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# Application of a decision classifier tree to evaluate energy consumption of an electric vehicle under real traffic conditions

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## ABSTRACT

The authors of the study undertook work on the development of a decision tree-based classifier for the evaluation of energy consumption by a vehicle traveling in real traffic conditions during normal daily operation over a period of one full year. Parameters affecting the speed profile in the form of power pedal position, averaged ambient temperature and averaged vehicle speed were used as classification parameters. The energy consumption of an electric vehicle while moving in traffic depends on many factors. These factors include: the driver's driving style, as well as the prevailing weather conditions and terrain. An element of the driver's direct influence on the shape of the speed profile is the set position of the power pedal. The value of the power pedal position depends on the instantaneous load on the vehicle resulting from the terrain and the driver's adopted speed value. As a result, a power consumption rate can be obtained for the vehicle's moving conditions, for which the ambient temperature also has an influence

**Keywords:** electric vehicle energy consumption, decision tree classifier, real traffic conditions, ambient temperature, vehicle speed, driving style impact, energy efficiency evaluation, long-term data analysis.

## INTRODUCTION

In the 21st century, societal development is inextricably linked to its mobility, leading to an increase in the number of vehicles on the roads. This is especially significant in large metropolitan areas, where air pollution caused by internal combustion engine vehicles is becoming increasingly problematic. In response to these challenges, automotive development is focusing on researching and exploring new design solutions for vehicle powertrains. One such solution is the electrification of transportation, which involves replacing combustion engines with electric powertrains. The use of electric vehicles (EVs) is considered a potential strategy to reduce emissions in the transportation sector. However, to fully understand their performance and characteristics, it is necessary to examine the factors affecting energy consumption under real driving conditions. Additionally, research is being conducted to assess the environmental impact of electric vehicles, providing information on energy consumption coefficients compared to conventional vehicles. For instance, studies [1] have shown that energy consumption by electric vehicles is less sensitive to speed dynamics in urban areas compared to conventional vehicles. The authors present results aimed at determining the differences between an electric-powered passenger car and a combustion-powered car in terms of energy consumption in various road scenarios. The findings confirm that energy consumption by electric vehicles is less affected by speed dynamics in urban areas than in the case of conventional vehicles. While the relative advantage in the baseline scenario is 68 percent, it increases to 77 percent for urban driving. The study highlights the lack of significant differences in the relative fuel consumption of BEVs during peak hours or during aggressive or calm driving.

Energy consumption in electric vehicles is a topic of numerous publications, which examine various models for determining energy consumption, enabling the prediction of energy use depending on multiple factors. In article [2], an analytical model is presented, using information on engine and powertrain efficiency. Another article [3] includes the results of literature reviews on factors influencing vehicle energy consumption. This article gathers information on how temperature, traffic conditions, or electric vehicle properties translate into energy consumption. The research results presented in various publications were compared, and the literature analysis allowed for the creation of a compilation that could serve as a compendium of knowledge on the energy consumption of electric cars. According to publication [4], in 2020, the number of newly registered electric vehicles in Europe accounted for 11% of all vehicles. Of these, 6% were BEVs (battery electric vehicles), and 5% were PHEVs (Plug-in Hybrid Electric Vehicles). Compared to 2019, this share nearly tripled (with 3.5% of electric cars registered). Given the increase in the number of electric vehicles and the still limited access to charging stations (especially fast ones) for drivers on the roads, the well-known phenomenon of range anxiety is evident in the literature. Many research studies are undertaken to identify and evaluate the factors influencing energy consumption. To maximize battery range, many factors that can reduce range must be considered.

In study [5], the authors investigated the real-world energy consumption of commercial BEVs in Thailand by conducting driving tests under actual conditions on various routes, including urban and rural roads. On-board diagnostic devices and global positioning system (GPS) equipment were used to record data. The results indicate that the average energy consumption of BEVs in this study was 148.03 Wh/km. To analyze the recorded data, the authors applied several machine learning (ML) techniques to predict energy consumption and identify key factors influencing energy usage. The authors conducted studies using the SHapley Additive ExPlanations (SHAP) algorithm, providing insights into the impact of battery current and vehicle speed on energy consumption by BEVs, particularly in the context of urban road conditions.

In article [6], an analysis was conducted on the energy consumption of electric vehicles in selected driving tests (NEDC, WLTC, and real-world driving conditions – RDC) in relation to different vehicle weights. The use of electric motors was also examined, providing data on their operating ranges, energy flow in batteries, and changes in their charge levels. The research and simulation analyses were performed using AVL Cruise software. It was found that despite similar energy consumption values in NEDC and RDC studies, there are significant differences in energy flow within the vehicle subsystems.

The issue of estimating energy consumption using neural networks is discussed in study [7]. A similar topic is also addressed in [8], where the impact of speed management on range limitation is analyzed. Publication [9] proposes a three-stage modeling approach based on real driving profiles, simulated energy consumption, and driver behavior, with the aim of determining primary energy consumption. The impact of various factors on changes in the energy efficiency of electric vehicles is also covered in other studies, which describe models for estimating energy consumption. In study [10], components were collected under real-world conditions to build a model. The authors considered variables such as gradient changes, the use of auxiliary devices, road types, and traffic conditions. This enabled the development of the Energy Consumption Rate (ECR) indicator and the integration of its components.

Energy consumption is linked to road traffic conditions. Therefore, driving cycles are created, which are speed profiles supplemented with information on braking, acceleration, cruising, and idle periods. The most popular cycles include NEDC (New European Driving Cycle), WLTC (Worldwide Harmonized Light Vehicles Test Procedure), HWFET (Highway Fuel Economy Test), and FTP (Federal Test Procedure by EPA), among others. These driving cycles were used in the studies described in [11] and [12] to test electric vehicles, particularly regarding energy consumption. For many regions, specific driving cycles have been developed that better reflect the condition of local roads. In study [13], changes in energy consumption are shown when varying speeds on highways in Perth, Australia. Article

[14] presents an analysis of the energy consumption of an electric passenger vehicle in the context of introducing numerous speed limits in cities or built-up areas. The study focuses on the energy efficiency of electric passenger cars traveling at a constant speed under real traffic conditions. The authors analyzed the energy consumption of a designated fleet of cars driving one after another (in a so-called traffic jam), maintaining a safe distance. This allowed for calculating the environmental energy demand caused by a fleet of vehicles moving along a given road section, indicating that reducing vehicle speed increases the energy consumption of the vehicles.

Weather conditions are among the factors that can significantly impact vehicle energy consumption. As reported in [3], negative temperatures can reduce the range by up to 37%, while at 40 °C, it is possible to extend the range by approximately 2%. Additionally, weather conditions influence other factors, such as the use of auxiliary systems, safety features, and driving comfort. Studies have shown that heating the vehicle is more energy-intensive than cooling its interior. Sudden acceleration and frequent speed changes have a negative impact, leading to faster battery discharge. As demonstrated in the review of the literature on electric vehicle studies, the issue of energy consumption in relation to environmental conditions and driving style is a topic that is actively analyzed and developed. This has led to the continuous development and creation of new algorithms to determine the range of vehicles under current traffic conditions.

The main goal of the authors of this article is to develop a new classifier aimed at assessing the impact of selected factors influencing the driver and determining energy consumption for electric vehicles in real-world road conditions. The objective is to define the significance level of the proposed new driver assessment method, which prioritizes minimal energy consumption per distance while ensuring the highest possible average driving speed over a given road segment.

To achieve this, energy consumption per distance and average driving speed were monitored for each individual drive of an electric vehicle under various weather conditions, traffic intensities, and driving styles. Input data were treated as normalized and a methodology based on multivalued decision trees, supplemented with inductive trees, was applied to create an efficient decision classifier capable of evaluating individual trips.

The presented solution represents a preliminary analysis in the process of developing a decision-making algorithm and holds significant importance in the context of estimating the range of electric vehicles. Understanding this mechanism can help address and mitigate the widespread phenomenon of range anxiety associated with the perceived insufficient range of electric vehicles.

## RESEARCH METHODOLOGY

In this work, data analysis methods combining multi- valued decision trees (MVDT) with inductive classifiers such as ID3, C4.5, and kNN were applied. The aim of this approach was to assess the energy consumption of electric vehicles under real road traffic conditions, taking into account various factors that affect energy efficiency.

### Multi- valued logic tree

Multi- valued logical decision trees are a complex classification tool that allows for the analysis of data with a large number of variables and multivalued attributes. The tree-building process is based on maximizing information gain, which enables the hierarchical organization of variables according to their importance for classification.

The method of multi-valued logic trees results from the development of logical decision trees and Boolean algebra [15]. Based on Boolean algebra, two important branches of mathematics like multiplicity theory and classical logic were defined. In this algebra, basic symbols, axioms and the set of theorems derived from them are defined. Figure 1 shows a logic tree that encodes a fixed Boolean function of three variables.

