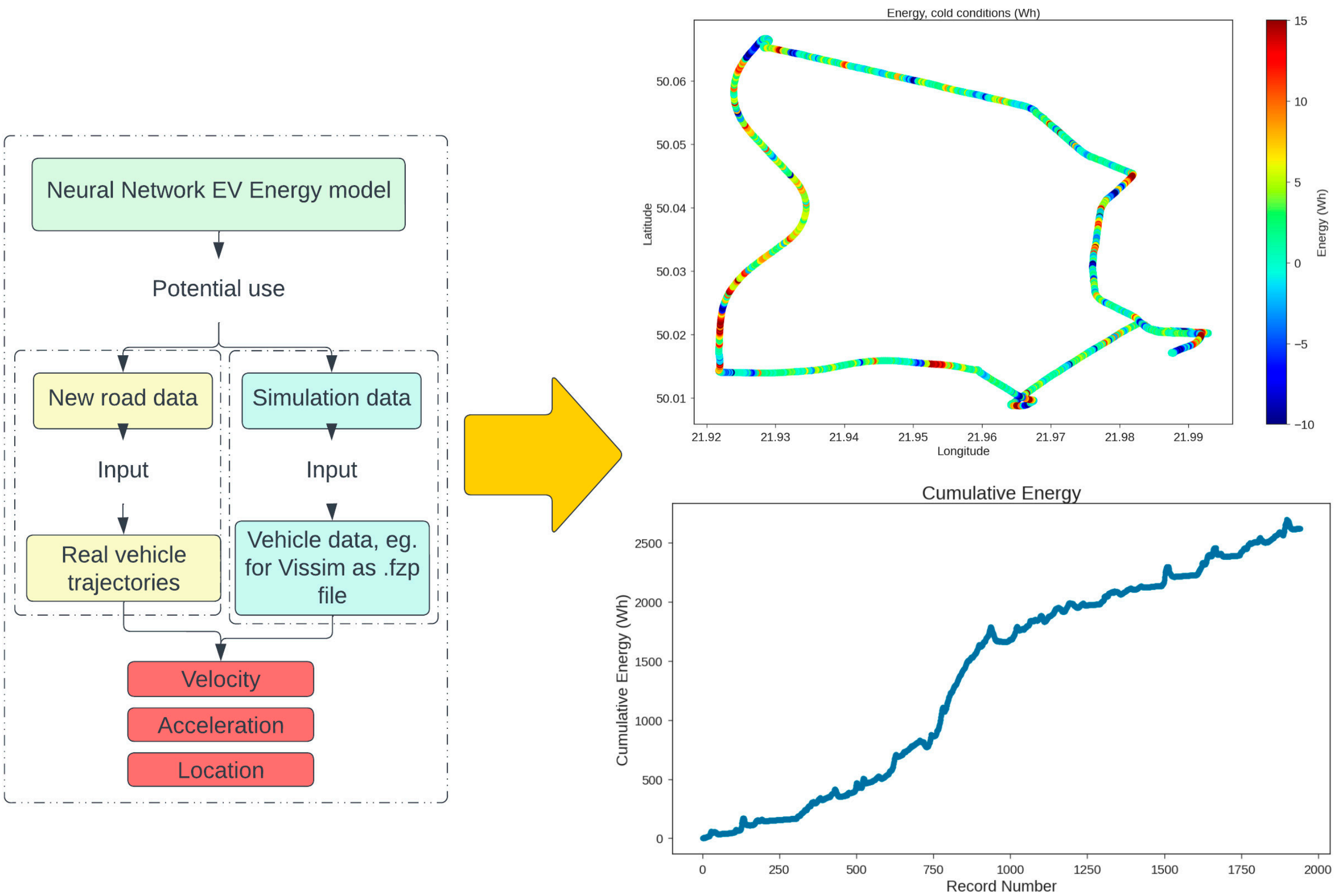

Figure 7. Simplified scheme of how to use the developed EV energy model.

