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QUANTITATIVE ANALYSIS AND OPTIMIZATION OF ENERGY EFFICIENCY IN ELECTRIC MULTIPLE UNITS

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Abstract. *The increasing urgency for sustainable transportation solutions necessitates a thorough examination of energy efficiency within railway systems. This study investigates the energy performance of Siemens Ventus (i.e., Siemens Desiro ML type) electric multiple units on Austria's Raaberbahn network, focusing on route-specific energy consumption and the optimization of regenerative braking. Utilizing data collected from January to May 2023, the research employs a robust methodology that integrates statistical analysis, curve-fitting, and geospatial modeling to assess energy trends along routes connecting Vienna, Bratislava, and Deutschkreutz. The findings reveal that terrain, operational practices, and external environmental factors significantly contribute to energy inefficiencies. Specifically, hotspots of energy overconsumption were identified, leading to the development of tailored optimization models for each route. The analysis also produced heatmaps that illustrate critical spatial and temporal patterns, which are essential for implementing targeted interventions aimed at enhancing energy efficiency.*

Key words: *Railway, Electric multiple unit, Siemens Ventus, Siemens Desiro ML, Energy consumption, Regenerative braking energy, Acceleration-deceleration, Energy optimization*

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1. INTRODUCTION

In the nineteenth century, steam locomotives played an essential role in connecting societies and boosting economic growth by bridging distances and fostering economic interconnectivity like never before [1]. The steam era laid the groundwork for future transportation advancements. It should be mentioned that aviation, space exploration, and maritime navigation, which also represent significant advances in human mobility, have increased global transportation efficiency, safety, and accessibility. The most considerable improvement and development started primarily following the Industrial Revolution. These advancements have collectively changed how people navigate their world, making it more connected and accessible [2]. Furthermore, fixed-rail systems [3-6] have played an essential role in this transportation evolution due to their inherent efficiency and dependability. They improve capacity, reliability, and energy efficiency, thereby strengthening the infrastructure of modern transportation and logistics networks [7-9].

The European Union's emphasis on multimodal transportation systems, particularly railways, demonstrates a strategic approach to improving supply chain management. This focus reflects an appreciation for efficient, dependable transportation's critical role in the economy [1]. Railway transportation, known for its punctuality and environmental friendliness, is highly valued in mass rapid transit systems. It emphasizes the transition to more sustainable modes of transportation, which is critical in today's environmentally conscious society [7]. Furthermore, a customer satisfaction analysis in the context of railway transport reveals how passenger satisfaction significantly impacts the relevance of railway transport. This insight emphasizes the importance of understanding and meeting passenger needs to keep railway services competitive and appealing [10]. Research into green freight railway operations highlights the importance of traffic management and transportation engineering. This emphasis is critical in reducing the environmental impact of freight transportation while demonstrating a commitment to sustainable logistics practices [11]. Furthermore, the life cycle assessment of Belgian railway freight highlights the significant environmental considerations, particularly electricity use, involved in railway operations, emphasizing the importance of environmentally friendly practices in the industry [12].

The transportation of hazardous materials by railway raises several complex safety, human, and environmental concerns. Because of its complexity, it is an essential area of research for policymakers and stakeholders who must navigate these challenges to ensure safe and responsible transportation [13]. Furthermore, railway transportation addresses the dual challenges of traffic congestion and environmental degradation. Railways play an essential role in achieving a more sustainable future by promoting sustainable development in densely populated urban areas as well as long-distance passenger and freight transport [14]. Railways, with a lower carbon footprint in the supply chain decarbonization process than trucks, emerge as a more environmentally friendly option, emphasizing the significance of rail transport in the larger context of environmental sustainability [15]. The impact of high-speed railway construction on the sustainability of urban agglomerations highlights the sector's commitment to reducing environmental impacts, focusing on the railways' role in shaping sustainable urban landscapes [16].

The role of transportation sustainability in Chinese higher education demonstrates the societal impact of the railway system. It emphasizes the broad implications of transportation infrastructure for social development and well-being [14]. Globally, transportation systems increasingly rely on electric traction and fixed-rail technology, indicating a shift toward more environmentally friendly and efficient modes of transportation. This shift is critical in addressing modern transportation challenges, such as increased energy efficiency and reduced environmental impact [17]. The advantages of electric traction batteries in terms of energy efficiency and performance highlight the advancements in transportation technology driving the transition to more sustainable mobility solutions [18]. Addressing the challenges of power quality and energy efficiency in railway transport electric traction systems, particularly in AC-electrified railway inter-substation zones, is critical for improving their performance and sustainability [17].

The creation of theoretical frameworks for calculating rational modes of traction electrical equipment operation is critical for comprehending and mitigating the environmental effects of electric traction systems. Such frameworks are crucial for developing more sustainable transportation solutions [19]. The competition between electric and combustion traction highlights the environmental benefits of electric vehicles, emphasizing the significance of sustainable transportation in the larger context of ecological stewardship [20] – emphasizing the relevance of mechanical engineering [21,22]. Urban electric traction drives, with their emphasis on improving energy performance, reflect ongoing efforts to reduce the environmental impact of transportation, which aligns with global sustainability goals [23].

Because of the high electrical energy losses associated with traffic, DC traction railway networks are being scrutinized for increased energy efficiency and sustainability. This necessity drives traction drive control system efficiency research, mathematical models for onboard energy storage, and power quality. These research efforts are critical to the development of more environmentally friendly and efficient railway and electric traction systems [24-26]. Furthermore, strategies for reducing the environmental impact of AC traction substation electric energy quality are vital in minimizing electric traction systems' ecological footprint [27]. The study of electric motors for electric vehicles, encompassing efficiency, cost, reliability, innovation, and controllability, is crucial for comprehending the environmental impact of fixed-rail transportation and electric traction, pointing to the need for continuous innovation in this field [28]. Intermittent electrification and the analysis of the annual variation in energy consumption of commuting electric vehicles are strategic approaches to decarbonizing traction energy, reflecting the importance of sustainability in the evolution of transportation systems [28,29]. Enhancing transportation system sustainability through electrical traction transmission by influencing railway vehicle dynamics showcases the potential for reducing environmental impact through technological advancements [30].

The efficiency of electric vehicles is closely linked to the optimization of train schedules, utilizing the longitudinal dynamic electric vehicle model of Sun et al. [31] for this purpose. This optimization, including using data to identify battery health states (if there are batteries), aims to improve energy efficiency and scheduling, showcasing the potential for technological advancements to enhance transportation efficiency [32]. Driver assistance systems (DASs) impact railway punctuality and energy efficiency by providing real-time driving data to operators, enabling them to make more energy-efficient decisions. This system is a prime example of how technology can be leveraged to improve the sustainability of transportation [33-36]. The implementation of railway DAS employs distributed computer systems and network technologies to monitor, detect, and manage energy-saving modes in power supply systems, reflecting the role of innovation in achieving energy efficiency in the railway sector [37]. Tao et al. [38] introduced a new energy optimization method for traction substations that addresses time-varying parameters and environmental characteristics in mechanism modeling. A data-driven model, dynamic programming, and MIMO-SOFNN (multi-input multi-output self-organizing fuzzy neural network) are used. Experimental analysis validates the model's accuracy, and the proposed method reduces energy consumption by 34.8% compared to Chinese freight railway company operation data. Yildiz et al. [39] proposed integrated train operation optimization to reduce traction energy and increase regeneration energy. The model optimized train speed trajectory and timetable to increase braking and accelerating train group overlap.

The Istanbul M3 subway system is modeled and simulated using genetic and simulated annealing algorithms. The study found that the best train speed profile and timetable reduce traction energy consumption. Fischer et al. [40] discussed the detection of energy loss in electric railway hauling vehicles, as well as the importance of railway energy efficiency. It examines the current situation and potential improvements for more efficient energy use. Seven measurement series were conducted using scheduled Railjet trains between Hegyeshalom and Győr railway stations in Hungary. The article looks into optimizing regenerative braking energy by identifying energy-waste sources and reasons for consumption. The global energy crisis and the imperative for cleaner, "greener" energies underscore the importance of reducing electricity consumption in railways, highlighting the need for the transportation sector to adapt to changing energy landscapes [41].

All train energy consumption must be analyzed to save energy. A complex interplay of infrastructure, transportation organization, and environmental factors influences energy use in railway operations. This interplay underscores the multifaceted nature of energy use in transportation, highlighting the importance of a comprehensive approach to energy efficiency [16,42-44]. Regenerative electricity is a critical technology in the quest for energy savings, illustrating the potential for innovative solutions to enhance the sustainability of transportation systems [45-47]. Optimizing the timetable by considering the horizontal and vertical geometries of the railway tracks, as well as the planned (and/or actual) speed, represents a strategic approach to improving energy efficiency, underscoring the potential for planning and technological innovation to contribute to more sustainable transportation practices [45,48-50]. Combining these methods produces the best results, emphasizing the importance of a holistic approach to enhancing energy efficiency in the railway sector.

The main focus of this paper is the analysis of energy consumption of electric multiple units.

Based on the energy consumption optimization, four main categories were defined [40,51]: (i) condition of the permanent way and connecting infrastructure, as well as the rolling stock, (ii) recovered energy from regenerative braking, (iii) external factors (i.e., environmental factors, temperature, etc.), finally (iv) the human factor.