In the Quine-McCluskey algorithm, by simplifying the Boolean functions written in canonical alternative normal form (KAPN), the truncated alternative normal form (SAPN) and finally the minimum alternative normal form (MAPN) are obtained (Figure 2).

The Quine-McCluskey algorithm makes it possible to find all prime implicants of a given logic function that is there is a shortened alternative normal form SAPN. The terms of incomplete gluing and elementary absorption have the main role in the search of prime implicants and are used for the APN of a given logic function. The following transformation is called the consensus operation [19]:

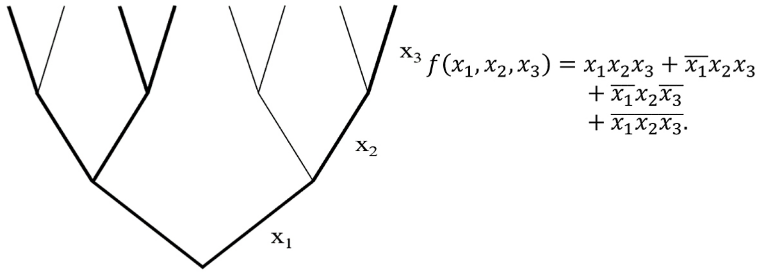


**Figure 1.** Boolean function of three variables encoded on a logic tree [16–18]

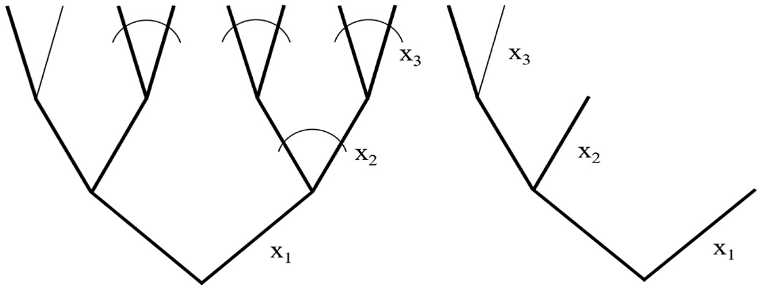


**Figure 2.** Logic tree and simplified logic tree

**Table 1.** NAPN and MAPN of a given logical function [21]

| | 020 | 200 | 101 | 021 | 201 | 210 | 111 | 022 | 121 | 202 | 211 | 212 | 221 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 02- | * | | | * | | | | * | | | | | |
| 20- | | * | | | * | | | | | * | | | |
| 1-1 | | | * | | | | * | | * | | | | |
| 21- | | | | | | * | | | | | * | * | |
| -21 | | | | * | | | | | * | | | | * |
| 2-1 | | | | | * | | | | | | * | | * |

$$Aj_o\left(x_r\right) + \ldots + Aj_{m_r-1}\left(x_r\right) = A \tag{1}$$

where: $r = 1, \ldots,$ n - indexing of logical variables from 1 to n, which means that we are dealing with n input variables (e.g. $x_1, x_2, \ldots, x_n$); $A$ – partial elementary product, representing the logical combination of variables in a given step, the literals of which possess variables belonging to the set: $\{x_1, \ldots, x_{r-1}, x_{r+1}, \ldots, x_n\}$.

The following transformation is called the operation of reduction:

$$Aj_u\left(x_r\right) + A = A \tag{2}$$

the above equation takes place, then $A$ absorbs $jA_u(x_r)$. In the case of multi-valued weighting factors, we get [20]:

$$Aj_0\left(x_r\right) + \ldots + Aj_{m-1}\left(x_r\right) = A, \quad Aj_u\left(x_r\right) + A = A \tag{3}$$

$$j_u\left(x_r\right) = \begin{cases} m-1 & , \quad u = x_r \\ 0 & , \quad u \neq x_r \end{cases} \quad 0 \leq u \leq m-1 \tag{4}$$

successive stages of the multi-valued logic function minimization: 020, 101, 200, 021, 111, 201, 210, 022, 121, 202, 211, 212, 221 can be presented in the following way (Table 1).

## Inductive classifiers

The inductive classifier builds a decision model based on observations from training data, which allows for predicting the class for new cases. The key algorithms used in this study are: ID3, C4.5, and k-Nearest Neighbors (kNN). Entropy is used to measure uncertainty in the dataset $S$. It is the primary metric applied in ID3 for selecting the best attribute for splitting [22]:

$$H(\mathrm{S}) = -\sum_{i=1}^{k} p_i \log_2 p_i \tag{5}$$

where: $H(S)$ – entropy of dataset $S$; $p_i$ – probability of event $i$ occurring in dataset $S$; $k$ – number of classes in dataset $S$.

For the purpose of the analysis, information gain compensation was applied for continuous variables, for which the information gain is calculated by dividing into intervals (6):

$$IG(A) = \max_{t \in T} \left[ H(S) - \left( \frac{|S_{A \le t}|}{|S|} \right) H(S_{A \le t}) + \right.$$
$$\left. + \frac{|S_{A>t}|}{|S|} H(S_{A>t}) \right] \quad (6)$$

where: $t$ – division point (threshold); $S_{a \le t}$ – subset of data for attribute $A$ values less than or equal to $t$; $S_{A>t}$ – subset of data for attribute A values greater than t; $|S_{A \le t}|$ and $|S_{A>t}|$ – the size of these subsets.

Additionally, algorithms C4.5 should be considered as an extension of the ID3 algorithm. The ID3 algorithm works well for discrete attributes, but for continuous variables, it requires additional processing (e.g., discretization). C4.5 is an extension of the ID3 algorithm, also proposed by J.R. Quinlan. It introduces significant improvements that increase the flexibility and accuracy of the model. The most important modification compared to ID3 is the introduction of the Gain Ratio metric [23] (Figure 3). The C4.5 algorithm eliminates the bias toward attributes with a large number of values by introducing the information value, defined as:

$$GainRatio(A) = \frac{IG(A)}{IV(A)} \quad (7)$$

where: $IG(A)$ – information gain for attribute $A$; $IV(A)$ – information value for attribute $A$.

### The k-Nearest Neighbors (kNN) classifier algorithm

Additionally, the kNN algorithm is used, where the classification of a new data point is performed by identifying the nearest neighbors (data points) in the training set, and then assigning a class based on the neighbors' voting. A fundamental element of the kNN algorithm is the distance metric, which determines how close two cases are to each other. The most commonly used metric is the Euclidean distance, defined as [24]:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (8)$$

where: $x_i$ and $y_i$ are the values of the $i$-th feature for the points $x$, $y$; $n$ is the number of features.

### Classifier-based Integrated decision system

For the purposes of this article, in order to achieve the most efficient and accurate classification and prediction of energy consumption by electric vehicles in real-world road conditions, all the described methods were combined-multivalued decision trees (MVDT), inductive classifiers (ID3, C4.5), and the kNN algorithm. The result of this combination is an integrated decision system that merges the advantages of each approach while minimizing their drawbacks. Such integration allows for more precise modeling of complex data relationships and more optimal decision-making [25]. The integrated decision system can be defined as:

$$D(x) = \alpha \cdot \phi(MVDT(x)) + \beta \cdot \psi(ID(x)) + \quad (9)$$
$$\gamma \cdot \theta(kNN(x)) + \lambda \cdot \xi(MVDT(x), ID(x), kNN(x)$$

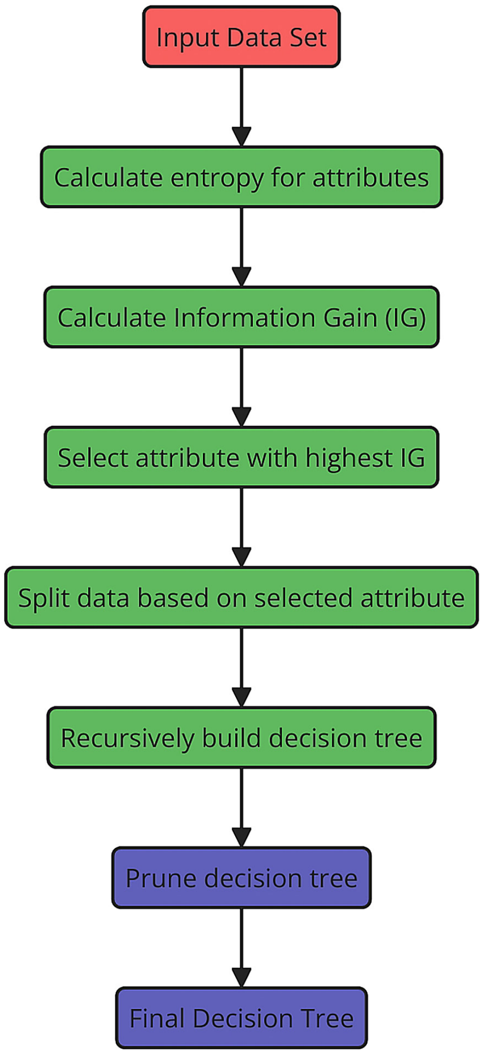


**Figure 3.** Schematic of the C4.5 decision tree algorithm

where: $\alpha$, $\beta$, $\gamma$ – weight coefficients for the respective methods (*MVDT, ID3/C4.5, kNN*); $\phi(MVDT(x))$; A function transforming the result from *MVDT*, e.g., a sigmoid function, which allows for better scaling of the result:

$$\phi(MVDT(x)) = \frac{1}{1+e^{-MVDT(x)}} \tag{10}$$

*where:* $\Psi(ID(x))$ – this is a function that transforms the classification result for the ID3/C4.5 algorithm, which can be, for example, a linear amplification or attenuation of the result depending on the entropy weight

$$\psi(I\,D(x)) = \frac{ID(X)}{\sum_{i=1}^{n} p_i \log_2 p_i} \tag{11}$$

$\theta(kNN(x))$ is a transformation function for the kNN result, which depends on the distance to the nearest neighbors [26].