4.1. Road Tests and Use of the Model

To create energy maps for the EV, a road trip was conducted in Rzeszów, Poland. Figure 8 shows the route under study and the vehicle used.

The route covered a passage through an urban area characterized by increased traffic density and a section of the expressway. Using the developed model, the energy consumption of the electric vehicle was calculated based on the data of the route. Figure 9 presents the results of the EV energy model for the route studied.

Based on Figure 9, areas of increased energy consumption can be observed for the examined EV. When comparing the summer environmental conditions of the model with the winter conditions, it can be noticed that, especially in the context of higher vehicle speeds on the highway, there are more areas that are characterized by a higher energy consumption of the EV. For the energy data records cumulated from 750 s of the test, a spike in energy consumption can be observed precisely at the beginning of the driving phase on the highway. Based on the cumulative amount of energy used for the entire driving cycle, significant differences due to ambient temperature can also be observed. For example, for summer conditions, the total accumulated energy use for the studied route was approximately 2700 Wh, while, for winter conditions, it was close to 4500 Wh. The potential benefits of analyzing such energy maps for EVs are that they can be used for the better planning of charging points, especially for highways and expressways, where the energy consumption of vehicles increases significantly. For micro-infrastructure analyses, we can also examine the detailed distribution of energy use by EVs during their passage through specific road areas, such as X-shaped intersections, T-shaped intersections, or roundabouts. This is crucial in the context of planning future investments or modifying traffic light controls in cities to minimize the energy consumption by vehicles. Regenerative braking is also possible on these vehicles to optimize traffic control in the city. Regeneration energy values in batteries are presented as negative values. The microscale for infrastructure solutions will be presented in the next subsection of this work.

Figure 8. Tested vehicle and the research route (red line) in the city of Rzeszow (Poland).

4.2. Simulation Studies and Use of the Model

In the next step, an attempt was made to use the developed model for microscale simulation analyses. Microscale simulation studies of vehicle and energy consumption prediction models for EVs are promising tools with potential significance in various fields. Firstly, these analyses can play a crucial role in planning the infrastructure for electric vehicles, enabling the precise placement of charging stations. In the field of electric vehicle engineering, these simulations can be utilized by manufacturers to optimize vehicle parameters, influencing their energy efficiency and range. In the context of urban traffic management, predictive models of energy consumption can support strategies for managing electric vehicle fleets, with the aim of minimizing emissions and operational costs. In the long term, the results of these studies have the potential to contribute to an overall improvement in energy efficiency in transportation, shaping a more sustainable approach to transport development.

Our simulation studies were conducted using Vissim 2024 software. PTV Vissim is a comprehensive traffic simulation software distinguished by its advanced microscopic traffic model [36]. Its uniqueness lies in its ability to accurately model individual vehicle behaviors, taking into account aspects such as lane changes, acceleration, and compliance with traffic signals [37,38]. This software allows for an accurate representation of complex traffic scenarios, which is crucial for planning and analyzing road infrastructure. The program is based on the Wiedemann traffic model developed by Wiedemann (versions 74 and 99) [39,40].