It plays a pivotal role in shaping energy efficiency and consumption within the railway transport sector. Extensive research has been conducted to dissect the various factors influencing driving behavior and its subsequent impact on energy efficiency. Notably, studies have delved into the significance of driver experience [52], highlighting its correlation with driving performance and energy consumption patterns. Moreover, there exists a delicate balance between driving efficiency and service quality [53]. Understanding this trade-off is essential for devising strategies that optimize energy usage without compromising operational standards. Additionally, identifying and addressing barriers to energy efficiency [54] is crucial for implementing effective measures across the rail industry. Further exploration into the intricacies of driver behavior reveals its profound implications for energy consumption. Studies focusing on heavy-haul iron ore trains [55] shed light on the substantial influence of driver actions on energy usage. Additionally, research into the physiological aspects of driving, particularly concerning monotonous tasks [56], underscores the need for strategies to mitigate fatigue and enhance driver engagement. Interventions are paramount in addressing the challenge of improving energy efficiency. Initiatives such as eco-driving training programs [57,58] offer promising avenues for instilling energy-conscious behaviors among drivers. Fischer et al. [40] determined that the train operator's driving style and habits are identified as the primary causes for the main part of the energy losses. (It is worth mentioning that Fuzzy methodology and evaluation techniques can also be applied in this field [59,60].)

The original aim of this article was to analyze the driving style of train drivers and its impact on the electricity consumption of electric traction units and EMUs (see the (iv) point from the previous list). Unfortunately, the authors were not able to do this because the received database did not contain the coding of the train drivers.

The authors decided to conduct a more detailed energy consumption analysis than they did in [40] as an innovative investigation. The main focus was to define typical consumption graphs (trends) on the analyzed routes (in this case, Vienna-Deutschkreutz, i.e., VD; and Vienna-Bratislava, i.e., VB) between January and May 2023, which would allow for the precise localization of the consumption outliers and their location. (The opposite direction routes have the abbreviations DV and BV, respectively). Only the Siemens Ventus (i.e., Siemens Desiro ML type) EMUs in service with Raaberbahn AG were included in the analysis (EMUs were, of course, exclusively used for passenger transport). Modern mathematical-statistical methods were used for the analysis.

The structure of the current paper is as follows: Section 2 deals with the applied methods, Section 3 contains the results and discussion, and Section 4 is the conclusions.

2. Applied Methods

In this article, data obtained from on-board computers of the Raaberbahn were provided in the following structure and detail for the VD and VB routes (see Fig. 1 and Table 1):

1. Duration: January-May 2023 (i.e., five monthly series in total).
2. Data series in bulk Excel files for Siemens Ventus multiple units only (for the five months, five Excel files were downloaded, containing all routes and all train numbers):
    a. 5-minute detail (sampling frequency) data with day:hour:minute accuracy,
    b. includes train number, current GPS coordinates, cumulative electricity consumed and recuperated,
    c. to the best of the authors' knowledge, Raaberbahn AG has provided the data of all trains operated during the given period,
    d. however, the data set did not include current speeds, accurate start and end times for accelerations and decelerations, nor did it include the identity of the drivers.
3. The segment numbers of stations and stops on the routes were taken from Raaberbahn and ÖBB (Austrian State Railways) reports, the GPS coordinates were determined accordingly, and the results were used for further calculations.
4. The speed values allowed on each section were taken from ÖBB, Raaberbahn AG registrations and public data on the openrailwaymap.com website.

The parameters that had to be calculated from the data (listed here; see Section 2.2 for a detailed explanation):

1. Because of the bulk structure of the data, a train (i.e., a train with a given train number) does not run on only one section, so the first step in the classification was to associate it with a route.

2. Since only GPS coordinates could identify each measurement point ("data row"), the actual distance traveled between two data points was needed. To handle this, a Python program was written. It was also necessary to determine the direction of traffic on the route.

3. The data thus sorted had to be filtered in the final analysis (Section 2.1, Section 2.2, and Section 3) because a professional decision was made to consider acceleration and regenerative braking energies only in the ±2 km environment calculated by the section numbers (GPS coordinates) of the general station and stop locations, considering the direction of travel. This meant that the focus was primarily on acceleration energy consumption, with the accumulation-accumulation of regenerative braking energy values being considered synchronously.

4. Statistical processing was performed considering the entire data set, as detailed in Section 2.2.

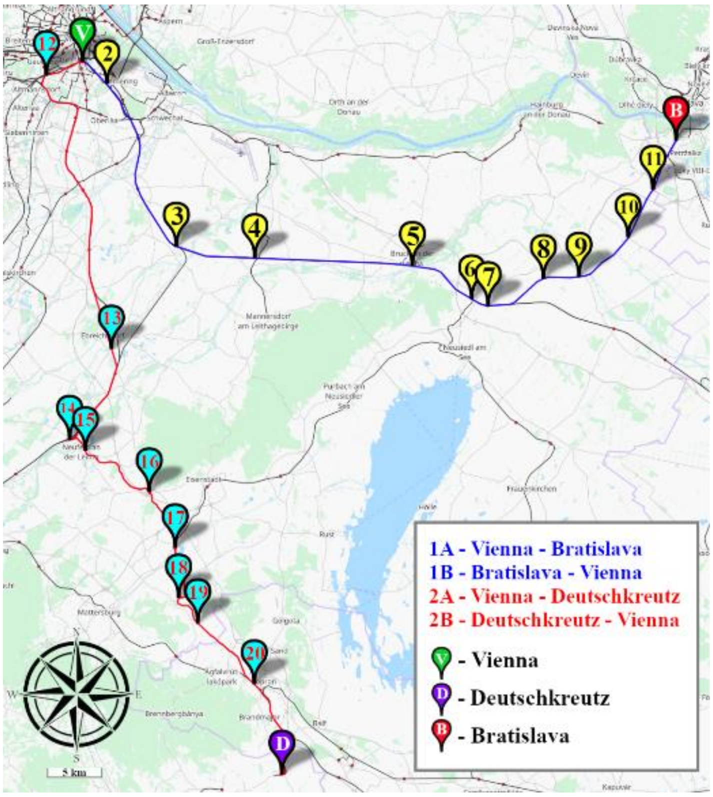

Fig. 1 Segregating of sections into shorter subsections

Table 1 Details of the considered routes (the IDs are illustrated in Fig. 1)

ID.	Railway station	Intermediate distance [m]	Cumulative distance [m]
	1A: Vienna – Bratislava (VB) 1B: Bratislava – Vienna (BV)		
V	Vienna Hauptbahnhof (Vienna)	0	0
2	Vienna Grillgasse	2858	2858
3	Gramatneusiedl	16550	19408
4	Götzendorf	7340	26748
5	Burck a.d. Leitha	14559	41307
6	Parndorf Ort	6356	47663
7	Parndorf	1585	49248
8	Neudorf	6120	55368
9	Gattendorf	3230	58598
10	Pama	5850	64448
11	Kittse	4980	69428
B	Bratislava-Petrzalka (Bratislava)	1920	71348
	2A: Vienna – Deutschkreutz (VD) 2B: Deutschkreutz – Vienna (DV)		
ID.	Railway station	Intermediate distance [m]	Cumulative distance [m]
V	Vienna Hauptbahnhof (Vienna)	0	0
12	Vienna Meidling	3637	3637
13	Ebreichsdorf	27193	30830
14	Ebenfurth	10713	41543
15	Neufeld a. d. Leitha	2000	43543
16	Müllendorf	7954	51497
17	Wulkaprodersdorf	5705	57202
18	Draßburg	5753	62955
19	Baumgarten-Schattendorf	3282	66237
20	Sopron	7787	74024
D	Deutschkreutz	9475	83499

2.1. Data Ordering

The distances were calculated using the Python GeoPy module. Previously, the Haversine formula was also applied, but the GeoPy module uses a geodesic line to determine the distance, which gives a more accurate result than the Haversine formula. However, due to the small distances involved, both are suitable for the task.

In Sections 2.1 and 2.2, the Python program was employed: (i) SciPy and (ii) GeoPy.

Preparations:

1. Create a helper database (collect the following information in a database):
   a. GPS coordinates of train stops: approximate, not exact. GPS coordinates are centered at the stops. Adding reference points for better route separation thereafter.
   b. GPS coordinates of routes: in the sandbox editor of the gpsvisualizer.com website, add reference points for the railway track. Later, calculate the cumulative distance to the reference points to obtain the length of the route and the distance to the stations from the starting point (comparison of reference points and station points.)
   c. Collection of distances between stations: based on information recorded by ÖBB and Raaberbahn.

2. Generating configuration files:
   d. To automate the database file to be created later, generate configuration files containing the variables needed to run the program.

Creating a database:

1. Determining the nearest stops: compare the GPS data in the initial Excel file with the GPS coordinates of the stations in the helper database. For each point, the closest station can be obtained.

2. Merge waiting times for end stations: In this case, the waiting times at end stations are merged for easier data processing afterward.

3. For all data points, it is possible to know the names of the nearest stations so that it is possible to determine from what time of day to what time of day a given train has been on which route.

4. Distance calculation for data points: for established route data points, the distance calculation for route reference points in the helper database is used to get the distance from the previous data point to the starting station. This operation was very time-consuming due to the distance calculation for thousands of reference points. As a solution, using the configuration files generated during the preparation, several routes and several trains were calculated in parallel.

5. Other calculations: Calculation of cumulative consumption and regenerative energy for specific runs (routes).

6. Calculation with IQR methodology: IQR, or interquartile range, is a statistical indicator of the variance of the data. The IQR is calculated as the difference between the lower and upper quartiles. The procedure for this was as follows:
   a. Sorting the data.

$$C = \{C_1, C_2, \dots, C_n\} \quad (1)$$

$$C_1 \leq C_2 \leq \dots \leq C_n \quad (2)$$

where $\{C_1, C_2, \dots, C_n\}$ are the individual railway consumption values.
   b. Calculating the first and third quartiles:
      - Q_1: the median of the lower 25% of the sorted data.
      - Q_3: the median of the upper 25% of the sorted data.
   c. Interquartile range (IQR calculation): obtained from the difference between the first and third quartile range.

$$IQR = Q_3 - Q_1 \quad (3)$$

   d. Determination of lower and upper bound:

$$Lower\ bound = Q_1 - 1.5 \cdot IQR \quad (4)$$

$$Upper\ bound = Q_3 + 1.5 \cdot IQR \quad (5)$$

   e. Filtering data: using the boundaries to filter out outliers.

$$C_{filtered} = \{c \in C | Lower\ bound \leq c \leq\ Upper\ bound\} \quad (6)$$

   f. Calculating the average of the filtered data (no outliers are found here)

$$C_{avr.} = \frac{\sum_i^m c_i}{m}\ ; c_i \in C_{filtered} \quad (7)$$

where $C_{avr.}$ is the average energy consumption, m is the number of elements in the filtered data $C_{filtered.}$

7. Creating and exporting summary statistics tables to Excel: for a given month, a given number of trains and a given route, create statistics: minimum, maximum, mean (average), standard deviation, average *IQR*/km calculation per station interval. The Excel files also contain the data points per station in separate worksheets. There are two types of Excel file generation, one where data points are filtered by station distance ±2 km and one where there is no filtering at all so that all data points can be found.