$$\theta(kNN(x)) = \frac{1}{\sum_{i=1}^{k}(x, x_i)} \tag{12}$$

$\lambda \cdot \xi(MVDT(x), ID(x), kNN(x)$ is a function of interaction between the methods:

$$\xi(MVDT(x), ID(x), kNN(x)) = \\ = MVDT(x) \cdot ID(x) \cdot kNN(x) \tag{13}$$

The values of the coefficients $\alpha$, $\beta$, $\gamma$, $\lambda$ are optimized based on cross-validation results to minimize the classification error

$$minimize \sum_{i=1}^{n} L(D(x_i), y_i) \tag{14}$$

where: $L(D(x_i),y_i)$ is a loss function that measures the difference between the predicted and actual class. Figure 4 shows the diagram of the classification system [27].

## ASSESSMENT OF ENERGY CONSUMPTION BY THE ELECTRIC VEHICLE

### Energy consumption in an electric vehicle

Energy consumption in an electric vehicle while driving in traffic depends on many factors. These factors include the driver's driving style, as well as prevailing weather conditions and terrain. A direct factor influenced by the driver that shapes the speed profile is the set position of the power pedal. The value of the power pedal position depends on the vehicle's current load, which is determined by the terrain and the speed chosen by the driver. As a result, an energy consumption indicator for vehicle operating conditions can be obtained, where ambient temperature also plays a role. Therefore, the study was conducted only under real vehicle operating conditions, recording data during daily trips on various road segments. Traction parameters were collected regularly, allowing for the consideration of varying traffic and environmental conditions, such as external temperature. Traction and energy parameters were monitored (Figure 5).

The platform enables simultaneous measurement of parameters from the onboard diagnostic system (OBD) and the CAN Bus data transmission network. Recorded traction parameters included distance, travel time, consumption, speed, and ambient temperature**.**

### Research object

The ZOE electric vehicle was used to study energy consumption. The parameters of the vehicle equipped with an electric motor are presented in Table 2. The research was conducted under normal operating conditions of the vehicle, recording selected parameters for the covered sections. A section was defined as the distance the vehicle travelled during the driver's journey (e.g., from home to work, from work to home). The regularity of parameter registration corresponds to the vehicle's daily operation, providing a cross-sectional indicator of varying traffic and environmental conditions (including ambient temperature).

A measurement platform was developed to monitor traction and energy parameters, allowing data to be recorded simultaneously from multiple sources. During the study, the following data were recorded: instantaneous and average energy consumption (kWh/100 km), instantaneous and average speed, instantaneous and total energy consumption [kWh], ambient temperature [°C], battery temperature [°C], capacity parameters [%], driver rating (scored from 0 to 100), and others. Figure 6 shows sample measurements from the computer program.

The data were collected over a period of specific duration (e.g., 6 months) under real-world

