https://doi.org/10.55343/CogSust.154

Possibilities for determining the energy consumption of electric locomotives during acceleration and constant-speed traction

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Abstract

Electric locomotives are integral to sustainable railway transportation, where optimizing energy consumption is crucial for efficiency and environmental impact reduction. This study investigates energy usage during acceleration and constant-speed traction in Siemens Taurus 0470-series locomotives operating on the Sopron–Győr railway line (Line 8 in Hungary). Using empirical data from onboard computer displays, video recordings, and Optical Character Recognition (OCR), the research applies statistical correlation methods to analyze energy consumption trends. The study identifies key influencing factors, including acceleration energy correction coefficients (α_1 = 1.2981, α_2 = 1.3151) and specific energy consumption values at constant speeds, averaging 0.00204 kWh/kN/km at 120 km/h with a 21.12% relative standard deviation value. Heatmaps illustrate energy consumption patterns, highlighting peak usage near stations and track turnouts. The findings support refining energy models and driving strategies while emphasizing the potential benefits of regenerative braking, timetable optimization, and advanced driver assistance systems. By integrating these insights, railway operations can achieve enhanced energy efficiency and long-term sustainability.

Keywords
electric locomotive, Siemens Taurus locomotive, energy consumption, acceleration, traction with constant speed

1. Introduction

Cognitive sustainability in transportation, particularly within the railway sector, involves the interplay between cognitive processes and sustainable practices to enhance operational efficiency and user experience (Zöldy and Baranyi, 2023; Zöldy et al., 2024; Zöldy, 2024). It emphasizes understanding how cognitive factors influence decision-making and behavior in sustainable transport systems. For example, cognitive mapping techniques can visualize and analyze users' mental representations of transport challenges, leading to improved strategies for promoting sustainable travel behaviors (Waleghwa and Ioannides, 2024). Integrating cognitive decision-making frameworks into railway planning and management can identify key performance indicators and sustainability criteria, enhancing transport infrastructure effectiveness (Oraegbune and

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Ugwu, 2020). This approach addresses immediate operational challenges and aligns with broader sustainability goals by fostering awareness and responsibility among stakeholders.

In railways, cognitive sustainability also considers the mental workload and cognitive performance of train operators, which are critical for safety and efficiency. Prolonged tasks and high mental workloads can lead to cognitive underload, decreasing attention and increasing error rates among train crew members (Currie et al., 2023). Cognitive load management strategies and advanced technologies, such as eye-tracking systems, can enhance staff cognitive performance, improving safety and sustainability in railway operations (Madleňák et al., 2023). Fostering a cognitive understanding of sustainable practices among operators and passengers can encourage environmentally friendly behaviors, such as using public transport instead of private vehicles, reducing emissions and improving urban air quality (Macassa, 2023). Cognitive sustainability also addresses public perceptions and attitudes towards sustainable transport, which shape travel behaviors. Cognitive dissonance arises when travel choices conflict with environmental values, leading to reluctance to shift towards sustainable modes of transport (Bina and Biassoni, 2023). Targeted educational programs and awareness campaigns can address this dissonance, empowering users to make informed decisions aligned with sustainability objectives. Integrating cognitive sustainability principles into transport planning and policy-making can create a resilient and sustainable railway system that meets current mobility needs and anticipates future challenges related to climate change and urbanization (de la Torre et al., 2021). This holistic approach fosters a sustainable transport culture prioritizing cognitive engagement and environmental stewardship. Although slightly outside the focus of the current research, it is worth mentioning – to provide a broad perspective on cognitive mobility – that some researchers have discussed the noises and vibrations of electric vehicles and their reduction possibilities (Zöldy and Pathy-Nagy, 2022; Zöldy and Dömötör, 2022), as well as the effects of long-term utilization on vehicle battery performance (Tollner and Zöldy, 2022).

Cognitive sustainability in railways enhances operational efficiency, decision-making, and broader sustainability objectives, including optimizing energy consumption in electric locomotives to reduce environmental impact and improve economic viability. Understanding and accurately calculating energy consumption is essential for designing efficient railway systems.

This study explores methodologies and technologies for determining energy consumption during acceleration and constant-speed traction, linking cognitive sustainability principles with technical advancements in railway energy management. The calculation of consumed energy in electric locomotives involves various methodologies, technologies, and operational practices. First, a literature review synthesizes studies on energy consumption, focusing on mathematical modeling, technological advancements, operational factors, and environmental implications.