Fig. 2 represents the entire block scheme of the applied data ordering.

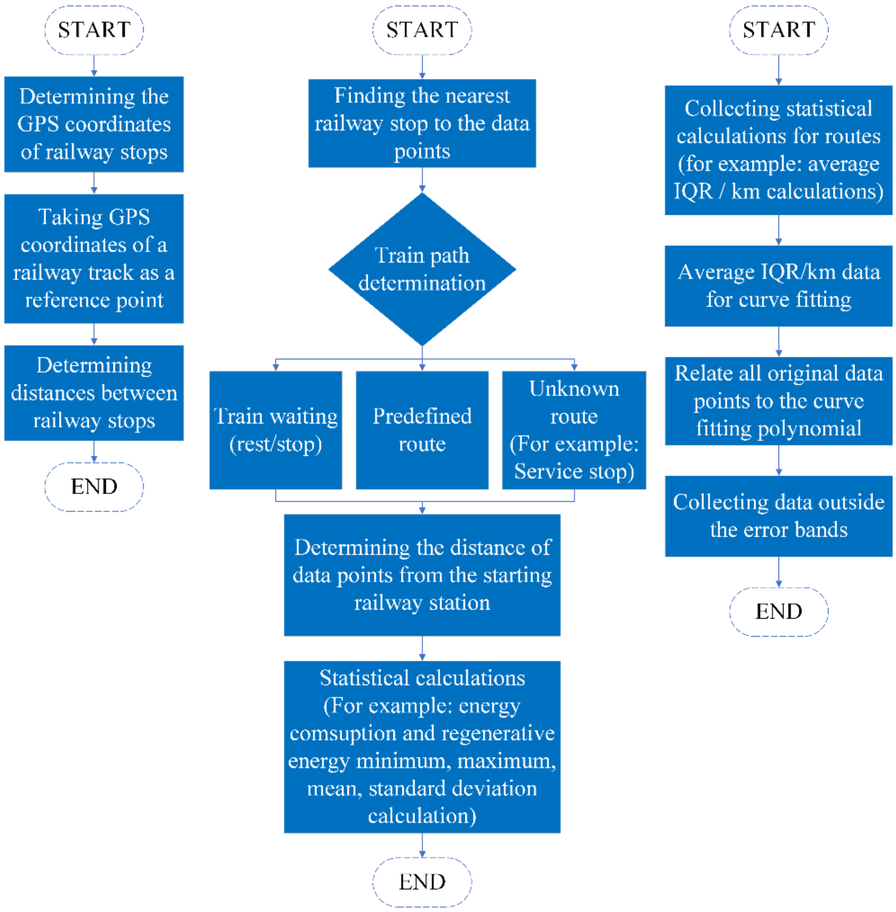

Fig. 2 Block scheme of the applied data ordering

2.2. Data Processing

The data processing used in the research is described in detail below. Data processing is further performed on data points covering the given station distance of ±2 km.

1. Generate statistical Excel files for specific routes: generate multiple worksheets. Calculate several parameters for given consumption values and regenerative values: minimum, maximum, mean (average), and standard deviation. On another worksheet, collect average

IQR/km calculations for kWh+ and kWh– values. Values were determined for a given route, for each station and each train.

2. Curve fitting: the curve fitting was done on the basis of the data from the previously generated Excel files of the average *IQR*/km worksheet. The fitting was done using the SciPy module available for Python (curve.fit function). Second, third- and fourth-degree polynomial regression functions were fitted to the points, and the Python module also provided a covariance matrix for each of them, based on which regression function was selected to fit the points better (the lower the covariance matrix value, the better the fit). In addition, the error bars were determined.

3. Identification of point locations using a polynomial regression function fitted to the curve. For all the data points exported earlier to Excel, the polynomial regression function fitted to the curve and the error bands were applied to determine the location of the points.

4. Data filtering: once the position of the points has been determined, it is now possible to filter which data points were overconsumption or too low regenerative braking energy for the average and outside the range of the specified one and two standard deviations.

5. Graphing: Graphing the filtered data. For this purpose, the energy consumption and regenerative braking energy values measured on each route were taken into account. In this phase, only the data series calculated by the authors in kWh/km units were used.

2.3. Limits of the Analysis of the Current Research

In any case, it is essential to note and highlight any factors that do not follow clearly from the chapters in Section 2.1 and Section 2.2 (for clarification, see Section 4, too):

- in the analyses, neither machine manual data nor other tractive force curves were used to calculate the acceleration and regenerative braking energies of Siemens Ventus trains and to take the measured values into account;
- analyses using layout and vertical geometry data of the railway lines have not been discussed or used in this article;
- the authors have not used official train timetables for their research on each route and in either direction, and they have neglected to take into account the through-rolled axle-ton values;
- the speeds allowed on each section are given for information only in Section 2.1, and are not included in the detailed analysis;
- the technical condition (possibly poor or good) of the railway track and the associated infrastructure, overhead contact line network, etc., and of the traction units were also neglected;
- the conducted and shown analyses use only the data series for January-May 2023, but the authors have not attempted to extrapolate using these to likely measurable values for other months, i.e., they have relied on factual data only;
- each month was treated as a unit (not merged), and the energy consumption (kWh+/km) and regenerative braking (kWh–/km) values were analyzed separately for each month.

3. Results and Discussion

Based on the methodology presented in Section 2, Section 3 reports the results in a more detailed manner. Due to the fact that two routes, and within them two directions, were considered, it was not possible to present and report a complete overview of the considerable amount of data. The first step in the evaluation of the results was to examine the different consumption data. Fig. 3 shows the consumption data of four different routes (2 railway lines, considering back and forth directions) for three different trains (i.e., 4744-300, 4744-301 and 4744-303).

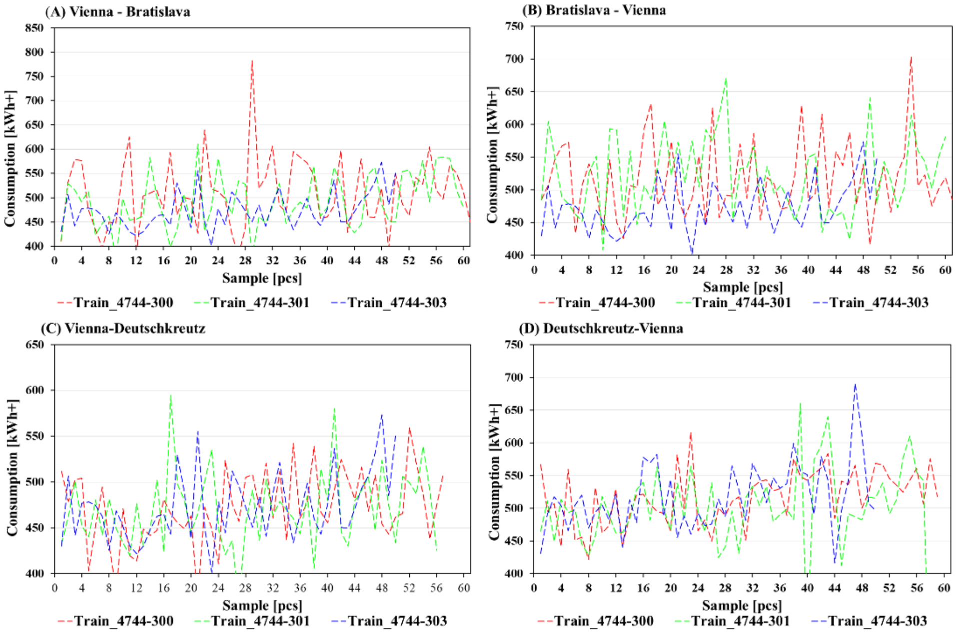

Fig. 3 Consumption data for different routes (BV, DV, as well as their opposite directions) considering four trains, the shown dashed lines are not real trend lines

On the horizontal axis Fig. 3, the serial number of the measurement is shown (it indicates the number of data series in the data set; note that the order was not relevant in this case) and on the vertical axis, the energy consumption values. The sample number shown on the horizontal axis contains about 60 values for each route. The consumption values show a significant standard deviation for all three train numbers presented, indicating that the energy consumption of the trains varies significantly between measurements. It varies between approximately 400 and 700 kWh, depending on the route and the vehicle. The VB section in subfigure A) shows medium consumption. There is also a significant standard deviation, with energy consumption peaks being less typical. The BV section is shown in subfigure B) of the figure. For all three vehicles, there is significant volatility. In subfigure C) of the figure, the VD section is shown, with the "smoothest" measured values. Although there is still a significant standard deviation, the consumption trends are less hectic than in subfigure D). The highest consumption is the red line

(4744-300 vehicles) with occasional higher peaks, approaching 700 kWh. The section DV, which is the section with the highest volatility, is shown in subfigure D). The consumption data show a wider range with significant peaks for all three train numbers. The results show that there are specific energy demands on routes, which are likely to depend on the route's inclination in the vertical plane, number of stops, train speed, etc. To further examine the differences, the results are analyzed separately by month as shown in Fig. 4.