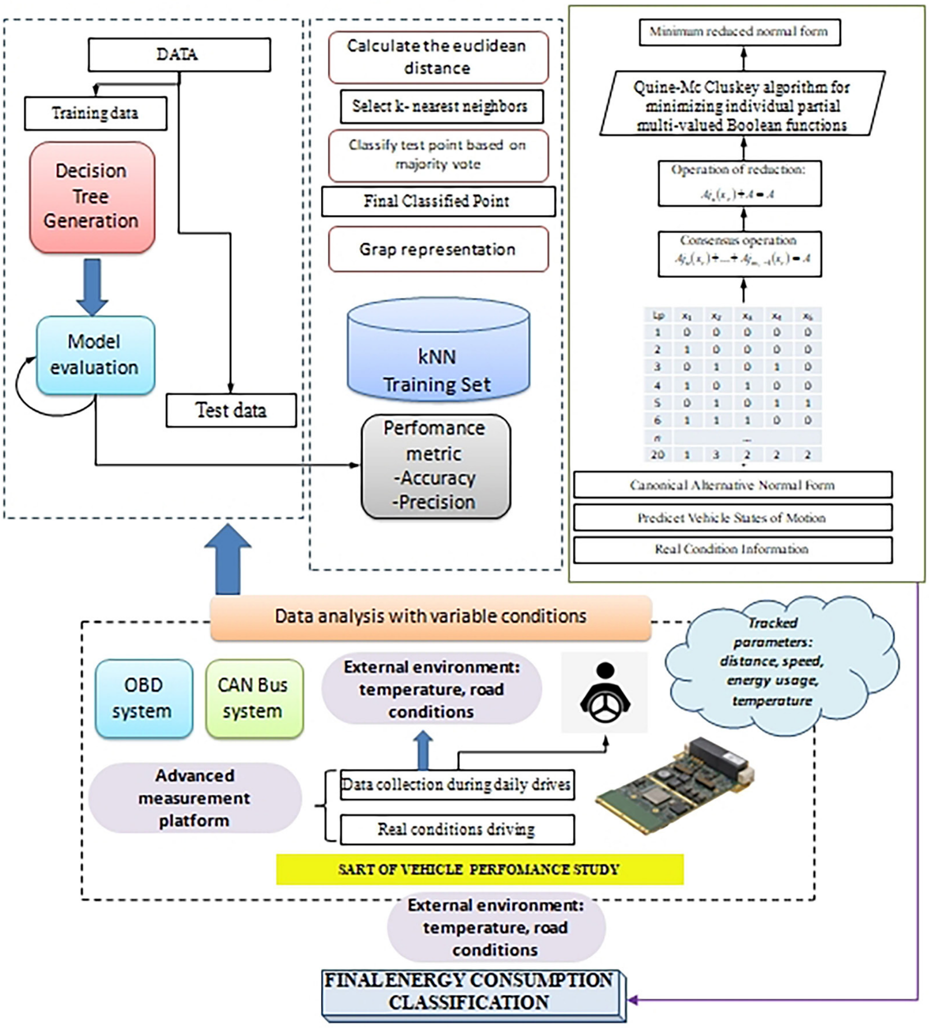


**Figure 4.** Decision diagram of the classifier integrated decision-making system

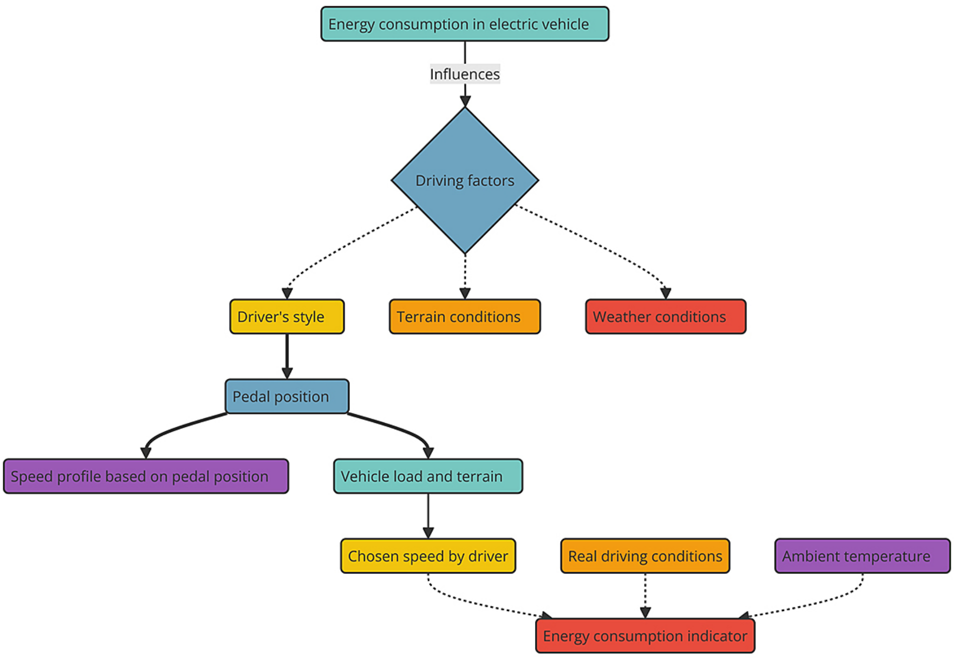


**Figure 5.** Relationships affecting energy consumption in an electric vehicle

**Table 2.**Tested vehicle parameters

| Manfacturer | Renault | Category | Parameter | Value |
|---|---|---|---|---|
| Type | ZOE | Technical data | Vehicle weight<br>battery capacity<br>engine power<br>engine type<br>range | 1500 kg<br>52 kWh<br>100 kW<br>Elektromotor<br>320 km |
| Electric engine's output | 68kW | | | |
| Electric engine's max. torque | 220 Nm | | | |
| Engine assembly | Front, transverse | | | |
| Engine system type | EV | | | |
| Transmission system | 1 gear | Driving conditions | Average speed<br>temperature<br>road conditions<br>route type | 60 km/h<br>20°C<br>Dry/Wet<br>Urban/Highway |
| Battery capacity | 41,1 kWh | | | |
| Vehicle mass | 1445 kg | | | |
| Vehicle travel range | 255 km | | | |
| Vehicle energy consumption | 165 Wh/km | Energy consumption | Average energy consumption<br>battery state of charge<br>energy efficiency<br>charging time | 150 Wh/km<br>80%<br>0.15 kWh/km<br>8 hours (standard) |
|  | | Performance parameters | Acceleration<br>maximum speed<br>driving comfort<br>stability | 0-100 km/h w 8 s<br>135 km/h<br>Level 4/5<br>High |

driving conditions. This timeframe was chosen to capture variations in scenarios such as seasonal changes, weather conditions, and traffic density. Throughout the data collection period, the vehicle was operated by a single driver. This approach minimized variability caused by differing driving styles and allowed us to focus on the impact of other factors such as speed, temperature and distance.

Particular attention was given to analyzing the average values for each trip. Figure 7 shows sample data recorded in the month of August. Figure 8 shows the relationship between speed and energy consumption. Figure 9 shows the relationship between temperature and energy consumption.

Figure 10 shows the correlation between distance and energy consumption. In the first stage, the multivalued decision trees method will be applied, and in the next stage, the results of the three models (kNN and ID3/C4.5) will be combined according to the formula of the integrated decision system.

| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Date | Total distance [km] | av. consumption 1-0 | avg. cons [kWh/100km] | avg. speed 0-1 | avg. speed [km/h] | total consum. [kWh] | saved cons. [kWh] | ECO | Total KM | Distance | temp [oC] |
| 54 | 01.11.2022 | 52 | 0,423529412 | 14,4 | 0,514916 | 39,7 | 7 | 0 | 85 | 34944 | 2474,7 | 10 |
| 55 | 01.11.2022 | 60,2 | 0,414705882 | 14,1 | 0,592737 | 45,7 | 8 | 1 | 83 | 35005 | 2535 | 14 |
| 56 | 02.11.2022 | 81,2 | 0,394117647 | 13,4 | 0,584955 | 45,1 | 10 | 1 | 84 | 35086 | 2616 | 10 |
| 57 | 03.11.2022 | 9,8 | 0,514705882 | 17,5 | 0,211414 | 16,3 | 1 | 0 | 89 | 35096 | 2626,1 | 4 |
| 58 | 03.11.2022 | 51,2 | 0,5 | 17 | 0,911803 | 70,3 | 8 | 1 | 70 | 35147 | 2677,4 | 8 |
| 59 | 04.11.2022 | 4,9 | 0,279411765 | 9,5 | 0,463035 | 35,7 | 0 | 0 | 94 | 35190 | 2720,5 | 10 |
| 60 | 05.11.2022 | 119,9 | 0,438235294 | 14,9 | 0,438392 | 33,8 | 17 | 1 | 84 | 35310 | 2840,5 | 6 |
| 61 | 05.11.2022 | 20,9 | 0,332352941 | 11,3 | 0,636835 | 49,1 | 2 | 0 | 96 | 35331 | 2861,4 | 12 |
| 62 | 06.11.2022 | 125,7 | 0,444117647 | 15,1 | 0,640726 | 49,4 | 19 | 4 | 82 | 35547 | 3076,9 | 5 |
| 63 | 08.11.2022 | 104,4 | 0,491176471 | 16,7 | 0,547341 | 42,2 | 17 | 1 | 76 | 35651 | 3181,3 | 5 |
| 64 | 08.11.2022 | 65,7 | 0,423529412 | 14,4 | 0,603113 | 46,5 | 9 | 1 | 82 | 35718 | 3248,8 | 13 |
| 65 | 09.11.2022 | 142,4 | 0,447058824 | 15,2 | 0,901427 | 69,5 | 21 | 3 | 63 | 35864 | 3394,2 | 8 |
| 66 | 09.11.2022 | 156,3 | 0,511764706 | 17,4 | 0,997406 | 76,9 | 27 | 1 | 47 | 36006,4 | 3536,6 | 12 |
| 67 | 10.11.2022 | 51,4 | 0,432352941 | 14,7 | 0,849546 | 65,5 | 7 | 0 | 74 | 36072 | 3601,9 | 10 |
| 68 | 14.11.2022 | 70,8 | 0,479411765 | 16,3 | 0,713359 | 55 | 11 | 1 | 78 | 36352 | 3882,3 | 8 |
| 69 | 17.11.2022 | 65,4 | 0,514705882 | 17,5 | 0,511025 | 39,4 | 11 | 1 | 81 | 36422,8 | 3953,1 | 2 |
| 70 | 17.11.2022 | 55,5 | 0,514705882 | 17,5 | 0,758755 | 58,5 | 9 | 1 | 71 | 36481 | 4011 | 3 |
| 71 | 17.11.2022 | 23,5 | 0,523529412 | 17,8 | 0,322957 | 24,9 | 4 | 0 | 90 | 36504 | 4034,6 | 4 |
| 72 | 18.11.2022 | 55,9 | 0,55 | 18,7 | 0,833982 | 64,3 | 10 | 1 | 63 | 36560 | 4090,5 | -3 |
| 73 | 18.11.2022 | 56,4 | 0,588235294 | 20 | 0,695201 | 53,6 | 11 | 1 | 67 | 36617 | 4147 | -2 |
| 74 | 18.11.2022 | 7,1 | 0,705882353 | 24 | 0,30869 | 23,8 | 1 | 0 | 91 | 36624 | 4154,8 | 2 |
| 75 | 18.11.2022 | 54,8 | 0,547058824 | 18,6 | 0,841764 | 64,9 | 10 | 0 | 79 | 36679 | 4209,7 | -2 |