The energy required to move trains depends on infrastructure effects such as traction and vehicle characteristics (Dižo et al., 2022; Mikhailov et al., 2021), permanent way characteristics (Kuchak et al., 2020; 2021; Ézsiás et al., 2024; Fischer et al., 2024; Fischer, 2025), transportation organization effects, for example speed, marshaling, stop plans, seat capacity utilization, handling, signal displays, logistics (Volkov et al., 2020; Saukenova et al., 2022), and external environmental impacts including altitude, climate and barometric pressure (Ren et al., 2020; Fischer, 2015; Fischer and Kocsis Szürke, 2023; Fischer et al., 2025). Train energy consumption includes operational energy (traction energy and regenerative braking energy) and auxiliary energy used by onboard service equipment, like air conditioning, lighting, and ventilation (Fischer and Kocsis Szürke, 2023)).

Mathematical modeling is crucial for estimating energy consumption. Rodriguez-Cabal et al. (2022) developed a methodology for estimating electrical power on undocumented railroad tracks, emphasizing accurate data collection and model validation. Liang et al. (2023) used machine learning to enhance prediction models for locomotive traction energy consumption, improving accuracy by incorporating operational variables. Technological advancements, such as modern multi-engine traction drives (Zarifyan et al., 2021) and hybrid systems, fpr example fuzzy PID control systems for mining electric locomotives (Ma et al., 2024), optimize energy use. Regenerative braking systems (Lu et al., 2019; Yan et al., 2018) improve energy recovery during braking, reducing overall consumption. Environmental considerations, such as carbon-neutral technologies (Lu and Allen, 2024) and battery technology (Kaleybar et al., 2022; Chen et al., 2013), align with global sustainability goals.

Operational factors (e.g., track conditions, load variations, driving behaviors) significantly influence energy consumption (Istomin, 2018; Cheremisin et al., 2020). Digital technologies and data analytics enable real-time monitoring and

https://doi.org/10.55343/CogSust.154

optimization of energy use (Istomin et al., 2018). Alternative energy sources, such as hydrogen fuel cells and battery technologies (Cole et al., 2023; Kaleybar et al., 2022) and energy storage systems (Domanov et al., 2019) enhance efficiency. Research on power losses (Nikitenko et al., 2022) and control strategies for traction converters (Rajibayev et al., 2023) further optimize energy consumption in electric locomotives.

The future of electric locomotives will likely involve a combination of these various approaches, integrating advanced modeling, innovative technologies, and operational best practices to optimize energy consumption. The ongoing research in this field will continue to shape the development of more efficient and sustainable electric locomotives, contributing to the broader goals of reducing greenhouse gas emissions and enhancing the efficiency of rail transport.

In the international literature, many articles and studies deal with the determination of the consumed energy of electric railway vehicles (i.e., locomotives and electric multiple units (EMUs)). Rochard and Schmid (2000) primarily examined the validity of train resistance formulae, by analyzing those developed by Davis, Armstrong and Swift, and others. They found that, typically, air resistance is the most important part of train resistance calculation. This makes the streamlined design of trains critical. The mass of trainsets (and hence their calculated weight) and their effect on train resistance are of particular interest and importance for freight trains. They go through the French, German and Japanese calculation formulae. Rochard and Schmid (2000) provide practical formulae for train resistance using second order polynomial functions (the detailed explanation of the railway resistances is discussed in Ihme (2022)). Lukaszewicz (2007) conducted full-scale tests in Sweden and derived train resistance equations related to several locomotive and wagon configurations. The considered formulae are also second order polynomial functions. The calculation possibilities of the consumed energy are detailed by Mandić et al. (2009), Ihme (2022), and Fischer (2015).

The present paper addresses the key research gap in the field of energy consumption analysis for electric locomotives, which is related to the refinement of energy consumption models. Therefore, this study suggests that the correlation functions and correction factors used in energy prediction models should be further refined to enhance forecasting accuracy (Fischer, 2015).

The structure of the paper is as follows: Section 2 summarizes the data and data processing methodologies, Section 3 presents the results and the discussion, and Section 4 provides the conclusions.

2. Data and methods

2.1. Data sources and collection

The data was collected by the authors through their measurements on intercity (IC) trains hauled by Siemens Taurus 0470-series locomotives between Sopron and Győr along the Sopron–Budapest and Budapest–Sopron routes. A total of five days of measurements were conducted, covering seven train runs:

- On November 28, 2024, Scarbantia IC train No. 997 operated between Sopron and Győr with locomotive 470 501 (91430470501-7) – Sisi – hauling 4 IC passenger wagons, with a total weight of 298 tons.
- On November 28, 2024, Scarbantia IC train No. 984 operated between Sopron and Győr with locomotive 470 503 (91430470503-3) – Wagner – hauling 4 IC passenger wagons, with a total weight of 300 tons.
- On December 13, 2024, Scarbantia IC train No. 997 operated between Sopron and Győr with locomotive 470 501 (91430470501-7) – Sisi – hauling 5 IC passenger wagons, with a total weight of 345 tons.
- On December 13, 2024, Scarbantia IC train No. 984 operated between Sopron and Győr with locomotive 470 503 (91430470503-3) – Wagner – hauling 5 IC passenger wagons, with a total weight of 345 tons.
- On December 16, 2024, Scarbantia IC train No. 987 operated between Sopron and Győr with locomotive 470 502 (91430470502-5) hauling 4 IC passenger wagons, with a total weight of 298 tons.
- On January 24, 2025, Scarbantia IC train No. 987 operated between Sopron and Győr with locomotive 470 502 (91430470502-5) hauling 5 IC passenger wagons, with a total weight of 351 tons.
- On January 31, 2025, Scarbantia IC train No. 987 operated between Sopron and Győr with locomotive 470 502 (91430470502-5) hauling 6 IC passenger wagons, with a total weight of 387 tons.