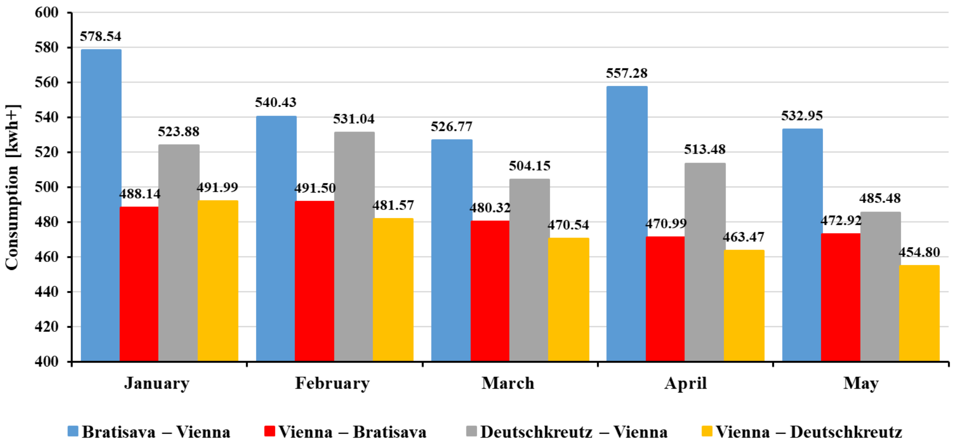

Fig. 4 Average consumption values by route in different months in 2023

Fig. 4 shows energy consumption data (in kWh dimension) assigned to different routes, broken down by month, from January to May. The routes analyzed are BV: blue bars; VB: red bars; DV: grey bars; VD: yellow bars. The results show that the highest average consumption on the BV route in January was 578.54 kWh. The lowest consumption recorded on the VD route in March was 450.32 kWh. Overall, the BV route has the highest fuel consumption, and the VD route has the lowest consumption. Consumption is decreasing on the BV and DV routes. Consumption on the VB and VD routes is relatively stable with minor fluctuations. Of the routes, BV is generally the most energy-consuming, while VD consumes the least energy. Considering the same route back and forth, BV vs. VB: the most significant difference is in January (90.40 kWh) and the smallest in March (22.62 kWh). This could be due to several reasons, e.g., higher loads in one direction, heavier vehicles, or more electricity needed in one direction due to different topography. When comparing the energy consumption between DV vs. VD, DV shows a higher energy consumption in all months compared to VD. The highest difference is observed in March (53.83 kWh), while the lowest difference is observed in May (30.65 kWh). All routes show a decrease in energy consumption from January to May, primarily due to better weather conditions. Monthly and route-level analysis of regenerative braking energy is done by means of Fig. 5. The BV route shows a particularly favorable regenerative energy use, especially in May. VD is the only route where a decrease is observed, which may indicate that traffic conditions or route characteristics do not support constant energy recovery. In the future, it may be worthwhile to investigate and optimize regenerative energy production, for example, by improving braking strategies or traffic management. When analyzing the differences between the routes, BV vs. VB, the differences between January and May are minimal, around 5-7 kWh. This suggests that the production of renewable energy is almost the same in both directions. On the other hand, the difference between DV vs. VD is more significant than the previous one, about 8-15 kWh per month. The DV route generates more regenerative energy, which may be due to higher braking or vertical inclination (e.g., more slopes in this direction; see Section 2.3 and Section 4).

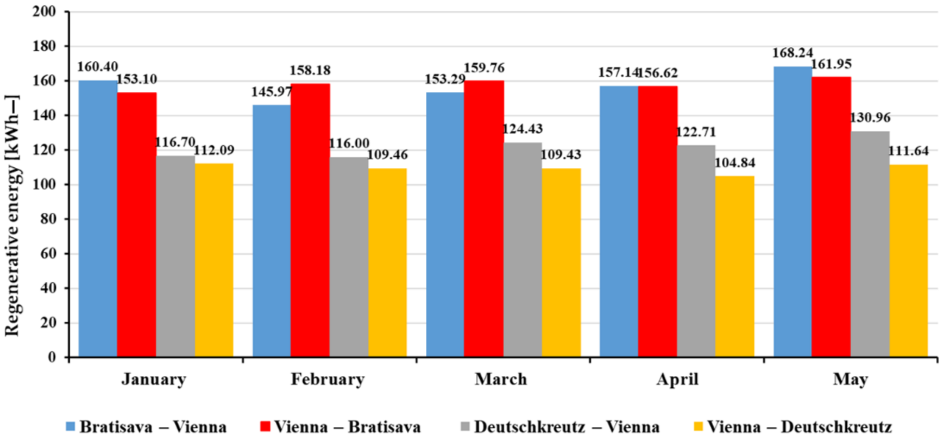

Fig. 5 Regenerative energy values by route in different months in 2023

Fig. 6 shows the variation of energy used between different months and routes. On the BV route, energy consumption was initially very volatile (winter period), but by the spring part, it had stabilized, and the standard deviation decreased. On the DV route, it showed a low standard deviation, indicating that energy consumption is predictable and steady. The slightly increasing variation (standard deviation) on the VD line requires further investigation to understand the reasons for the variability of energy use (e.g., vehicle load, line management characteristics, weather, etc.; see Section 2.3 and Section 4).

For further analysis of energy use, the variance of regenerative energy was also analyzed as given in Fig. 7. Fig. 7 shows the BV section in blue, where the variance is initially very high (54.68% in January) but decreases significantly (24.36% by May), indicating an improving trend. This is probably due to better weather conditions. VB (red line) is one of the best routes for energy recovery. DV (grey line): the variance is initially low (7.39%) but reaches a peak in April (38.52%) and then "returns" in May (10.89%). VD (yellow line) shows a similar trend to DV, with a peak in April (47.09%). By May, however, it "returns" to a lower level (10.08%). The April spikes on the DV and VD routes may indicate irregular conditions (e.g., weather, traffic, etc.; see Section 2.3 and Section 4) that are worth investigating. The analysis shows that the specificities of the routes have a substantial impact on the variability of energy recovery. Table 2 shows the ten different trains in different months and routes.

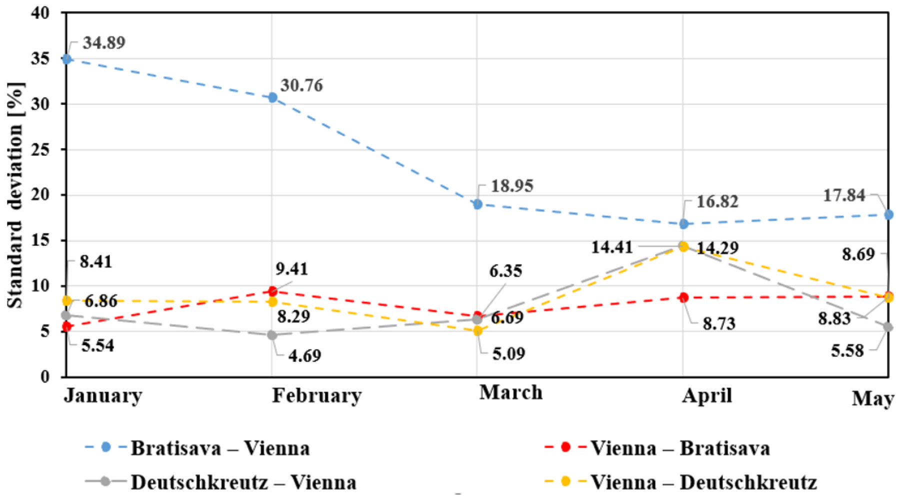

Fig. 6 Spread of consumption by road for different months

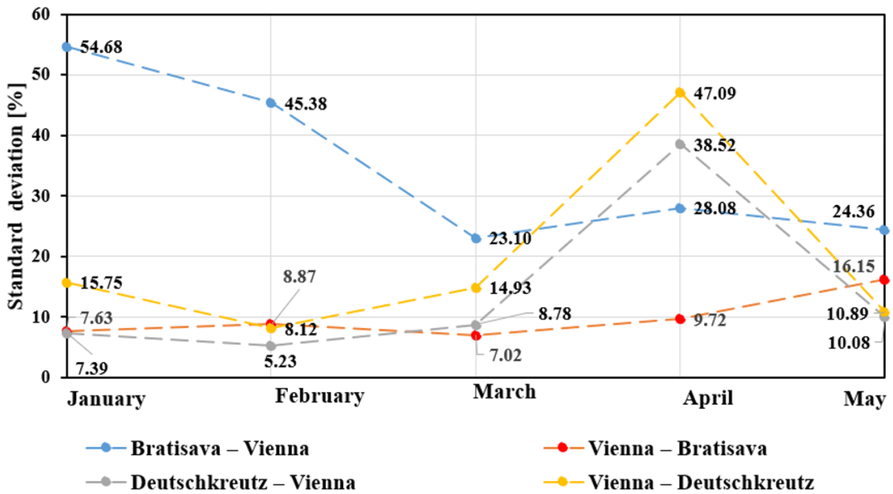

Fig. 7 The spread of the regenerative energy generated in the different months per road

Table 2 shows the consumption of each train, with a monthly and route-by-route breakdown of deviations from the average consumption of the fleet. In each case, the average consumption of the fleet for the month and route were used to compare. No data is available for the grey-shaded part; the green-shaded part had a deviation of 2.5% or less. The trains marked in yellow are those where there was an average deviation of between 2.5% and 5% from the average consumption. Orange indicates a deviation of 5-10%, and red indicates a deviation of 10% or more. It is important to note that individual outliers were not filtered out in the evaluation. The performance of the 4746-313 vehicles is shown to be the worst among the fleet. Exceptionally high values (e.g., overconsumption in January and March) indicate significant energy efficiency problems that require urgent intervention. This vehicle should be a priority for fleet optimization. Other poorly performing trains are 4746-309 and 4746-315. These discrepancies may already be related to the drivers. However, no information on the drivers of each train was available during the analysis. Therefore, for the reasons mentioned above, a more detailed examination of this is not evaluated.