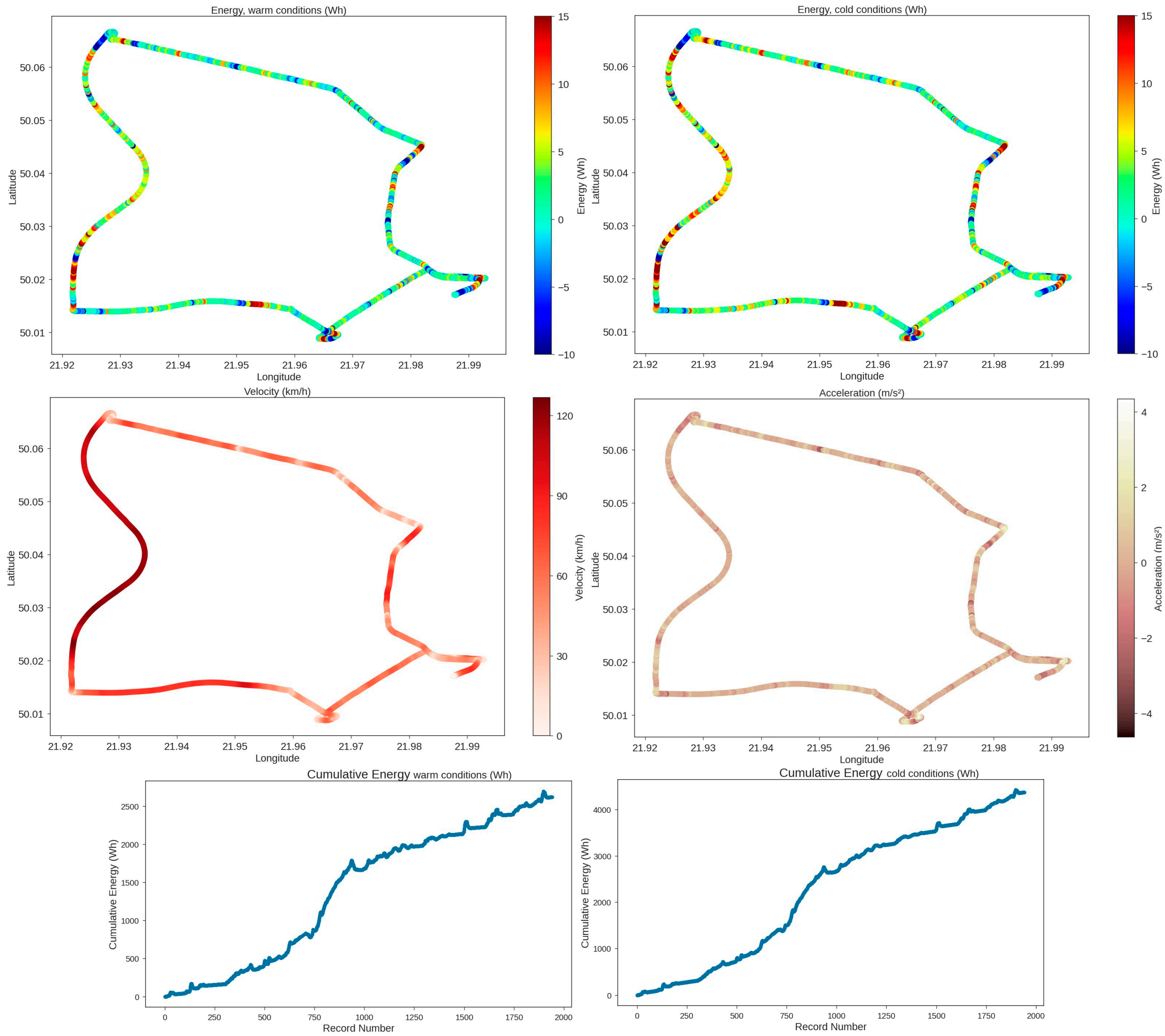

Figure 9. Maps of energy consumed by an EV for two temperature conditions, as well as its speed and acceleration for the route under study.

This study involved modeling an existing roundabout to assess the energy consumption of vehicles at its entrances, exits, and while traveling along the circulatory road. The study was based on real traffic intensity data during peak hours. There is also a planned reconstruction of this roundabout in the future; making use of these models highly recommended for developing road projects that are as sustainable as possible. Vehicle traffic on the roundabout was also calibrated for driving conditions in Rzeszów, based on the real driving cycles of Rzeszów drivers. Figure 10 presents a view of the modeled scenario.