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The data were collected by the following methods:

- During the measurements conducted on November 28, 2024, December 13and 16, 2024, GoPro 11 action cameras were used for visual recording, while GoPro 13 action cameras were employed during the measurements on January 24 and 31, 2025. The cameras recorded the display of the locomotives' onboard computers, which showed the exact time, train number, consumed and regenerated energy values (in kWh), as well as the total traction force (considering all four traction electric motors/engines together) in kN. Additionally, the catenary voltage was displayed. Three data points were recorded using the GoPro cameras at 60 fps. The GPS data from the GoPro cameras was utilized for location identification, and the timestamps were synchronized according to the GoPro camera's internet-based time updates.
- The video records captured by the GoPro cameras were subsequently processed on a desktop computer, where they were converted into individual frames and downsampled to a 1 Hz sampling rate (from 60 fps). Optical Character Recognition (OCR) technology was applied to extract the data, which was then saved in CSV format.
- The applied software and processing motors are controlled by custom-written Python routines.

Fig. 1 shows some parts of the measurement setup.

Figure 1. The measurement setup (there is the GoPro camera in front of the displays; here its display is in stand-by mode because the energy consumption is much less than with switched on display)

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2.2. Data processing

The data collected, as described in Section 2.1, was imported into an MS Excel environment and analyzed according to the following methodology:

- As mentioned at the end of Introduction, the primary objective of this study was to conduct a statistical correlation comparison between two different calculation methods for the measured acceleration energy values, as well as to estimate energy consumption during constant-speed traction.
- To achieve the above, it was necessary to document and implement detailed calculation procedures, which are defined by Eqs. (1–3).

$$E_{calc.,me,i,j} = 0.5 \cdot m_i \sum_{j=1}^{n} \left(v_{j+1}^2 - v_j^2\right) \cdot 3.6 \cdot 10^6 \quad (1)$$

$$E_{calc.,tf,k,l} = \sum_{k=1}^{p} \sum_{l=1}^{q} [0.5 \cdot (v_{k+1} + v_k) \cdot (v_{k+1} - v_k) \cdot s_l] \cdot 3.6 \cdot 10^6 \quad (2)$$

$$E_{meas.,i,j} = E_{calc.,me,i,j} \cdot \alpha_1 = E_{calc.,tf,k} \cdot \alpha_2 \quad (3)$$

where,

- $E_{calc.,me,i,j}$ is the calculated acceleration energy of the train mass m_i [kg] in [kWh] based on the equation of the motion energy (of course, during a given acceleration, the m_i does not change);
- v_j and v_{j+1} are the values of acceleration speed step in [m/s];
- $E_{calc.,tf,k,l}$ is the calculated acceleration energy of the train mass m_i [kg] in [kWh] based on the equation of traction force $F_{traction}$;
- v_k is the so-called specific acceleration force of the considered locomotive at the speed (v_k [m/s]) that hauls the train mass m_i [kg], for the determination of v_k the traction force of the locomotive ($F_{traction}$ [kN]) as a function of the speed (v [m/s]), as well as the train resistance (μ_{train} [N/kN]) and the weight of the whole train (Q_{train} [kN]) should be taken into consideration;
- s_l is the driven distance between the points [m] where there are the considered train at speed values v_{k+1} and v_k (the frequency of the data was 1 Hz in the current study);
- let us consider that $E_{calc.,me,i,j}$ and $E_{calc.,tf,k,l}$ are related to the same acceleration between v_j and v_{j+1}, which can be measured with $E_{meas.,i,j}$ in [kWh];
- the values of *i*, *j*, *k* and *l* indexes are shown differently because more sub-distances and subparts can be during an acceleration according to the traction force measurements; it is the reason for the consideration of the *n*, *p* and *q* values;
- α_1 and α_2 are correction parameters (factors) that should be determined from the correlation calculation between the calculated and the measured acceleration energies.