Table 2 Evolution of average consumption of different trains by month and route

Train	January				February				March				April				May			
Number	BV	VB	DV	VD	BV	VB	DV	VD	BV	VB	DV	VD	BV	VB	DV	VD	BV	VB	DV	VD
4744-300																				
4744-301																				
4744-303																				
4744-304																				
4746-308																				
4746-309																				
4746-310																				
4746-312																				
4746-313																				
4746-315																				

For a more accurate evaluation, each section is examined separately. For each stage, the energy consumed, the regenerative energy and the energy balance are analyzed. Fig. 8 shows the consumption data associated with the route analysis.

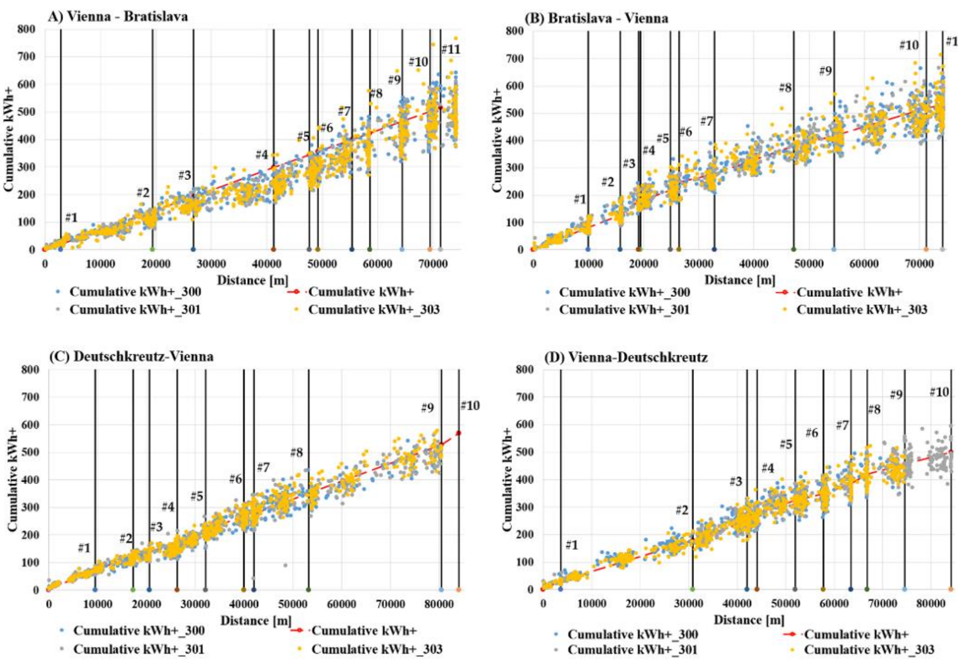

Fig. 8 Consumption data associated with railway stations on different routes

In Fig. 8, the data points for each section are presented. In each case, the distance traveled is on the horizontal axis, and the energy used is on the vertical axis. In the sub-plots of Fig. 8, the numbering and the additional vertical lines represent the station markers, which are related to the designations defined in Table 1. For the simplicity of the presentation, the results of three measurements are shown; later calculations have been made with the entire measurement database. The values from the different trains are shown in different colors: blue for 4744-300, grey for 4744-301 and yellow for 4744-303. The red line indicates the proportional average consumption. The dot plot shows that several values are significantly above or below the average. Furthermore, it can be seen that there is no clearly identifiable section where consumption is significantly above or below the average. The next step in the analysis is to analyze each station separately.

The section to be analyzed is the section between Bratislava and Vienna (BV), which includes 9 stops between the two capitals. It is important to note that trains do not always stop at all stops, but energy consumption is presented in aggregate. Unfortunately, it is not possible from the available data to identify precisely at which station a train has spent exactly how much time. The primary aim is to observe the average consumption of each section and to discover and identify the factors that influence it. In the following, the method will be illustrated by means of an example, and for ease of reference, not all the data will be used (see Fig. 9).

Fig. 9 shows the energy consumption of train 4744-300 on the BV route as a function of distance traveled, with three different values: MIN (green), the lowest consumption value over a range; MAX (red), the highest consumption value over a range; and AVR (blue), the average consumption over a range. There is a significant difference between the maximum and minimum values, indicating that the energy efficiency of some routes may vary significantly. Fig. 10 shows the energy consumption of three different trains (4744-300, 4744-301, 4744-303) on the BV route as a function of distance traveled.

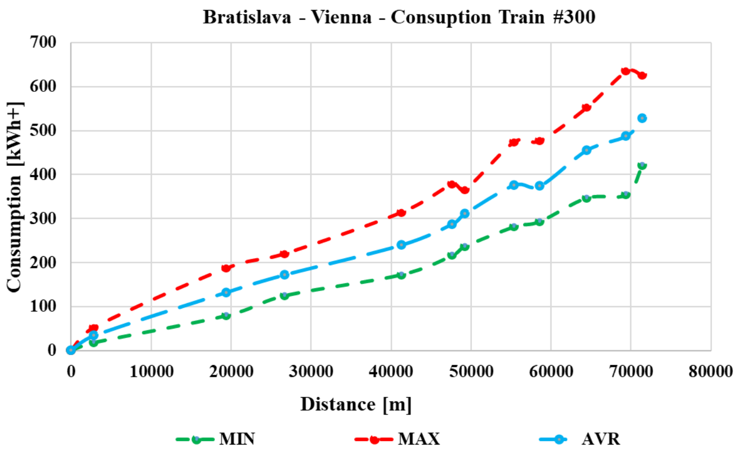

Fig. 9 Consumption values for BV route – train #300

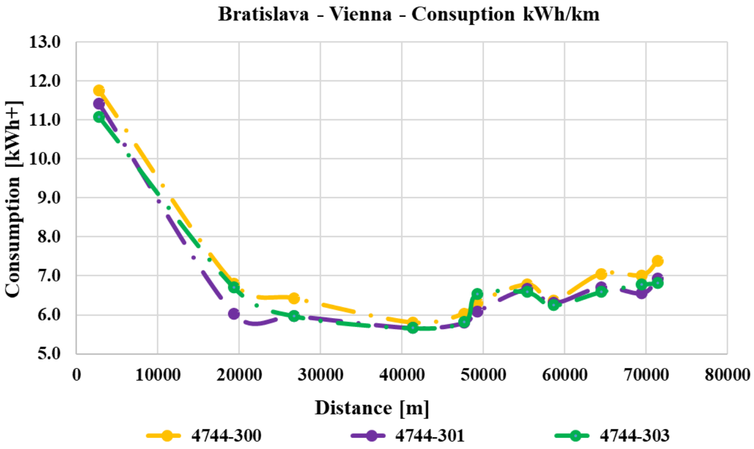

Fig. 10 Consumption values for BV route in kWh/km for three different trains

For all trains, energy consumption starts from a higher value (around 12 kWh/km) and then decreases rapidly within the first 10-20 km. After this decrease, the consumption stabilizes and settles at around 6-7 kWh/km for the later sections. It is important to note that the increased consumption in some places may be due to the route conditions and that delays during the start-up may also contribute to the higher value at the beginning of the measurement. Fig. 11 shows the regenerative energy consumption (in kWh) of three different trains (4744-300, 4744-301, 4744-303) on the BV route as a function of distance traveled.

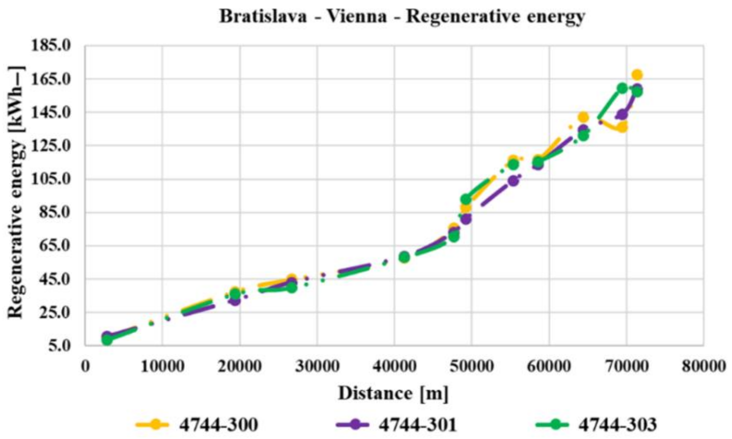

Fig. 11 Regenerative energy values for the BV route in kWh/km for three different trains

In general, there are no significant differences in the values of regenerative energy. The increase becomes faster from about the middle of the route to the end of the route (50 km), which may indicate that there are more maneuvers requiring braking on this section (e.g., more curved sections or sections with more stops; see Section 2.3 and Section 4). The next step in the analysis is to perform curve fitting for the average energy consumption.

Curve fitting was performed for the values measured per route in the approach. Fig. 12 plots the evolution of consumption (red line: kWh+), regenerative energy (Regenerative energy (kWh–): green line), and total consumption (net consumption: Consumption_sum (kWh+): yellow line) as a function of distance traveled (m) for a specific section after curve fitting. Thus, all three polynomials are assigned to the given path, and the total length can be analyzed. All that is needed is a coordinate and a consumption (and or regenerative energy) value, and it is possible to see how the train performs compared to the average.