Based on Figure 10, it can be observed that the roundabout studied was a two-lane roundabout, and that all the entrance and exit roads from it were also two-lane. In the simulation, it was assumed that all vehicles on this roundabout were electric vehicles (EV). Of course, a mixed simulation with conventional vehicles (powered by gasoline and diesel) is also possible, but then it is necessary to additionally use a model for predicting the energy consumption of vehicles powered by such fuels.

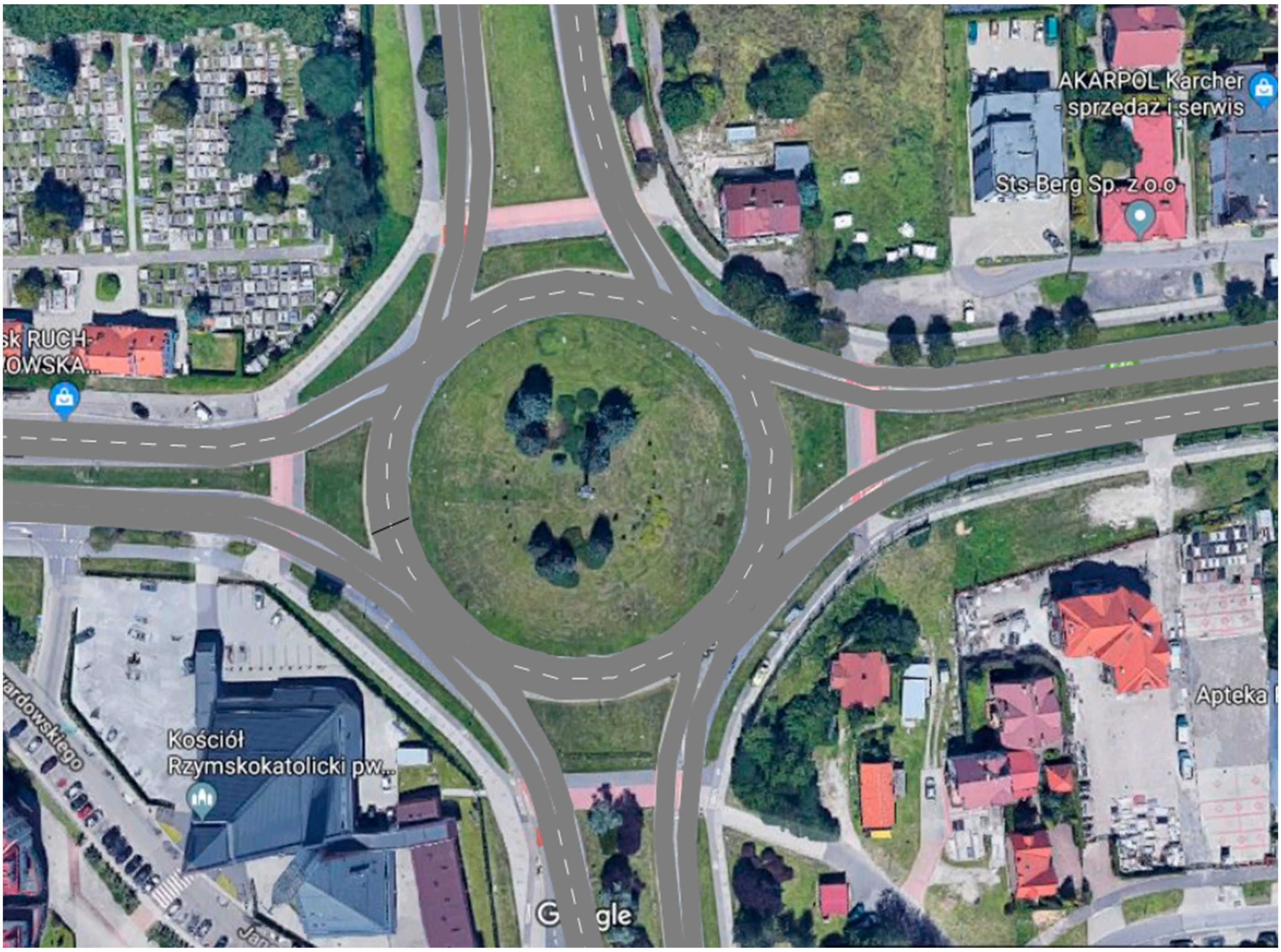

Figure 10. Investigated roundabout for EV traffic.