The parameter μ_{train} can be determined by many equations and formulas (Rochard and Schmid, 2000; Lukaszewicz, 2007; Ihme, 2022; Mandić et al., 2009), from which the one shown in Eq. (4) is applied in the current study, using the Hungarian Railways for passenger trains (Fischer, 2015):

$$\mu_{train} = 2.0 + 0.047 \cdot 3.6 \cdot \frac{v}{100} \quad (4)$$

The traction with constant speed was defined by the unit [kWh/kN/km] related to Q_{train} [kN] and *S* [km] (i.e., the distance driven with the constant speed (v [m/s]) in question). For this parameter, no calculation was executed; only the data processing of the measurements was done.

Data processing consists of two methodologies: first, using unfiltered data pairs (i.e., the calculated and the measured energy values in the case of accelerations and measured energy values in the case of traction with constant speed); and second, using filtered data pairs. In the case of accelerations, the filter eliminates data pairs that fall outside the mean ±20%. For traction with constant speed, contiguous section lengths shorter than 3 km are filtered out. In the latter case, it was necessary to apply this method, which is not entirely accurate, due to the absence of an accurate calculation method. The specified filtering criteria assume that the measurement error margin of ±20% is acceptable; these are primarily engineering assumptions and approximations that include the simplifications detailed in Section 2.3. These limitations should, of course, be clarified in future research and publications.

Heatmaps are also presented in Section 3, which illustrate not only the consumed energy but the regenerative braking energies considering both the Sopron–Győr and the Győr–Sopron runs. When the heatmap is created, it sets a color scale based on the difference in consumption considering 1.0 second timesteps, i.e., it determines the intensity (local average). It

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places the points with the differences in consumption on the map. In turn, the interpretation of the colors on the heatmap is the averaged density (weighted average) of the values of the points within a given area. As the map is zoomed in or out, it contracts the colors of the points in a given area, with the colors around the points contracting by 10 pixels, i.e., the intensity increases. Zooming the map out, larger areas are several points higher on average.

2.3. Limitations

The following limitations were considered during the research:

- Measurements were conducted exclusively with Siemens Taurus 0470-series locomotives (502 “green-yellow” Taurus locomotive, and ones with nicknames Sisi and Wagner).
- Only the Sopron–Győr and Győr–Sopron segments of Railway Line 8 were considered for analysis due to two main reasons (this railway line is a single track line):
    1. In the Kisalföld region, gradient values (longitudinal-vertical inclinations) are relatively low, with a maximum of 5.8‰ between Kapuvár and Fertőendréd, as well as between Sopron and Fertőboz. Typical gradient values range between 3‰ and 5‰; however, the gradient signs were not available for the study.
    2. After Győr, intercity trains departing from Sopron continue on Railway Line 1, where significantly steeper gradients are characteristic of the Győr–Budapest section.
- It is important to note that for trains departing from Sopron towards Budapest, acceleration from 0 to 100 km/h at Győr Station was included in the analysis. For trains in the opposite direction, only the segment from the stop at Győr Station to Sopron was examined.
- Curve resistance was not considered. The minimum curve radius on the Győr–Sopron section is R = 410 m (at Fertőboz Station), while curves with $R \leq 500$ m are the most common in this section.
- Constant-speed segments were analyzed at predefined values of $V_{const.}$ = 60…80…100…120 km/h, with 120 km/h being the most frequently occurring and longest-sustained speed (approximately 50% of the total Győr–Sopron section is covered at this speed).
- In the case of acceleration, all identifiable acceleration events within the measured train runs were analyzed.
- Only electrical energy consumption values were considered and included in further analysis; regenerative braking energy was not taken into account.
- A single train resistance equation was applied – see Eq. (4) –, which is specified for passenger trains (Fischer, 2015).
- The effects of temperature, humidity, and variations in the adhesion-friction coefficient at the wheel-rail interface were not considered.
- The influence of locomotive sanding during acceleration was omitted.
- Train weight values were taken exclusively from GYSEV (ROeEE, i.e., the Győr–Sopron–Ebenfurt Railways Ltd.) records. Variations in train car types between different runs and their potential impact were not analyzed.
- Track and track geometry defects were not considered.
- The influence of locomotive drivers’ driving styles was disregarded.
- In some cases, locomotive 0470 502 was subject to a service-imposed speed restriction of V = 140 km/h due to transformer oil cooling issues. The impact of this restriction on acceleration and traction energy consumption was not analyzed.
- It is crucial to mention that the recorded energy values relied solely on the onboard computer system of the Siemens Taurus 0470-series locomotives, including its update frequency and accuracy, which were not precisely verified.
- The timetable optimization was currently neglected; however, in the Conclusions the related recommendations are determined.