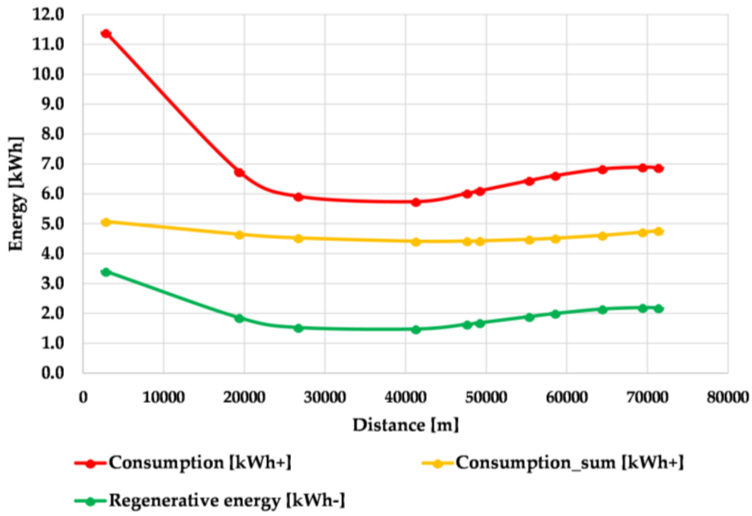

Fig. 12 Curve fittings for the BV route

Such curve fitting has been performed for each month and each direction (Fig. 13). It is important to note that the *IQR* method has been applied to the data used for curve fitting (see Section 2.1, part 6).

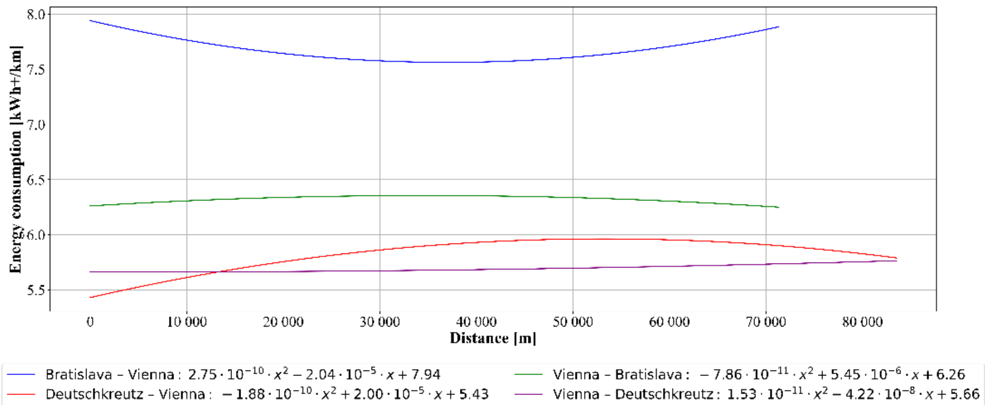

Fig. 13 Consumption curve fits for a January month on different routes (x means the distance in meter dimension)

Fig. 13 shows the energy consumption of trains on different routes (BV, VB, DV, VD) as a function of distance traveled in kWh/km. The curves in Fig. 13 give the expected energy consumption as the distance increases. It can be seen that the different routes can be modeled with significantly different regression functions, and it is necessary to treat each of them separately. The regression functions for different months for the same route have a more minor, but not negligible, difference.

Fig. 14 shows the evolution of regenerative braking energy in kWh/km for four different routes as a function of distance traveled: BV (blue); DV (red); VB (green); and VD (purple).

Fig. 14 provides a model of how regenerative energy recovery varies with distance along each route. As before, there are significant differences between the regression functions, so it is appropriate to use a different one for each distance. The following step of the analysis was to determine the deviations from the curve fits defined for the different months and routes (Figs. 15-16).

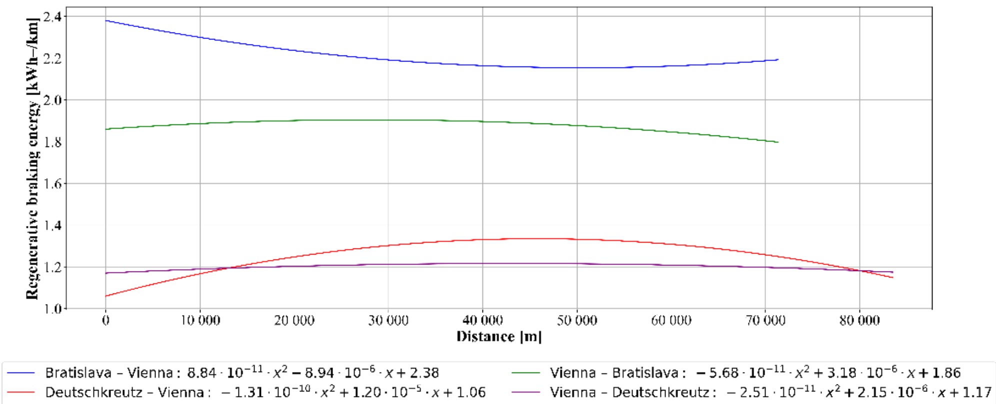

Fig. 14 Regenerative energy curve fits for January on different routes (x means the distance in meter dimension)

Fig. 15 shows the energy consumption (kWh/km) for the BV route as a function of distance traveled (m). The horizontal axis shows the distance traveled (in meters), and the vertical axis indicates the energy consumption (kWh/km). The analysis is for January data and only shows points that are outside the $\pm 2\times\sigma$ (standard deviation) band. The graph shows two grey bars indicating the limits of the standard deviation ($\pm 1\times\sigma$ and $\pm 2\times\sigma$). It has to be mentioned that considering Student-distribution the $\pm 1\times\sigma$ means 68.03%; hence, the $\pm 2\times\sigma$ means approx. 95% confidence interval in the case of 100 values, which is only an approximation). These can be used to examine which values are considered normal and which are outliers, respectively. Points that are located outside the $\pm 2\sigma$ band are shown as colored points on the graph. The graph shows data from different trains with different color codes. It can be observed that the outliers in energy consumption are not necessarily related to a specific train. The black curve in the graph shows the predetermined trend (as shown in the previous sections) between energy consumption and distance. The outliers indicate that energy consumption is significantly higher for certain trains.

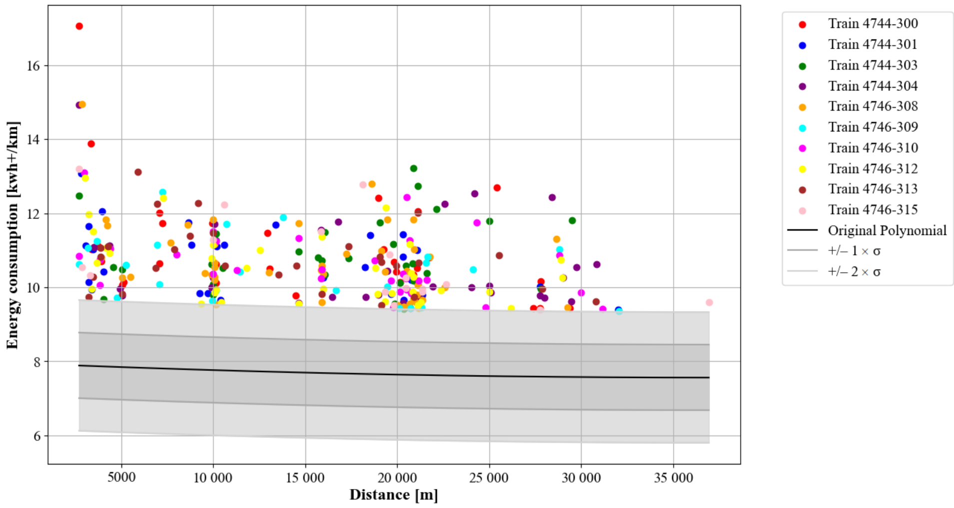

Fig. 15 Energy consumption diagram for the BV route, 2023 January, only the points which are out of the 2×σ band (σ means the standard deviation)

Fig. 16 shows the energy (kWh/km) from regenerative braking on the BV route in January. The figure plots energy data as a function of distance (m) and shows only points outside the ±2×σ (standard deviation) band. The regenerative energy (kWh/km) values are on a smaller scale (0.5-3.0 kWh/km) than the energy consumption data. In this case, the number of values outside the ±2×σ bands is much lower. The outliers in this case mean that for some trains, the energy recovered is significantly lower than expected.

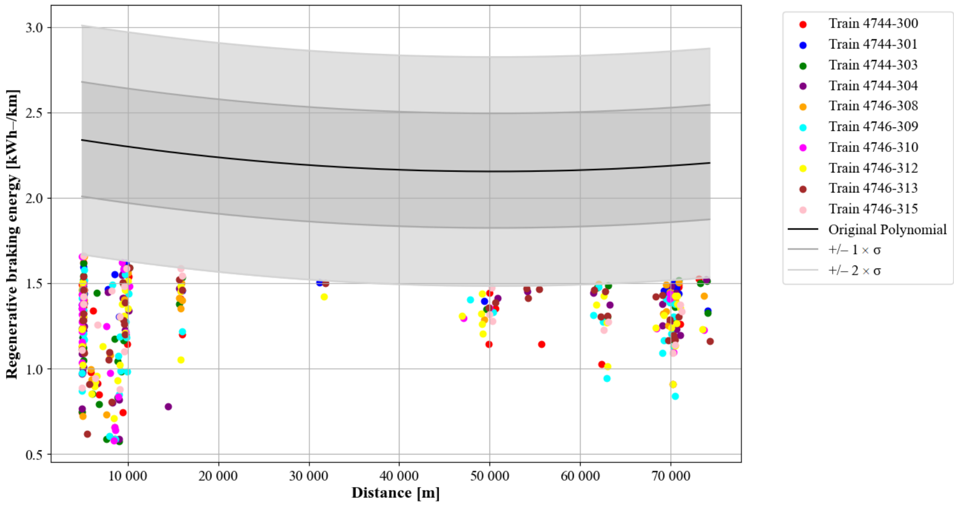

Fig. 16 Regenerative braking energy diagram, for the BV route, 2023 January, only the points which are out of the 2×σ band (σ means the standard deviation)

Fig. 17 visualizes the overconsumption values back mapped. All months of the BV route are included in the figure. In the heat map, red markers show the most frequently overconsumed area, while yellow markers show still critical parts. Areas that are not marked where overconsumption was not significant.