**Figure 6.** Example measurements from the computer program

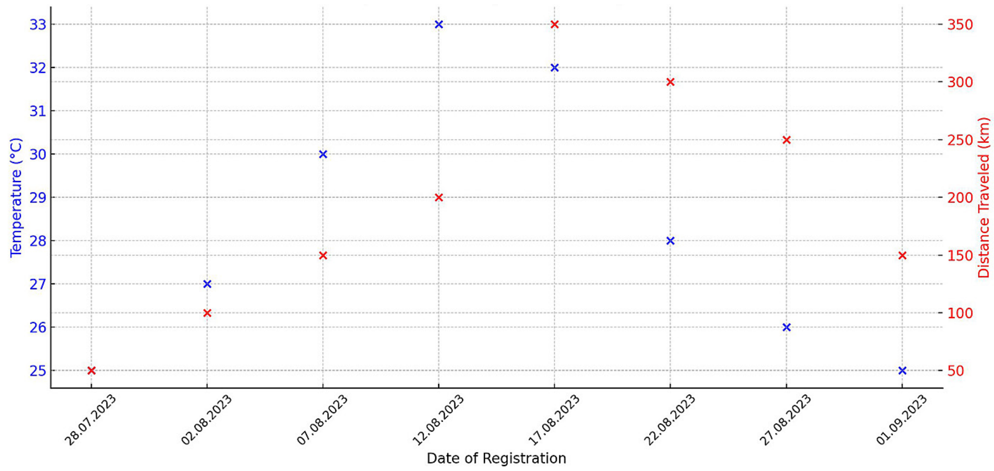


**Figure 7.** Sample data recorded in the month of August

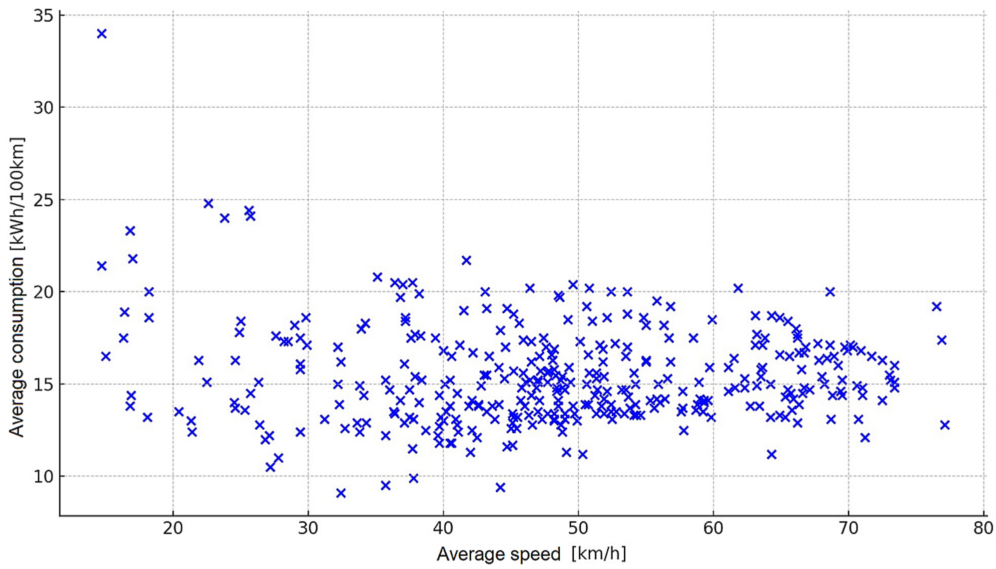


**Figure 8.** Relationship between temperature and energy consumption

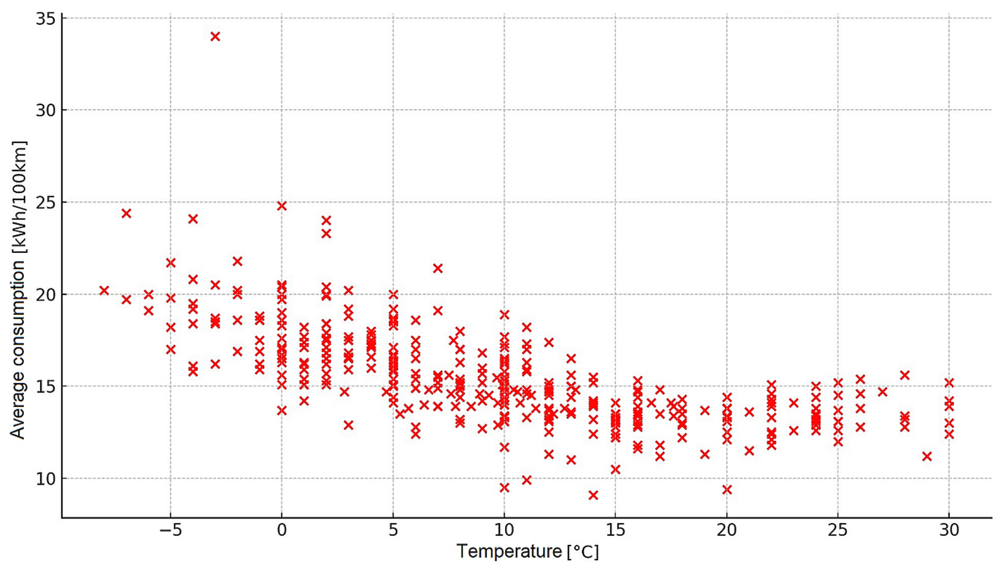


**Figure 9.** Correlation between temperature and energy consumption

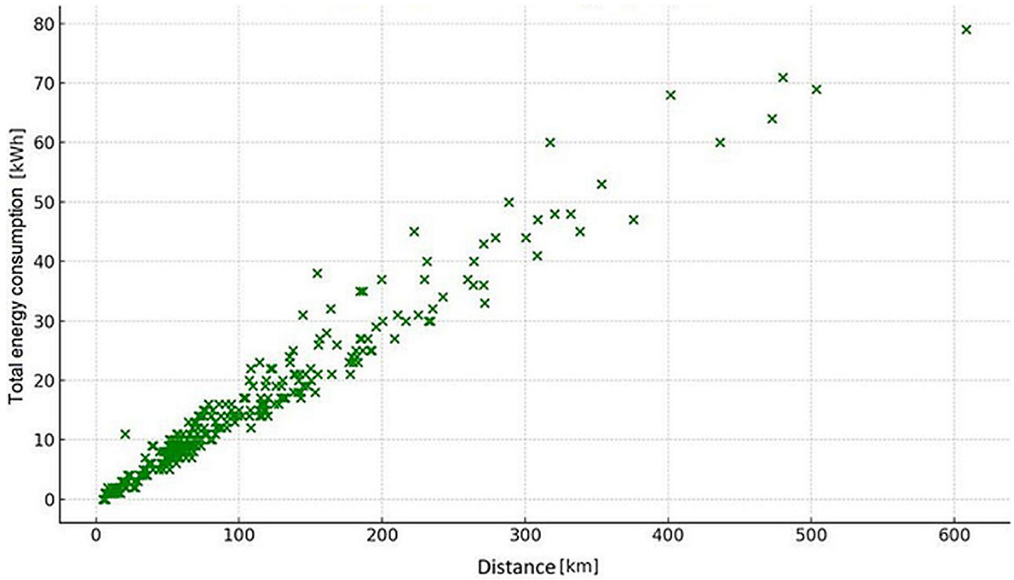


**Figure 10.** Correlation between distance and energy consumption

Figures 7–10 provide key insights into the relationships between various factors influencing energy consumption in electric vehicles under real-world conditions. Figure 7 presents the relationship between the distance traveled and ambient temperature, based on data recorded during the month of August. Each point represents a segment of a journey on a specific day, illustrating the variability in driving conditions. For example, on August 2nd, the vehicle traveled 150 km and 330 km at ambient temperatures of 23 °C and 24 °C, respectively. To improve clarity, the x-axis labels have been tilted for better readability.

Figure 8 highlights the relationship between vehicle speed and energy consumption, revealing that higher speeds are associated with a significant increase in energy consumption. This is due to greater aerodynamic resistance and engine load at higher velocities. Understanding this relationship is essential for balancing energy efficiency with maintaining a higher average speed during trips.

Figure 9 demonstrates the impact of ambient temperature on energy consumption. The data reveal that extreme temperatures, whether low or high, result in increased energy usage due to the additional demands of auxiliary systems, such as heating or air conditioning. For example, colder temperatures require more energy to maintain cabin warmth, while higher temperatures increase cooling demands. This highlights how environmental factors influence the efficiency of electric vehicles.

Finally, Figure 10 examines the relationship between distance traveled and energy consumption. The data show that shorter trips often result in higher energy consumption per kilometer, likely due to frequent acceleration phases and stop-and-go traffic conditions. In contrast, longer trips tend to exhibit more stable energy consumption rates, reflecting the benefits of steady-state driving.

## APPLICATION OF THE INTEGRATED CLASSIFIER IN THE ANALYSIS AND ASSESSMENT OF ENERGY CONSUMPTION BY AN ELECTRIC VEHICLE

This chapter discusses the application of an integrated classification system based on three models: k-NN (k-nearest neighbours), ID3/C4.5, and multivalued decision trees, for the analysis of operational data from an electric vehicle. The main goal is to determine which parameters have the greatest impact on energy consumption and which driving conditions promote minimizing energy usage.

### Application of multi-valued decision trees

To determine the optimal arrangement of tiers affecting average energy consumption, three selected encoded parameters of the electric vehicle were used: Distance (s) = 0,1,2,3, average external temperature (T) = 0,1,2,3,4, and average speed $V\_avg$ = 0,1,2. Arithmetic values were chosen for the analysis of the examined parameters, which were then encoded as logical decision variables for the purpose of decision trees in the discrete optimization of selected parameters of the electric vehicle.

In the next step, logical decision variables were encoded into comprehensive multivalued decision trees (Table 3). Numerical values were adopted for the range of average energy consumption up to 20 [kWh/100 km]. To obtain accurate results, 3! = 6 decision trees were drawn, representing all possible combinations of the selected parameter substitutions. Figure 11 shows all the generated multivalued decision trees. Based on the results of the multivalued decision trees, indication of the most important parameter affecting average energy consumption while driving is the average speed, this information was used for further calculations.