To utilize the model, it is necessary to obtain speed and acceleration data for all vehicles present in the model. For this purpose, there was an option of saving the data of the desired attributes in an .fzp file. The simulation data were saved with a sampling frequency of 1 Hz. An example view of the saved data is presented in Figure 11.

Figure 11 presents an exemplary set of data saved in the .fzp format, which was automatically recorded during the simulation. Saving data in this format allows for their quick adaptation to the data processing requirements of the Python language. The data are separated by semicolons, and only an adjustment of attribute names for the input data to the model is necessary. After uploading such a file in a modified .csv format to the data repository, it is possible to quickly use it to calculate an EV's energy consumption based on its speed and acceleration data. To create EV energy maps, vehicle position data, which are also recorded, are additionally utilized.

```
* Table: Vehicles In Network
*
* COORDF Coordinate front (Coordinate of front end of vehicle at the end of the time step)
* NO: No Number (Unique vehicle number)
* SIMSEC: Simulation second (Simulation time [s]) [s]
* SPEED: S Speed (Speed at the end of the time step) [km/h]
* VEHTYPE Vehicle type\Number (Unique number of the vehicle type)
* VEHTYPE Vehicle type\Name (Vehicle type label)
* LANE\LII Lane\Link\Gradient (Uphill and downhill slopes of the connector in percent. Downhill slopes have a negative value.
* ACCELER Acceleration (Acceleration during the time step) [m/s2]
* DISTTRA Distance traveled (total) [m]
*
* CoordFront; No; SimSec; Speed; VehType\No; VehType\Name; Lane\Link\Gradient; Acceleration; DistTravTot
*
$VEHICLE:COORDFRONT;NO;SIMSEC;SPEED;VEHTYPE\NO;VEHTYPE\NAME;LANE\LINK\GRADIENT;ACCELERATION;DISTTRAVTOT
176.572 -0.426 0.000;182;900.10;39.74;100;Car;0.00 %;0.00;584.57
-141.691 134.650 0.000;185;900.10;36.18;630;Car;0.00 %;0.00;492.51
189.745 148.115 0.000;188;900.10;32.04;100;Car;0.00 %;0.00;376.40
-30.838 129.157 0.000;189;900.10;43.69;630;Car;0.00 %;0.00;381.18
182.359 163.106 0.000;190;900.10;32.30;100;Car;0.00 %;0.00;389.32
-32.674 125.744 0.000;191;900.10;60.07;630;Car;0.00 %;0.00;382.77
-3.752 127.815 0.000;192;900.10;50.92;630;Car;0.00 %;-0.20;353.84
0.458 124.102 0.000;193;900.10;59.65;630;Car;0.00 %;0.00;350.95
21.611 126.558 0.000;194;900.10;58.10;630;Car;0.00 %;-0.27;329.03
150.138 150.431 0.000;195;900.10;35.53;630;Car;0.00 %;0.00;193.45
175.950 73.171 0.000;196;900.10;53.13;630;Car;0.00 %;0.48;60.17
```

Figure 11. Example view of data recorded from simulations in Vissim 2024 software.

The results of the conducted simulations and maps of the EVs' energy consumption are shown in Figure 12.