Tables 3 and 4 summarize the overconsumption values for each route and station.

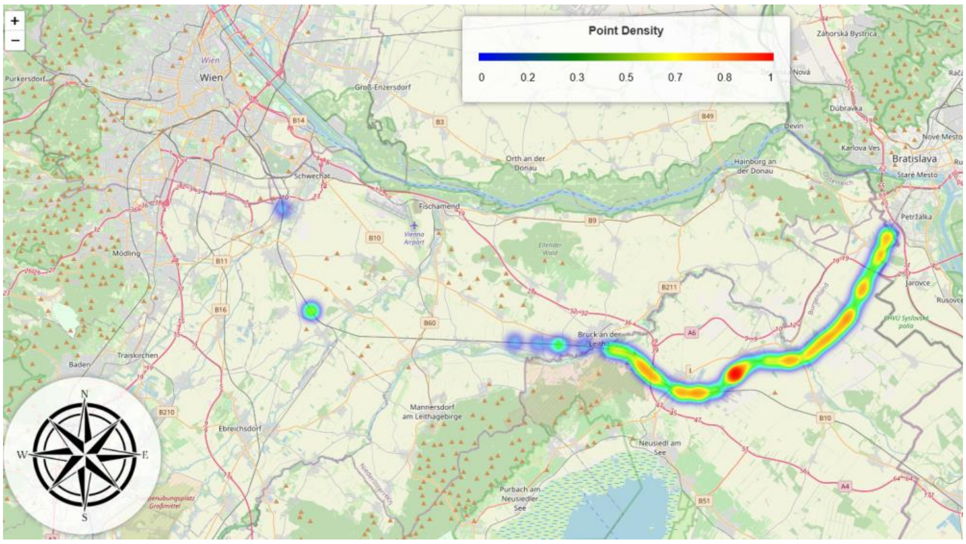

Fig. 17 Energy over consumption heat map for the BV route (the value 1.0 is related to the highest value, i.e., 17.02%, in Table 3 as a reference)

Table 3 The overconsumption values expressed as percentages associated with the nearest stations of various routes (VB and BV)

VB	[%]	BV	[%]
Vienna Hauptbahnhof	2.82	Bratislava	5.01
Vienna Grillgasse	18.40	Kittse	8.11
Gramatneusiedl	2.15	Pama	12.74
Götzendorf	0.75	Gattendorf	4.89
Bruck-Leitha	0.36	Neudorf b.Parndorf	17.02
Parndorf Ort	0.18	Parndorf	1.74
Parndorf	1.33	Parndorf Ort	3.70
Neudorf b.Parndorf	1.75	Bruck-Leitha	0.19
Gattendorf	3.13	Götzendorf	0.00
Pama	6.17	Gramatneusiedl	0.05
Kittse	3.93	Vienna Grillgasse	0.00
		Vienna Hauptbahnhof	0.00

Table 4 The overconsumption values expressed as percentages associated with the nearest stations of various routes (VD and DV)

VD	[%]	DV	[%]
Vienna Hauptbahnhof	4.90	Deutschkreutz	7.22
Vienna Meidling	6.61	Sopron	5.46
Ebreichsdorf	0.83	Baumgarten-Schattendorf	2.82
Ebenfurth	0.52	Drassburg	0.12
Neufeld-Leitha	1.28	Wulkaprodersdorf	0.75
Müllendorf	0.35	Müllendorf	3.61
Wulkaprodersdorf	22.49	Neufeld/Leitha	0.64
Drassburg	0.47	Ebenfurth	6.03
Baumgarten-Schattendorf	0.41	Ebreichsdorf	8.37
Sopron	0.00	Vienna Meidling	0.40
Deutschkreutz	0.00	Vienna Hauptbahnhof	0.67

In Tables 3 and 4, the odd-numbered columns display the routes and their corresponding stops, while the even-numbered columns present overconsumption values expressed as percentages. These percentages represent the relative magnitude of outliers associated with a given station. For ease of identification, each overconsumption value has been linked to the nearest station. It is important to note that this does not necessarily indicate that the overconsumption occurred precisely at the station but rather somewhere along the route leading up to that station. Furthermore, only values falling outside the 2×σ standard deviation range were considered in the calculations. This approach facilitates the identification of segments that appear to be critical.

4. CONCLUSIONS

The aim of the research was to improve railway energy efficiency by developing route-specific strategies. This study utilized a unique methodology to analyze the energy consumption of various railway routes and the utilization of regenerative braking energy. The analysis covered four routes (BV, VB, DV and VD, respectively) over a five-month period (January to May 2023). The results revealed significant variations in energy consumption driven by terrain characteristics, speed profiles, and stop frequencies. The findings also indicated substantial differences in energy consumption and regenerative feedback across the routes. Understanding and decoding the causes of individual cases of overconsumption is a complex process.

To address this complexity, the research analyzed not only aggregated consumption data but also processed a large volume of route-specific and direction-specific data. The study modeled the spatial (location-based) and temporal (monthly) patterns of energy use and regenerative feedback. Route-specific consumption models were developed using the Interquartile Range (*IQR*) method and curve-fitting techniques to evaluate the data. These models enabled the quantification and prediction of energy consumption patterns for individual routes. Deviation bands were established to identify outliers. Overconsumption cases were flagged when values exceeded the upper deviation limit, while cases of low regenerative feedback were analyzed when values fell below the lower limit. This allowed the localization of outliers by route and station.

The spatial distribution and temporal trends of energy consumption were also analyzed using integrated heatmap-based visualizations, facilitating the spatial identification of critical segments. To implement this approach, it is sufficient to associate consumption (or regenerative) values with coordinates along the analyzed routes. This makes it possible to evaluate how a given train performs compared to average values on the respective route.

It is essential to emphasize that further investigations and analyses are required for the evaluation of consumed and regenerated electrical energy. These investigations should account for the following complex and parallel factors, which are part of future research:

- Continuous monitoring of schedules and deviations from the timetable.
- Simultaneous analysis of the railway track's geometric and elevation profiles.
- Accurate consideration of train loads, including the continuous calculation and recording of boarding and alighting passengers at each station.
- Evaluation of locomotive driving styles, supported by the collection and analysis of driver-specific data in compliance with the General Data Protection Regulation.

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REFERENCES

1. Prymachenko, H., Shapatina, O., Pestremenko-Skrypka, O., Shevchenko, A., Halkevych, M. 2022, *Improving the technology of product supply chain management in the context of the development of multimodal transportation systems in the European Union countries*, International Journal of Agricultural Extension, 10(2), pp. 77-89.
2. Zhu, S., Zhou, Z., Li, R., Li, W., 2022, *Impact of high-speed rail construction on the environmental sustainability of China's three major urban agglomerations*, Sustainability, 14(5), 2567.
3. Kuchak, A.T.J., Marinkovic, D., Zehn, M., 2021, *Parametric investigation of a rail damper design based on a lab-scaled model*, Journal of Vibration Engineering & Technologies, 9, pp. 51-60.
4. Kuchak, A.T.J., Marinkovic, D., Zehn, M., 2020, *Finite element model updating—Case study of a rail damper*, Structural Engineering and Mechanics, 73(1), pp. 27-35.
5. Ézsiás, L., Tompa, R., Fischer, S., 2024, *Investigation of the possible correlations between specific characteristics of crushed stone aggregates*, Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 10-26.
6. Fischer, S., 2025, *Investigation of the Settlement Behavior of Ballasted Railway Tracks Due to Dynamic Loading*, Spectrum of Mechanical Engineering and Operational Research, 2(1), pp. 24-46.
7. Larumbe, J., 2021, *Evaluating sustainability of mass rapid transit stations in Dubai*, Sustainability, 13(23), 12965.
8. Volkov, V., Taran, I., Volkova, T., Pavlenko, O., Berezhnaja, N., 2020, *Determining the efficient management system for a specialized transport enterprise*, Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu, 2020(4), pp. 185-191.
9. Saukenova, I., Oliskevych, M., Taran, I., Toktamyssova, A., Aliakbarkyzy, D., Pelo, R., 2022, *Optimization of schedules for early garbage collection and disposal in the megapolis*, Eastern-European Journal of Enterprise Technologies, 1(3(115)), pp. 13-23.
10. Nastisin, L., Gavurova, B., Kopor, I., Bačík, R., 2022, *Analysis of perceived customer satisfaction in the context of rail transport: A case study of the Slovak market*, Entrepreneurship and Sustainability Issues, 9(4), pp. 427-438.
11. Bektaş, T., Ehmke, J., Psaraftis, H., Puchinger, J., 2019, *The role of operational research in green freight transportation*, European Journal of Operational Research, 274(3), pp. 807-823.
12. Arribas, A., Belboom, S., Léonard, A., 2020, *Life cycle assessment of rail freight transport in Belgium*, Clean Technologies and Environmental Policy, 22, pp. 1109-1131.