3. Results and discussion

Figs. 2–7 depict the results of the analyses. Figs. 2–3 (unfiltered) and Figs. 5–6 (filtered according to the method described in Section 2.2) deal with the measurement of acceleration energies and their determination by linear regression functions, taking into account the kinetic energy and the traction force curve. In each graph, the values of the parameters alpha1 (Figs. 2 and 5) and alpha2 (Figs. 3 and 6) are given. In the unfiltered cases, the coefficient of determination (R^2) was above 0.95, while values above 0.99 were obtained for the filtered data set. If the filtering criterion defined by the engineering approach (see Section 2.2) is acceptable, it can be stated that for passenger trains hauled by Siemens Taurus 0470 locomotives (considering hauled IC wagons), α_1 = 1.2981, while α_2 = 1.3151. The number of data points is lower for Figs. 3 and 5 because, during measurements on 13.12.2024 and 31.01.2025, there were unfavorable lighting conditions that made it impossible to evaluate the bright (yellow) traction data displayed on the locomotive’s on-board computer display, so they were neglected (omitted from the evaluations).

Figs. 4 and 7 show that there is significant variation in the specific energy consumption data for each (constant) speed (V = 60...100...120 km/h). For V = 60 km/h, since only one measurement data point is available, this calculation was not performed. In contrast, for V = 100 km/h, for the unfiltered data set, the mean value is 0.00138 kWh/kN/km and the standard deviation is 0.00077 kWh/kN/km, while the relative standard deviation is 56.02%; the same values for V = 120 km/h – for

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the same unfiltered data set – the mean value is 0.00197 kWh/kN/km, the standard deviation is 0.00052 kWh/kN/km, while the relative standard deviation is 26.36% – all are shown in Fig. 4. For filtered datasets (see Fig. 7) the results are as follows: for V = 100 km/h, the previously reported results remain valid, with no changes observed); for V = 120 km/h, the mean value is 0.00204 kWh/kN/km, the standard deviation is 0.00043 kWh/kN/km, while the relative standard deviation is 21.12%. For both the unfiltered and filtered datasets, the coefficient of determination (R^2) was above 0.92.

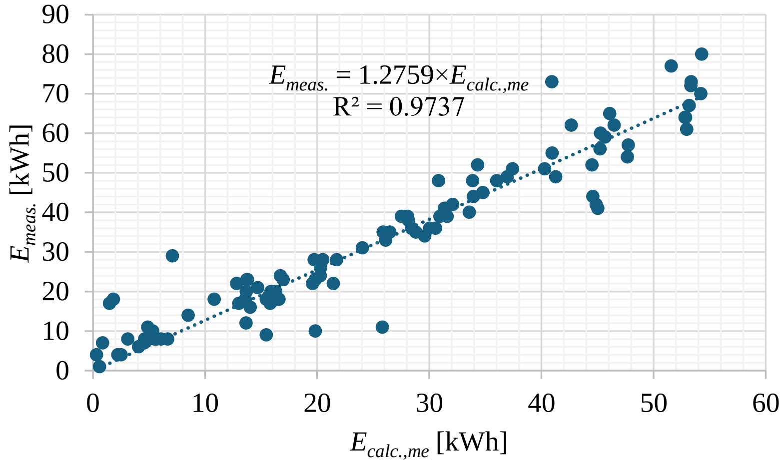

Figure 2. Regression function and determination of α_1 considering unfiltered dataset, for runs between both Sopron–Győr and Győr–Sopron (total: 105 data points)

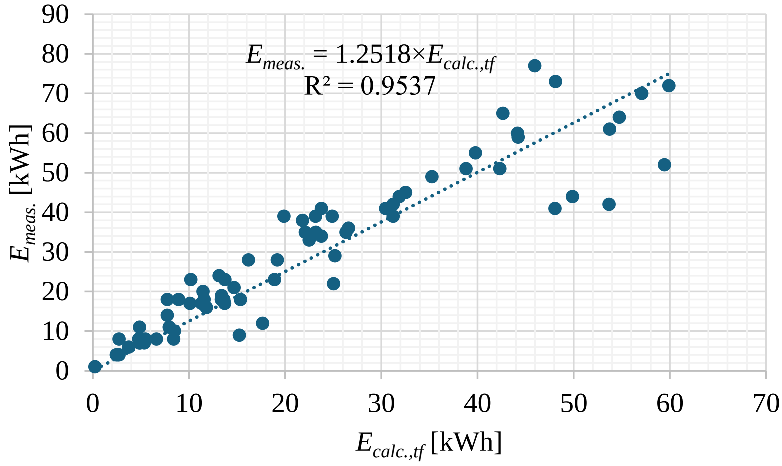

Figure 3. Regression function and determination of α_2 considering unfiltered dataset, for runs between both Sopron–Győr and Győr–Sopron (total: 75 data points)