Figure 12 presents a portion of the results obtained from the EV traffic on the roundabout. Based on this, we can compare the model's utilization of summer and winter conditions. For winter conditions, especially for roundabout exits, a significant energy consumption by electric vehicles can be observed. For summer conditions, this consumption is lower and the length of time of a higher consumption is shorter. Importantly, the energy recovery by electric vehicles during braking is also significant in this context. The example presented demonstrates the high-density conditions and general congestion in this area. The roundabout itself is located at the intersection of main traffic routes and the national road, with numerous shops, hospitals, and shopping centers in the vicinity. The model obtained shows significant potential in the context of microanalyses because the results obtained can serve as potential information sets for the planned reconstruction of this intersection. In addition to the emission maps, cumulative energy charts for both conditions analyzed can be observed. The total energy consumed by all vehicles that appeared in the model of winter conditions is over four times higher than that of the summer conditions. These observations of the increase in electric vehicle (EV) energy consumption on the roundabout in winter conditions compared to summer conditions can be justified by several factors. Firstly, low ambient temperatures in winter negatively affect the efficiency of electric vehicle batteries, leading to increased energy consumption. In addition, the need to heat the vehicle's interior in the colder months contributes to a higher energy consumption, causing an additional load on the battery. Winter tires also increase the vehicle's rolling resistance. As a result, electric vehicles experience a reduced range in winter conditions, requiring more energy consumption to cover the same distance compared to the summer period. Consequently, studies on roundabouts show that their energy consumption in winter conditions can be more than four times higher than it is in summer conditions, which poses a significant challenge in the context of the efficient management of electric vehicle energy resources.