13. Kolesnykova, T., Matveyeva, O., Manashkin, L., Mishchenko, M., 2019, *Railway transportation of dangerous goods: A bibliometric aspect*, MATEC Web Conferences, 2nd International Scientific and Practical Conference "Energy-Optimal Technologies, Logistic and Safety on Transport" (EOT-2019), Lviv, 294, 03014.
14. Zu, D., Cao, K., Xu, J., 2021, *The impacts of transportation sustainability on higher education in China*, Sustainability, 13(22), 12579.
15. Xu, L., Jia, F., Lin, X., Chen, L., 2023, *The role of technology in supply chain decarbonisation: Towards an integrated conceptual framework*, Supply Chain Management: An International Journal, 28(4), pp. 803-824.
16. Kondratieva, L., 2023, *Research on the application of on-board energy storage on an electric locomotive for quarry railway transport*, IOP Conference Series: Earth and Environmental Science, 1254, 012024.
17. Kostin, M., Nikitenko, A., Mishchenko, T., Shumikhina, L., 2021, *Electrodynamics of reactive power in the space of inter-substation zones of AC electrified railway line*, Energies 2021, 14(12), 3510.
18. Małek, A., Taccani, R., 2021, *Innovative approach to electric vehicle diagnostics*, Archiwum Motoryzacji, 92(2), pp. 49-67.
19. Auhadeev, A., Idiyatullin, R., Pavlov, P., Butakov, V., Kisneeva, L., Tukhbatullina, D., 2019, *Improving the theory for calculating the rational modes of traction electrical equipment*, E3S Web Conferences, 124, 05077.
20. Lima, S., Rodrigues, A., Magalhães, V., Lopes, I., 2022, *Challenges of the deployment of electric cars in Brazil*, Journal of Engineering Research, 2(17), pp. 1-21.
21. Blatnický, M., Dižo, J., Gerlici, J., Sága, M., Lack, T., Kuba, E., 2020, *Design of a robotic manipulator for handling products of the automotive industry*, International Journal of Advanced Robotic Systems, 17(1), 1729881420906290.
22. Dižo, J., Blatnický, M., Sága, M., Harušinec, J., Gerlici, J., Legutko, S., 2020, *Development of a new system for attaching the wheels of the front axle in the cross-country vehicle*, Symmetry, 12(7), 1156.
23. Shpika, N., Smyrnyi, M., Herasymenko, V., Pryanicka, V., 2019, *Increasing energy performance of urban electric transport*, Prace Komisji Geografii Komunikacji PTG, 22(1), pp. 44-51.
24. Goolak, S., Liubarskyi, B., Riabov, I., Lukoševičius, V., Keršys, A., Kilikevičius, S., 2023, *Analysis of the efficiency of traction drive control systems of electric locomotives with asynchronous traction motors*, Energies, 16(9), 3689.
25. Bharati, S., Upadhyay, M., 2020, *Review on electric traction systems driving induction motor and associated power quality issues*, Smart Moves Journal IJOSTHE, 7(1), pp. 22-25.
26. Bialobrzheskyi, O., Gladyr, A., Yakimets, S., Sulym, A., 2021, *Need of technical accounting at electric energy quality reduction under conditions of ac traction substation*, Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu, 2021(3), pp. 75-80.
27. Isaicheva, A., Basharkin, M., Zolkin, A., Losev, A., Giniyatullina, D., 2022, *Estimation of electrical energy losses in a DC traction rail network during heavy traffic*, IOP Conference Series: Earth and Environmental Science, 990(1), 012023.
28. Stead, C., Wadud, Z., Nash, C., Li, H., 2019, *Introduction of biodiesel to rail transport: lessons from the road sector*, Sustainability, 11(3), 904.
29. Santos, G., Macário, R., Delaplace, M., Vita, S., 2022, *The long-standing issue of mobility at the Olympics: from host cities to host regions in the ongoing case study of Milan–Cortina 2026*, Sustainability, 14(2), 910.
30. Malkus, R., Liebuvienė, J., Jokubynienė, V., 2020, *Inland water transport applicability for sustainable sea port hinterland infrastructure development: Klaipeda sea-port case*, Transport Problems, 15(2), pp. 25-31.
31. Ku, B., Liu, J., 2019, *Modelling and numerical solution of ungrounded DC rail traction system load flow using a ladder circuit – Part I: Circuit modelling*, IET Generation, Transmission & Distribution, 14(1), pp. 1-10.
32. Leushin, V., Yusupov, R., Isaicheva, A., 2023, *Evaluation of noise immunity of channels with rail and inductive-rail lines*, BIO Web of Conferences, 63, 03016.
33. Liu, W., Tang, T., Su, S., Yin, J., Chen, Y., Cheng, W., 2019, *Energy-efficient train driving strategy with considering the steep downhill segment*, Processes, 7(2), 77.
34. Gorobchenko, O., 2021, *Development of the method of clusterization of train situations*, Transport Systems and Technologies, 2021(37), pp. 187-195.
35. Ficzere, P., 2023, *The role of artificial intelligence in the development of rail transport*, Cognitive Sustainability, 2(4), 81.
36. Suslov, K., Zatsarinnaya, Y., Logacheva, A., Olentsevich, V., Karlina, A., Shtayger, M., 2021, *Calculation of operating modes of the traction power network system and the capacity of the 27.5 kV railway line section systems for batch train schedules*, IOP Conference Series: Materials Science and Engineering, 1151(1), 012038.
37. Białoń, A., Białek, K., Wetoszka, P., 2019, *Analysis of emission tests of electromagnetic disturbances in diesel-electric locomotives*, MATEC Web of Conferences, 294, 02001.

38. Tao, X., Sun, P., Xiao, Z., Fu, C., Feng, X., Wang, Q., 2024, *Modeling and Energy-Optimal Control for Freight Trains based on Data-Driven Approaches*, Future Generation Computer Systems, 152, pp. 346-360.
39. Yildiz, A., Arikan, O., Cakiroglu, H., 2024, *A Timetable Optimization Model for the Istanbul, Turkey, Metro Network Considering a Novel Regenerative Braking Energy Model*, Journal of Transportation Engineering, Part A: Systems, 150(2), 04023139
40. Fischer, S., Kocsis Szürke, S., 2023, *Detection process of energy loss in electric railway vehicles*, Facta Universitatis, Series: Mechanical Engineering, 21(1), pp. 81-99.
41. Jiang, X., Hu, H., Yang, X., He, Z., Qing-Quan, Q., Tricoli, P., 2019, *Analysis and adaptive mitigation scheme of low-frequency oscillations in ac railway traction power systems*, IEEE Transactions on Transportation Electrification, 5(3), pp. 715-726.
42. Dmitrienko, V., Zakovorotnii, O., Mezentsev, M., 2022, *Linearization of a mathematical model asynchronous traction drive methods geometrical theory of control*, Bulletin of the National Technical University "Kharkiv Polytechnic Institute", 2022(1-2), pp. 18-29. (in Ukrainian)
43. Fernández, P., Zuriaga, P., Sanchis, I., Franco, R., 2019, *Neural networks for modelling the energy consumption of metro trains*, Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 234(7), pp. 722-733.
44. Cipolletta, G., Femine, A., Gallo, D., Luiso, M., Landi, C., 2021, *Design of a stationary energy recovery system in rail transport*, Energies, 14(9), 2560.
45. Kierzkowski, A., Haładyn, S., 2022, *Method for reconfiguring train schedules taking into account the global reduction of railway energy consumption*, Energies 2022, 15(5), 1946.
46. Liang, H., Zhang, Y., Yang, P., Wang, L., Gao, C., 2023, *Comparison and analysis of prediction models for locomotive traction energy consumption based on the machine learning*, IEEE Access, 11, pp. 38502-38513.
47. Urbaniak, M., Kardas-Cinal, E., 2021, *Optimization of train energy cooperation using scheduled service time reserve*, Energies, 15(1), 119.
48. Deng, L., Chen, M., Duan, K., Ouyang, L., Shi, F., 2023, *Integrated energy-efficient optimization for urban rail transit timetable*, IET Intelligent Transport Systems, 17(9), pp. 1819-1834.
49. Li, J., Pan, F., Tong, S., Zhang, L., Li, X., Yang, X., 2022, *Energy-saving metro train timetable optimization method based on a dynamic passenger flow distribution*, J of Advanced Transportation, 2022, 9776845.
50. Wang, X., Luo, Y., Zhou, Y., Qin, Y., Qin, B., 2021, *Hybrid energy management strategy based on dynamic setting and coordinated control for urban rail train with PMSM*, IET Renewable Power Generation, 15(12), pp. 2740-2752.
51. Ren, J., Zhang, Q., Liu, F., 2020, *Analysis of factors affecting traction energy consumption of electric multiple unit trains based on data mining*, Journal of Cleaner Production, 262, 121374.
52. Du, Y., Zhi, J., He, S., 2022, *Impact of experience on visual behavior and driving performance of high-speed train drivers*, Scientific Reports, 12(1), 5956.
53. Gao, Z., Lu, Q., Fu, J., He, B., 2019, *Energy-storage-based smart electrical infrastructure and regenerative braking energy management in ac-fed railways with neutral zones*, Energies, 12(21), 4053.
54. Hasan, A., Tuhin, R., Ullah, M., Sakib, T., Thollander, P., Trianni, A., 2021, *A comprehensive investigation of energy management practices within energy-intensive industries in Bangladesh*, Energy, 232, 120932.
55. Geiberger, P., Liu, Z., Berg, M., Domay, C., 2023, Monitoring energy usage of heavy-haul iron ore trains with on-board energy meter for improving energy efficiency, Railway Sciences, 2(2), pp. 243-256.
56. Lees, T., Chalmers, T., Burton, D., Zilberg, E., Penzel, T., Lal, S., 2021, *Electrophysiological brain-cardiac coupling in train drivers during monotonous driving*, International Journal of Environmental Research and Public Health, 18(7), 3741.
57. Agrawal, R., Tommasi, L., Lyons, P., Zanoni, S., Papagiannis, G., Karakosta, C., 2023, *Challenges and opportunities for improving energy efficiency in SMEs: Learnings from seven European projects*, Energy Efficiency, 16(3), 17.
58. Savković, T., Miličić, M., Pitka, P., Milenković, I., Koleška, D., 2019, *Evaluation of the eco-driving training of professional truck drivers*, Operational Research in Engineering Sciences: Theory and Applications, 2(1), pp. 15-26.
59. Luo, J., Gao, S., Wei, X., Tian, Z., 2024, *Adaptive energy management strategy for high-speed railway hybrid energy storage system based on double-layer fuzzy logic control*, International Journal of Electrical Power & Energy Systems, 156, 109739.
60. Eisinger Balassa, B., Németh, A., Major, Z., Kegyes-Brassai, O., 2022, *Comparative life cycle analyses of regular and irregular maintenance of bridges with different support systems and construction technologies*, Chemical Engineering Transactions, 94, pp. 571-576.