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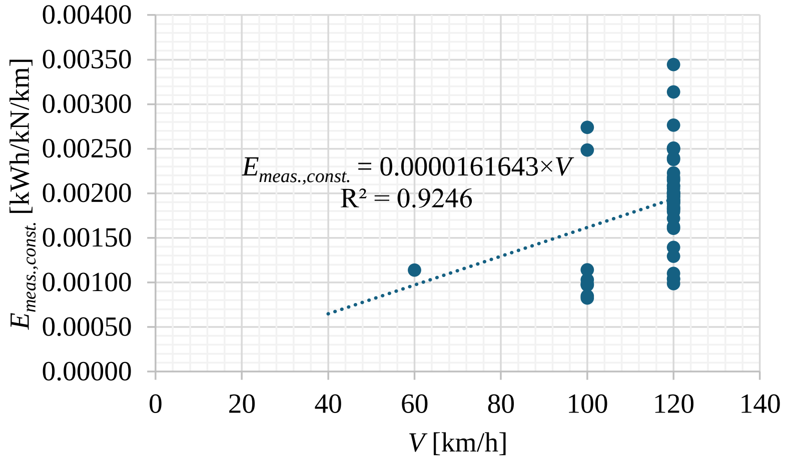

Figure 4. Regression function for traction with constant speed considering unfiltered dataset, for runs between both Sopron–Győr and Győr–Sopron (total: 52 data points)

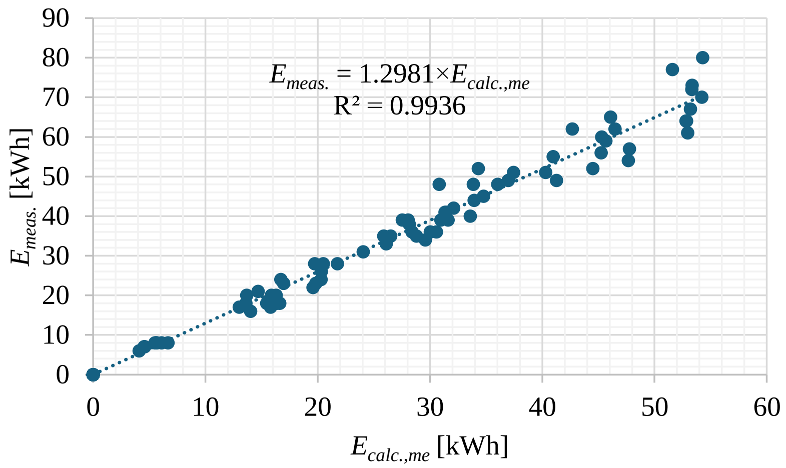

Figure 5. Regression function and determination of α_1 considering filtered dataset, for runs between both Sopron–Győr and Győr–Sopron (total: 76 data points)

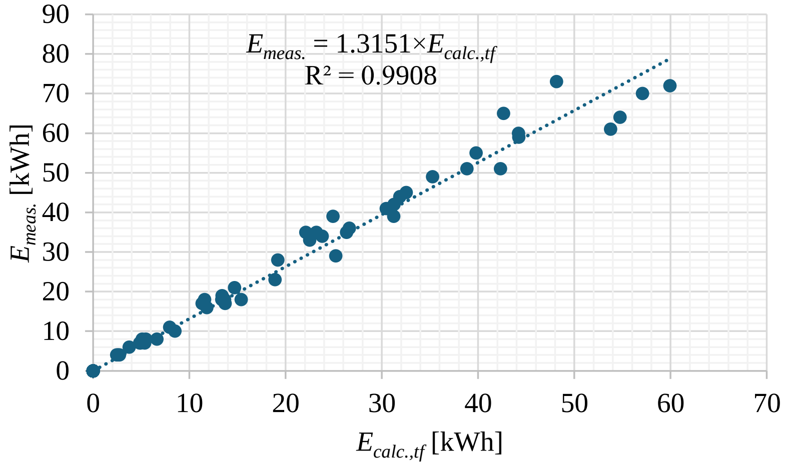

Figure 6. Regression function and determination of α_2 considering unfiltered dataset, for runs between both Sopron–Győr and Győr–Sopron (total: 48 data points)

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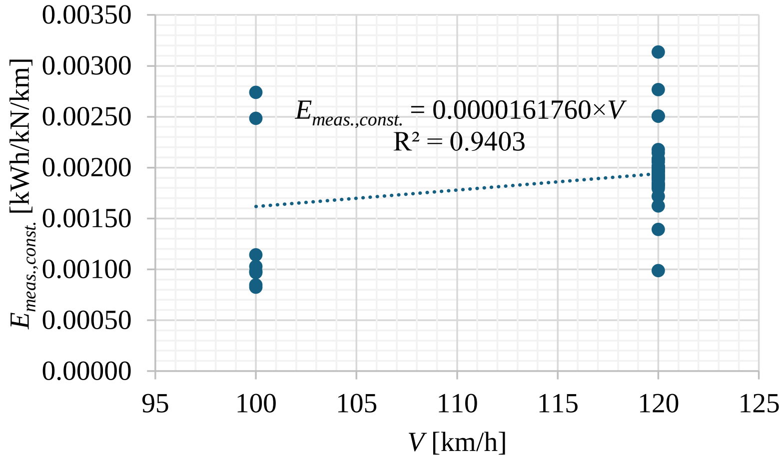