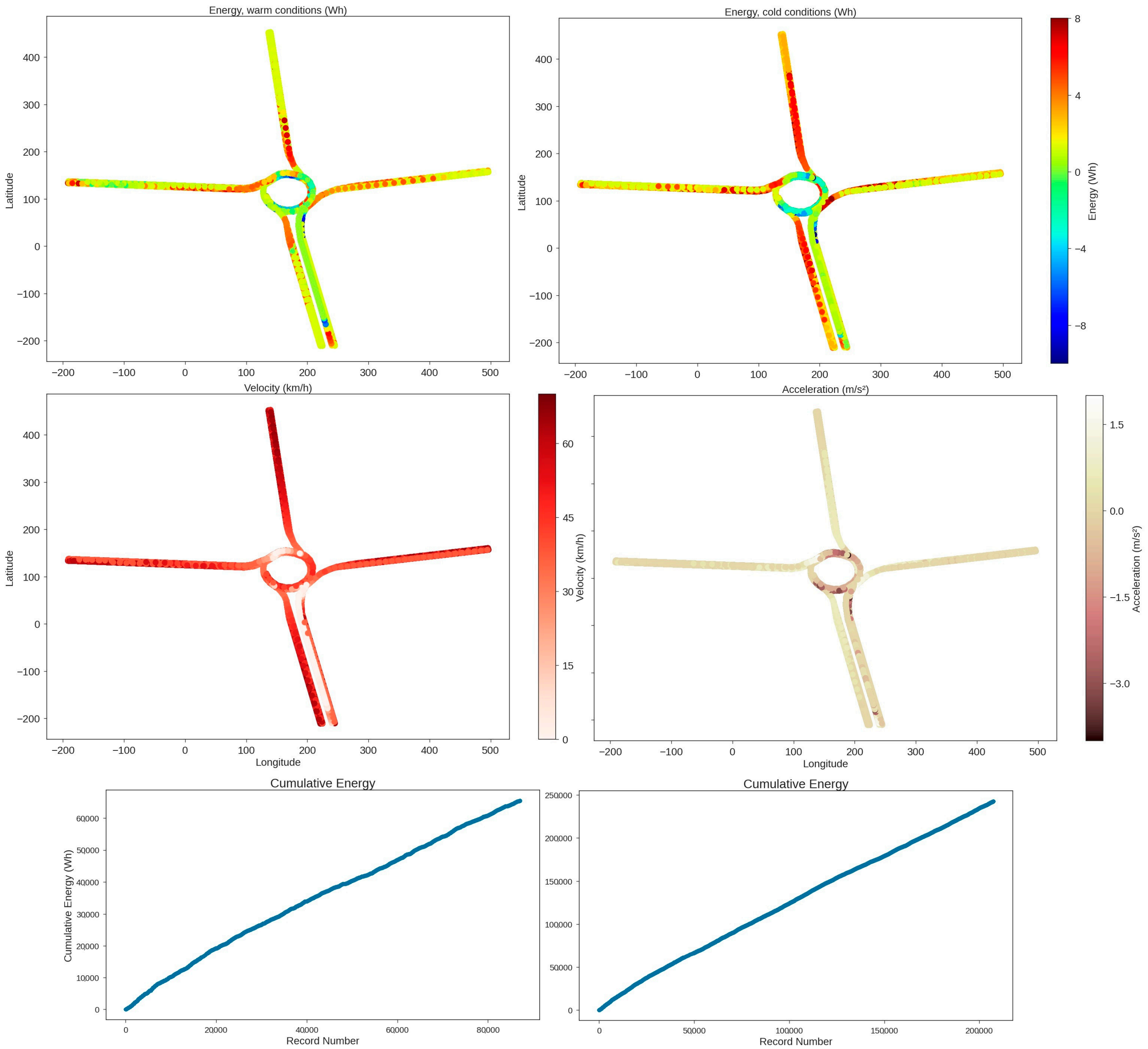

Figure 12. Example EV energy maps of the studied traffic circle in the Vissim program, along with cumulative energy graphs for all vehicles that appeared in the simulation.

5. Discussion

Models of EVs' energy consumption can be useful on various fronts:

- For urban transport decision makers when making decisions about the location of charging stations, especially on highways.
- For analyzing and reporting the energy efficiency of infrastructure objects for transport planning, which can be valuable in the design phase.
- This model is scalable to other EVs.
- The utilization of this model is versatile and its input data can come from various sources.

- It is possible to determine the average energy consumption indicators of different road objects and classes of roads, which can result in the development of universal energy consumption indicators for the evaluation of future projects.

In the above points, selected possible scenarios for utilizing the developed electric vehicle energy models have been described. An important aspect in the context of preparing such computational models is also the consideration of regenerative braking, which allows for energy recovery. In this case, the electric motor acts as an energy generator and transfers the generated energy to the vehicle's battery system. Some studies [41] suggest that electric vehicles (EVs) are more efficient when driving in stop-and-go conditions on urban roads. In particular, differences in this regard are noticeable during free-flowing traffic on highways and expressways, where energy recovery does not occur at all. This situation contrasts with that of vehicles with internal combustion engines, where the excess energy produced during braking, along with heat loss, leads to a significant decrease in their fuel efficiency [42]. Road studies have shown that electric vehicles consume less energy when driving in urban areas because energy recovery is possible under these conditions [43]. In the context of this, as well as our developed energy models, which also allow for the reflection of regenerative braking phenomena, these propositions can be confirmed. This is an extremely useful feature of these models, adding value for stakeholders who can utilize such models to design road networks and better plan infrastructure, such as fast charging points, which are desirable on roads. In winter conditions, with cabin heating and negative air temperatures, electric vehicles consume a considerable amount of energy during travel, reducing their range, which can be decreased by up to 40% compared to in higher summer temperatures.

The creation of new energy models for electric vehicles is also significant in the context of the increasing number of new models of these vehicles. In addition to the leading global automotive manufacturers, new EV manufacturers, many of them from China [44], are entering into the competition for the consumer market. Battery technology is also undergoing continuous modifications and changes to its material technology. This creates a continuous need to create accurate models estimating the energy consumption of these vehicles. Although there is already a library of works dedicated to this issue, few of them address the microscale while remaining simple, fast, and accurate, and enabling the creation of emission maps.