**Table 3.** Table with encoding for multivalued decision trees

| Distance [km] | Logical value | Temperature [°C] | Logical value | Average speed [km/h] | Logical value |
|---|---|---|---|---|---|
| do 50 | 0 | od -2 do 3 | 0 | 0–30 | 0 |
| od 51–100 | 1 | od 4 do 9 | 1 | 31–50 | 1 |
| od 101–150 | 2 | od 10 do 15 | 2 | above 51 | 2 |
| od 151–200 | 3 | od 16 do 21 | 3 | | |
| | | od 22 do 27 | 4 | | |

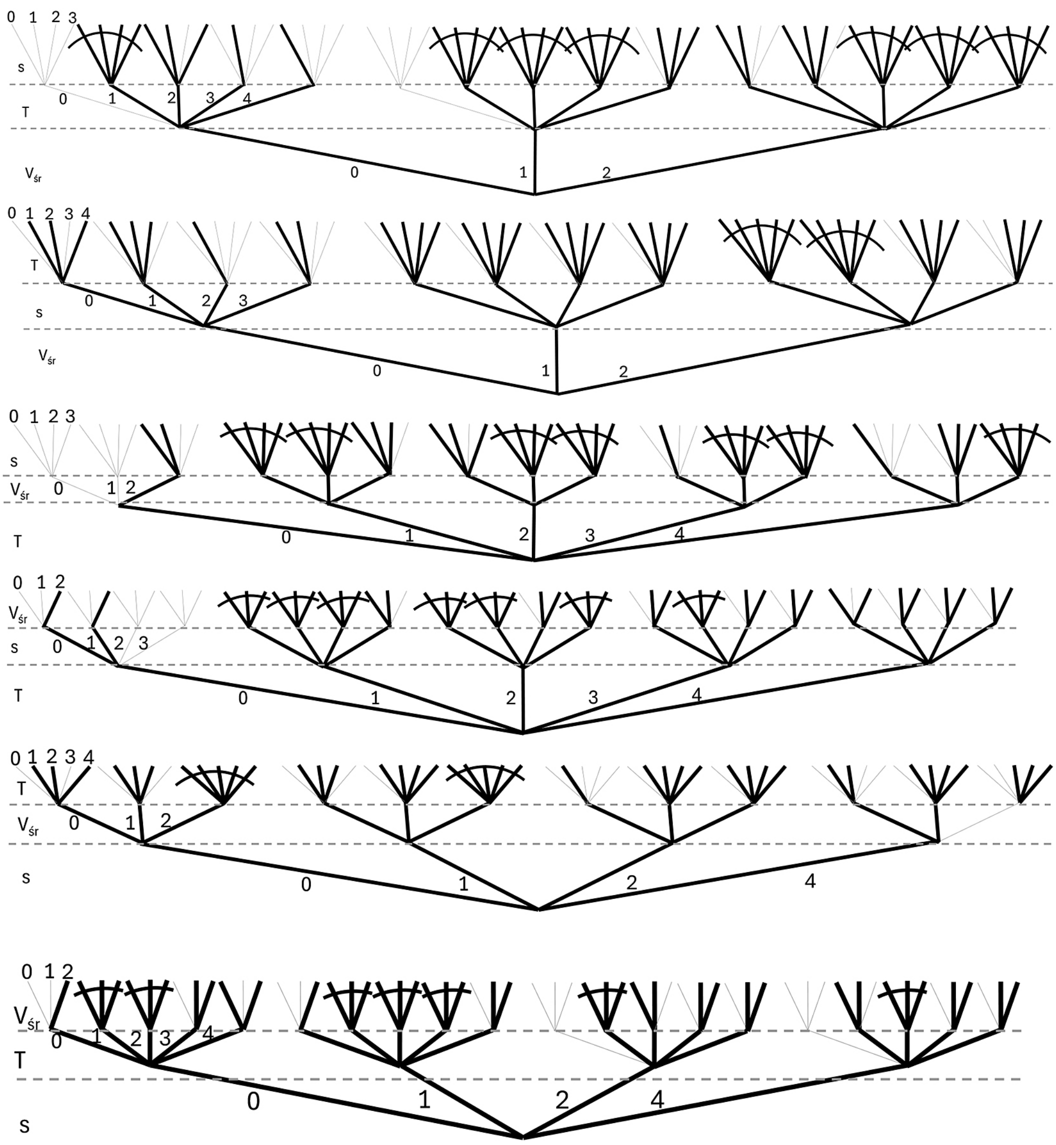


**Figure 11.** Multi- valued decision trees with tier arrangements: (a) V_avgTs, (b) V_avg sT, (c) TV_avg s, (d) TsV_avg, (e) sV_avg T, (f) sTV_avg

### Application of the k-NN algorithm

Ultimately, all the data is utilized and subjected to a normalization (standardization) process.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (15)$$

For each sample in the training set, we calculate the Euclidean distance relative to the test sample

$$d = \sqrt{(V_{test} - V_{train})^2 + (D_{test} - D_{train})^2 + (T_{test} - T_{train})^2} \quad (16)$$

where: $V_{new}$, $D_{new}$, $T_{new}$ – These are the values of speed, distance, and temperature for the new sample.

$V_{sample}$, $D_{sample}$, $T_{sample}$ – These are the values of speed, distance, and temperature for the sample from the data.

For simplicity, the calculations for several samples with data (speed, distance, temperature) where performed:

- Sample 1: V = 40 km/h, D = 70 km, T = 12 °C (consumption = 12.8 kWh/100 km)
- Sample 2: V = 55 km/h, D = 50 km, T = 8 °C (consumption = 15.0 kWh/100 km)
- Sample 3: V = 45 km/h, D = 65 km, T = 15 °C (consumption = 13.5 kWh/100 km)
- Sample X... (consumption = X kWh/X km)
- Overdone consumption $E_{kNN}$= 13.77 kWh.

### Implementation and results of the ID3/C4.5 algorithms

This subsection discusses the implementation of the *ID3* and *C4.5* algorithms within the framework of multivalued decision trees. These algorithms were applied to the dataset to classify instances based on attributes such as "Speed," "Distance," and "Temperature." The purpose of this section is to explain the algorithms' methodology and present their results in terms of classification accuracy and performance. The ID3 algorithm employs Information Gain as a criterion for splitting nodes in the decision tree. The entropy of the dataset is calculated as (5) and information Gain for an attribute A is then A (6). C4.5 extends ID3 by using the Gain Ratio criterion, defined as:

$$GainRatio(A) = \frac{IG(A)}{SplitInfo(A)} \quad (17)$$

where: *SplitInfo*(*A*) measures the entropy of the partitioning of SSS by attribute A. Additionally, C4.5 handles continuous attributes by discretizing them based on thresholds that maximize the *Gain Ratio.*

#### *Implementation details*

The dataset contained continuous attributes such as "Speed" and "Temperature," which were discretized into meaningful intervals to facilitate the construction of decision trees. For instance, "Speed" was divided into three ranges: 0–30 km/h, 31–50 km/h, and above 51 km/h. This discretization ensured that the models could effectively capture the relationships between attribute ranges and the target variable. The implementation of ID3 and C4.5 algorithms was carried out in Python, utilizing a combination of custom-developed scripts and libraries such as scikit-learn for certain auxiliary functionalities. This approach enabled efficient processing and analysis while maintaining flexibility for customization to meet the specific requirements of the study

### Example calculation

For the attribute "Speed," assume the dataset is divided as follows:

- [0−30]: 30 instances of class 1, 10 instances of class 0,
- [31−50]: 20 instances of class 1, 20 instances of class 0,
- [51+]: 10 instances of class 1, 30 instances of class 0.

The calculated entropies for each interval

$$H(S) = -p_1 log_2(p_1) - p_0 log_2(p_0) \quad (18)$$

where: $p_1$ - is the proportion of instances in class 1, and $p_0$ is the proportion in class 0.

The conditional entropy H(S|Speed) H(S|Speed)H(S|Speed) is computed as a weighted sum of the entropies for each interval:

- Interval 1 (0–30 km/h):

$$H(S[0-30] = -\frac{30}{40} log_2\left(\frac{30}{40}\right) - \frac{10}{40} log_2\left(\frac{30}{40}\right) = 0.811$$

- Interval 2 (31–50 km/h):

$$H(S[31-50] = -\frac{20}{40} log_2\left(\frac{20}{40}\right) - \frac{10}{20} log_2\left(\frac{20}{40}\right) = 1$$

- Interval 3 (51+ km/h)

$$H(S[51+] = -\frac{10}{40} log_2\left(\frac{10}{40}\right) - \frac{30}{40} log_2\left(\frac{3\ 0}{40}\right) = 0.811$$

Information gain tells us how much information we gain by selecting a given attribute for splitting in the tree. We calculate entropy for each of the subsets (low, medium, and high speed): $H_{(Slow)}$, $H_{(Smedium)}$, $H_{(Shigh)}$. Sample calculations can be presented as follows:

$$IG(Speed) = H(S) -$$

$$-\left(\frac{4}{10}\cdot 0{,}5 + \frac{3}{10}\cdot 1{,}585 + \frac{3}{10}\cdot 1{,}585\right) = 0.42 \quad (19)$$

Model performance comparison:
- ID3: accuracy = 85%, precision = 80%, recall = 83%.
- C4.5: accuracy = 88%, precision = 85%, recall = 87%.
- MVDT: accuracy = 90%, precision = 87%, recall = 89%.
- k-NN: accuracy = 86%, precision = 82%, recall = 84%.