Figure 7 Regression function for traction with constant speed considering filtered dataset, for runs between both Sopron–Győr and Győr–Sopron (total: 40 data points)

Figs. 8–11 show the above results in heat maps. Figs. 8 and 10 connect to Figs. 2–3 and Figs. 5–6, hence Figs. 9 and 11 represent the parallel measured regenerative braking energies. The meaning of the colors in Figs. 8–11 are detailed in Section 2.2. The heatmaps clearly show that the peak consumption values are concentrated around railway stations and possible turnout tracks (yellowish colors) but also appear in purple between stations due to constant speed traction along the whole section – see. Fig. 8 and Fig. 10. In Figs. 9 and 11, the regenerative braking energies are concentrated around the stations. This also indicates that the intermediate sections are typically not subject to speed restrictions – likely because train crossings at turnout tracks and/or other traffic reasons for the train to slow down occur mainly near stations.

Based on the observations made during the measurements, the train drivers preferred to use the electric brake instead of traditional pneumatic-mechanic brake (the regenerative energy can be recovered by using electric brake), despite the limited braking force of the Siemens Taurus locomotives, which is only 150 kN (Baur, 2003) for safety and derailment protection reasons. In this respect, it would be more advantageous to use Siemens Vectron locomotives, because they can be equipped with an electric braking force of double that amount, i.e., 300 kN (or in some countries, 240 kN) (Siemens, 2024). In the case of Siemens Vectron locomotives, the measurement procedure is not available for small time-frames, because the onboard computer of the locomotive shows the measured data only every (approx.) 20 seconds, which is not appropriate for detailed and accurate analysis.

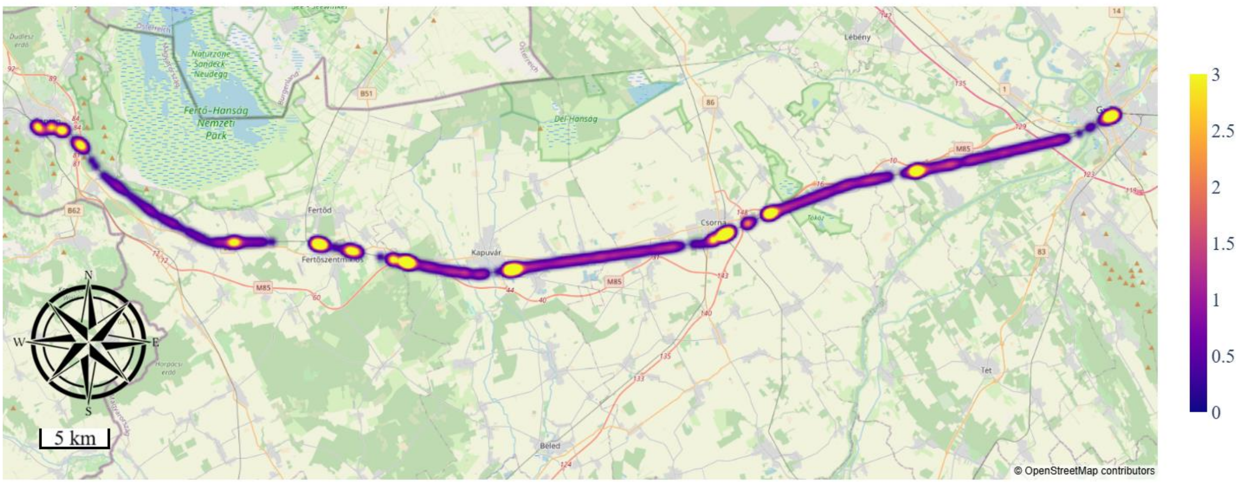

Figure 8. Consumed energy heatmap, Sopron (left) –Győr (right) route, date: 28 November 2024