One of the works that focuses on microscale modeling is [45], where the authors created models for EVs with various energy systems related to their battery technology. That work presents models for EV parameters such as voltage, SOC, and current. However, as seen, it covers a different range of forecasted parameters than ours. However, such created models have limited usability. Another work in this area is [46], where the authors describe the issues related to the creation of models of the energy of EV batteries. They emphasize that most works are conducted on battery models and simulated results. They point out the limitations of these models and propose the creation of a new dynamic battery model that also considers temperature changes. The simulations in that work were performed using Matlab/Simulink software.

Another work that employs similar methods for developing models is [47]. In this work, the authors used the XGBoost method to create a model for predicting the charging demand for PEVs (Plug-in Electric Vehicles). Their work is practically significant as it predicts the demand for session charging at different times of the day, which can improve the vehicle charging network. However, the model obtained by the authors shows only a prediction capability with an R^2 coefficient. A thematically related work is [48], where the authors created an electric vehicle performance model characterized by greater detail. Their model was calibrated on experimental data. The authors point out, based on their results, that the average speed of the vehicle has the greatest impact on its energy consumption. They also indicate that regenerative braking recovers 2.43% of the energy used in congested traffic conditions on city roads.

In the context of the growing importance of artificial intelligence methods, the direction of model development is indicated in the work [49], where the authors demonstrate examples of the use of Python libraries to create future predictive models for electric vehicles.

As the importance and quantity of EVs increase, the importance of vehicle traffic simulations of them also grows [50]. Many works concern the combination of vehicle energy models and traffic simulations, especially at the microscale [51,52]. This is a crucial issue as it allows for the better planning of road space, the layout of these roads, and allows better future projects. It also allows for better planning of vehicle charging points in urban and suburban areas.

This paper presents a sample pilot energy model for EVs, from which energy consumption results and energy maps can be quickly obtained. Of course, the methodology presented has certain limitations. In the future, it is worth expanding this model with additional EV energy indicators, such as Wh/km or the battery's state of charge (SOC), for sample vehicles traveling in different parts of cities. It is also necessary to expand the input data for vehicles to include other models. In this way, it will become necessary to differentiate future EV vehicle models into additional weight, segment, and battery capacity categories. In its current form, the model can be freely used for road and simulation data and for generated vehicle speed and acceleration data.

In terms of its particular use by decision makers in urban road management, assistance can be provided in planning future road infrastructure, especially in countries that are just beginning to electrify mobility, such as Poland. By generating results for a given urban network, suburban area, or residential neighborhood and for known initial state of charge (SOC) level of vehicles, it is possible to estimate where the greatest need for vehicle charging is. Such energy consumption results can be generated using test drives or by simulating specific traffic conditions in simulation software [53,54]. These issues will be the subject of the further development of this work.

6. Conclusions

Using artificial intelligence techniques to model electric vehicle energy enables the creation of precise predictive models that include both energy consumption and its recuperation during regenerative braking. The application of such models holds significant potential, notably due to the model developed in this study featuring a minimal input dataset and flexibility in the source of its data.

The key points of this study include:

- For data based on summer temperatures, the model validation indicators for the test data show an MSE of 1.5 and an R^2 of 0.87.
- For data based on winter temperatures, the model validation indicators for test data indicate an MSE of 2.8 and an R^2 of 0.89.
- The energy consumption data for a single driving cycle under winter conditions are 40% higher than under summer conditions.
- In the simulated data, for a large number of vehicles passing through a studied microscale object, the differences in the total energy consumption of a 100% electric vehicle fleet reach up to 400% for winter conditions compared to summer conditions.

In light of the observed differences in energy consumption based on real-world and simulated driving data, it is essential to emphasize the importance of developing these models for various environmental conditions. The future direction of this research is undoubtedly to expand the database to include additional road driving cycle scenarios, extend the study to other regions, and examine a greater variety of vehicles.

The future research directions also serve as the limitations of this pilot model, as they mainly concern our uncertainties regarding how these constrained models will perform with different driving styles and on diverse terrains. Additionally, among the model's limitations, one must also consider the possibility of extreme conditions occurring, such as very low ambient temperatures.

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