While ID3 and C4.5 achieved slightly lower accuracy than MVDT, their interpretability and structured outputs make them particularly valuable for practical applications where decision-making transparency is essential. The results demonstrate that ID3 and C4.5 provide a good balance between accuracy and interpretability. While MVDT achieved slightly higher accuracy, the decision trees built using ID3 and C4.5 offer clear, hierarchical decision structures, making them suitable for applications where understanding the model's decisions is crucia.

### *Dataset splitting strategy*

The dataset was divided into three subsets to ensure balanced and reliable analysis:
- training set: 70% of the data was used for training the models. This subset allowed the algorithms (ID3, C4.5, and k-NN) to learn the relationships between the input attributes and the output class. The large proportion ensured that the models had sufficient data to develop robust decision-making rules,
- validation set: 15% of the data was used for validation. This subset played a key role in hyperparameter tuning, such as determining the optimal depth of decision trees or selecting the appropriate value of kkk in the k-NN model. By using a separate validation set, we minimized the risk of overfitting and ensured that the models generalized well to unseen data,
- test set: 15% of the data was allocated as an independent test set. This subset was not used during the training or validation process, ensuring an unbiased evaluation of the models' performance.

To ensure the subsets were representative of the entire dataset, stratified sampling was employed. This approach preserved the distribution of classes across all subsets, preventing bias and ensuring that each subset accurately reflected the characteristics of the original dataset.

### *Evaluation methodology*

The performance metrics reported in the manuscript were computed using the independent test set. This approach ensured that the results reflect the true predictive capabilities of the models under unseen conditions. The following metrics were calculated to evaluate the models:
- accuracy: the proportion of correctly classified instances in the test set,
- precision and recall: to assess the models' performance in distinguishing between classes effectively,
- mean absolute error (MAE) and root mean square error (RMSE): to quantify the error between the predicted and actual values, providing an objective measure of the models' ability to generalize.

The Figures 12 presents the Information Gain for three attributes: "Speed", "Temperature" and "Distance". Each bar represents the Information Gain value for the respective attribute, with the exact values displayed above the bars for clarity.

This analysis can be used to prioritize attributes in decision-making processes or feature selection for machine learning models.

To validate the effectiveness of the applied models in predicting energy consumption, the results of three different methods – multi-valued decision trees (MVDT), k-Nearest Neighbors (k-NN), and the Integrated Decision System – were compared against actual measured values. These comparisons were conducted to evaluate the predictive accuracy and robustness of each approach in modeling the energy consumption of electric vehicles under real-world driving conditions. Figure 13 presents the performance of the multi- valued decision tree method, showcasing its ability to hierarchically segment the data and make predictions based on the most significant

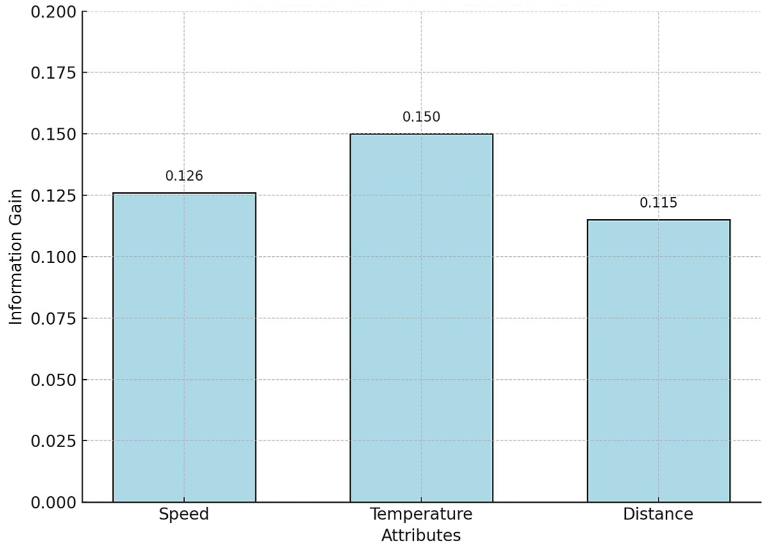


**Figure 12.** Information gain for different attributes

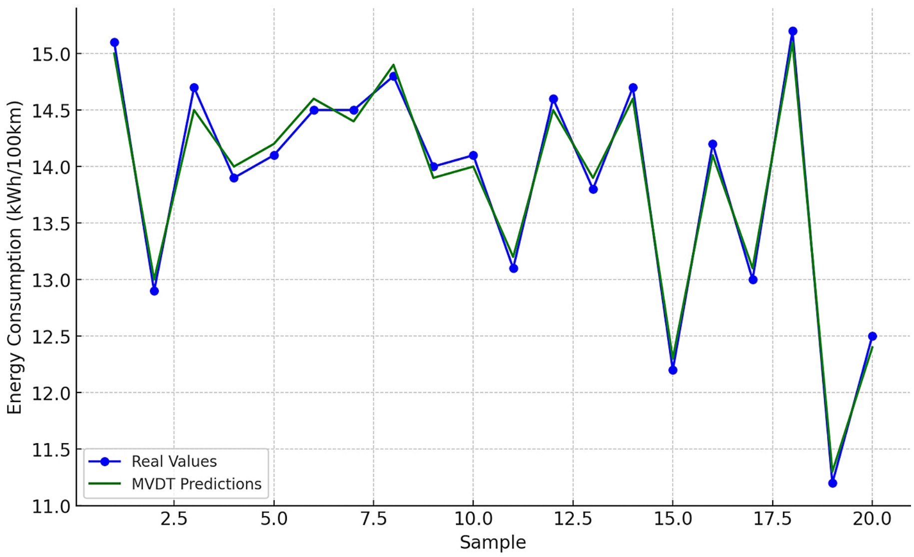


**Figure 13.** Comparison of actual values with predictions for the multivalued logic tree method

attributes. Figure 14 illustrates the k-Nearest Neighbors method, highlighting its reliance on proximity-based classification and its ability to capture nuanced relationships in the data. Figure 15 demonstrates the integrated decision dystem, which combines the strengths of all three methods (MVDT, ID3/C4.5, and k-NN) into a unified framework for enhanced prediction accuracy.

These Figure 13–15 provide a comparative visualization of actual energy consumption values and their predicted counterparts, offering insights into the reliability and efficiency of the applied algorithms.

The excellent alignment between predicted and actual values is attributed to the robustness of the models (MVDT, k-NN, and the integrated system), which effectively capture relationships in the dataset, combined with high-quality preprocessing and feature selection. Additionally, the dataset's inherent characteristics may naturally favor strong performance without indicating overfitting.

To further address potential overfitting concerns, we calculated additional metrics, including MAE and RMSE, for the independent test set. These metrics, now included in the manuscript, confirm that the models generalize well to unseen data and do not merely memorize patterns from the training set.