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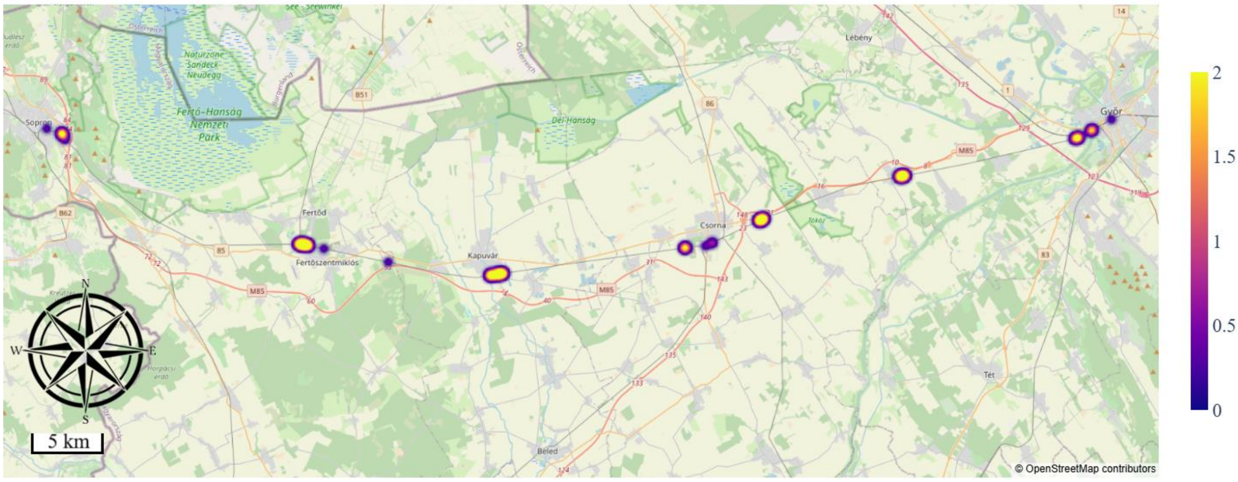

Figure 9. Regenerative braking energy heatmap, Sopron (left) –Győr (right) route, date: 28 November 2024

Figure 10. Consumed energy heatmap, Győr (right) – Sopron (left) route, date: 28 November 2024

https://doi.org/10.55343/CogSust.154

Figure 11. Regenerative braking energy heatmap, Győr (right) – Sopron (left) route, date: 28.11.2024

It is worth mentioning that these results can be compared with Fischer (2015). The value of α_2 in Fischer (2015) is 1.331, while the current study found 1.2759 (without filtering, see Fig. 2) and 1.2981 (with filtering, see Fig. 5). Similar results are contained in Fischer (2015) related to earlier investigations: 1.415. If the filtering is taken into account, the current article results in approx. 2.5% and 8.3% lower calculation factors than previous studies (i.e., 1.2981 vs. 1.331; 1.2981 vs. 1.415, respectively). The assumed reason for the differences is the effect of less accurate measurement possibilities and manual measurements, as well as train weights calculated from braking forces (Fischer (2015)). These two factors caused/could cause significant differences in the results obtained.

4. Conclusion

The following conclusions can be drawn from the obtained results:

- Cognitive sustainability and energy efficiency: frequent acceleration due to speed restrictions increases energy consumption. Long-term investments in track improvements could enhance efficiency and reduce operational costs.
- Energy consumption findings:
  1. Acceleration and constant-speed traction energy use can be estimated with correction factors α_1 = 1.2981 and α_2 = 1.3151 for Siemens Taurus 0470-series locomotives. The results were compared with earlier studies. Based on them, there is a 2.5…8.3% difference.
  2. At 120 km/h, the average specific energy consumption is 0.00204 kWh/kN/km (filtered dataset).
  3. Heatmaps of energy consumption and regenerative braking show peak energy use around stations and turnout tracks, reflecting the impact of frequent acceleration and deceleration.
- Regenerative braking concerns:
  1. It remains unclear whether regenerative braking energy is credited at full value.
  2. There is potential to redirect unused regenerative energy to power auxiliary systems.
  3. Siemens Vectron locomotives, with 300 kN regenerative braking force (compared to 150 kN in Taurus models), could improve energy recapture, reduce brake wear, and lower maintenance costs.
- Operational improvements for energy efficiency:
  1. Implementing driver assistance systems (DAS) could optimize train operation and reduce energy use.
  2. Timetable optimization should be explored to minimize unnecessary acceleration and braking.
  3. Expanding the Sopron–Győr railway line to a double-track system could reduce delays caused by passing loops and enhance overall efficiency.
  4. Analyzing train operators' driving styles is crucial, as stress from schedule adherence affects energy consumption.
  5. Incentive programs could be introduced to reward energy-efficient driving and regenerative braking performance; it is one of the authors' future research plans.

- Infrastructure and locomotive modernization:
  1. Upgrading locomotives and passenger cars, along with regular maintenance, can reduce rolling resistance and improve energy efficiency; it is one of the authors' future research plans.
  2. The derived correlation functions and correction coefficients from this study provide a more precise framework for energy consumption calculations and forecasting.

Acknowledgement

This paper was supported by the János Bolyai Research Scholarship of the Hungarian Academy of Sciences. The paper was technically supported by the SZE-RAIL Research Team. The research has not received any financing for the article process charge. The authors express their most profound respect for the technical support of the Raaberbahn Hungary, especially Endre Lőkkös and Bálint Huszár.

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