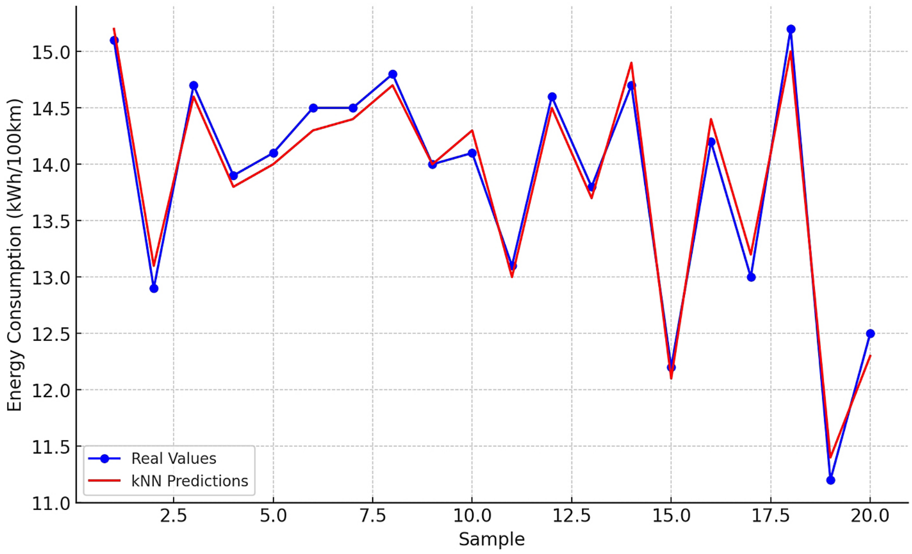


**Figure 14.** Comparison of actual values with predictions for the kNN method

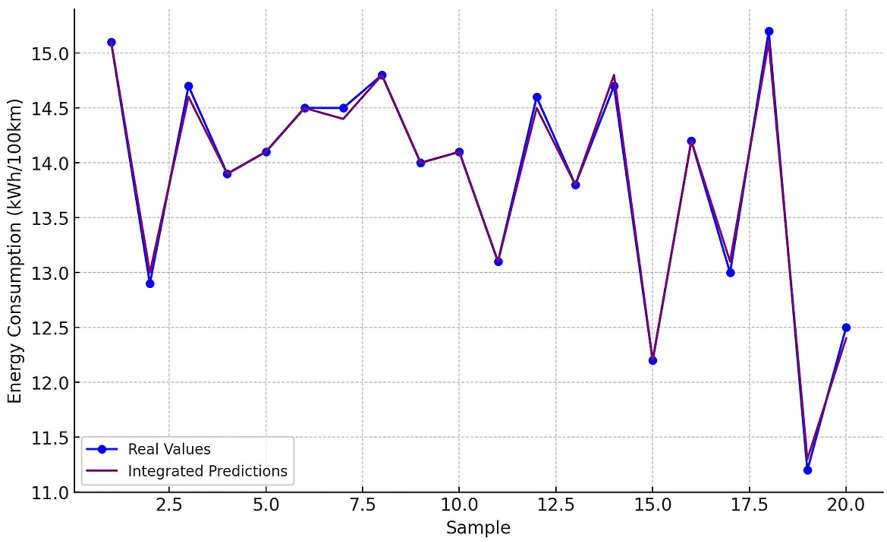


**Figure 15.** Comparison of actual values with integrated predictions

*Qualitym metrics*

We report the mean absolute error (MAE) and root mean square error (RMSE) for each model as follows:

- Mean absolute error (MAE):
  - multi-valued decision tree (MVDT): 2.35
  - k-nearest neighbors (k-NN): 2.12
  - Integrated system: 1.98
- Root mean square error (RMSE):
  - multi-valued decision tree (MVDT): 2.89
  - k-nearest neighbors (k-NN): 2.45
  - Integrated system: 2.21

These metrics were calculated based on the absolute and squared differences between the predicted and actual values for the independent test set. They provide an objective measure of the prediction error, with lower values indicating better performance. The reported metrics confirm that the integrated system achieves the best performance, with the lowest MAE and RMSE values. This indicates that the integrated system not only provides a good fit but also generalizes well to unseen data. The relatively low values for the individual models (MVDT and k-NN) further demonstrate their reliability.

In Figure 16, the comparison of MAE and RMSE values for different modelsis presented. This chart illustrates the performance of each model in terms of error metrics, highlighting the

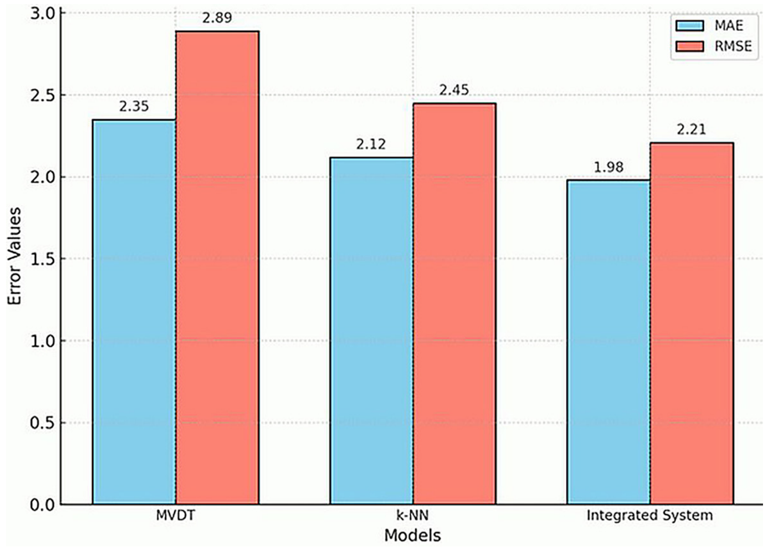


**Figure 16.** Comparison of MAE and RMSE values for different models

superior generalization capability of the integrated system, which achieves the lowest MAE and RMSE values among the three.

### Integrated decision classifier

The integrated decision classifier combines the results from three models using established weights. All three models contribute differently to the final prediction, thus we introduce the following weights:
- α = 0.4 for MVDT (multivalued decision trees), as this model is more stable in regression;
- β = 0.3 for ID3/C4.5, as the classification is more simplified;
- γ = 0.3 for k-NN, which provides accuracy through proximity but can be prone to deviations.

The final integrated formula::

$$Prediction(x) = \begin{cases} \alpha \cdot PredictionMVVDT(x) + \ldots \\ \beta \cdot PredictionID3/C4.5(x) + \ldots \\ \gamma Predictionk-NN(x) \end{cases} \quad (20)$$

For example, for the input data:
- average speed [V]: 50 km/h,
- distance [D]: 60 km,
- temperature [T]: 10 °C,
- MVDT prediction: the decision tree predicted energy consumption at 14 kWh/100 km,
- k-NN prediction: k-NN estimated energy consumption based on the nearest neighbors at 13.5 kWh/100 km,
- ID3/C4.5 prediction: ID3/C4.5 assigned this sample to the medium category (medium consumption), which corresponds to a value of 2 (on a classification scale where low = 1, medium = 2, high = 3). Prediction(x) = 5.6 + 0.6 + 4.05 = 10.25 kWh/100 km.

## CONCLUSIONS

This study analyzed several approaches to predicting energy consumption based on parameters such as speed, distance, and temperature. Three different classification and regression methods were used to obtain more accurate results:
- k-NN (k-nearest neighbors) – this algorithm predicts the result based on the similarity of new data to previously known samples. Calculations are performed by measuring the Euclidean distance between samples and selecting the nearest neighbor.
- ID3/C4.5 – the decision tree algorithm classifies data based on entropy and information gain measures. Splitting the data at each node allows classification into categories such as “low”, “medium,” and “high” energy consumption.
- MVDT (multivalue decision trees) – multivalued decision trees rely on logical data splits into different values, with speed being a key factor.

An integrated approach was taken by combining the results from three different methods: k-NN, ID3/C4.5, and MVDT. Each of these methods brings a unique approach to data analysis—k-NN is based on sample similarity, ID3/C4.5 uses decision trees, and MVDT employs multivalued logic. Combining the results of these methods provides more accurate and balanced predictions. The integration of results from three different models yielded more precise predictions than each method individually. MVDT provided more logical and intuitive results for higher speeds, while k-NN and ID3/C4.5 effectively supplemented predictions for more diverse samples. Key factors affecting energy consumption:

- speed was found to be the most important parameter. As speed increases, energy consumption rises significantly, which was evident in the results of both MVDT and k-NN,
- distance also plays a significant role, especially in the ID3/C4.5 method, where classification was largely based on distance,
- speed (V): vehicle speed is one of the most significant factors influencing energy consumption. As speed increases, energy demand rises due to higher aerodynamic resistance and the need for the engine to maintain more power.
- speed values such as 40 km/h, 50 km/h, and 60 km/h allowed for differentiating energy consumption, especially in methods like MVDT, where higher speeds caused notable increases in energy consumption (e.g., from 13 kWh/100 km to 15 kWh/100 km).

In conclusion, analyzing parameter values in the integrated system enabled more accurate energy consumption predictions in vehicles, allowing for better route planning and more efficient resource management. The next step will be the application of the integrated decision-making system, which will combine the described classification methods – k-NN, ID3/C4.5, and MVDT – into a single advanced predictive mechanism. The integrated system will enable better energy consumption predictions by leveraging the strengths of each method, taking into account their individual weights and strengths. This approach will allow the model to flexibly adapt to various scenarios, helping to make more accurate decisions and optimize resource utilization in changing conditions. This work serves as an introduction to further research, where an integrated decision system will be applied, considering a broader spectrum of data and more advanced analyses. Future work will demonstrate how the integrated system affects prediction efficiency compared to individual methods, leading to a better understanding of the importance of weights and parameters in the decision-making process.

The purpose of this study was to develop a comprehensive and efficient decision- making framework for evaluating the energy consumption of electric vehicles under real-world traffic conditions. This research addressed the need for accurate, interpretable, and practical models to support real-time decision-making and energy optimization in EV operations. Long-established methods such as multivalued decision trees, ID3/C4.5, and k-nearest neighbors were employed due to their proven effectiveness in various domains. Their combination in this study leveraged their individual strengths – multivalued decision trees provided hierarchical interpretability, ID3/C4.5 ensured robust classification, and k-NN captured nuanced relationships in complex data. The novelty of this research lay in integrating these well-known methods into a unified decision-making framework tailored to the specific challenges of energy consumption analysis in electric vehicles. Unlike previous studies, this approach considered long-term, real-world operational data, including varying environmental and traffic conditions. The research demonstrated the potential of this integrated framework to enhance energy efficiency and resource management for sustainable transportation systems.

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