SUMO User Conference 2026
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Energy- and Emission-Conscious Extension of TAPAS-SUMO Coupling - A Case Study in Delmenhorst

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Abstract. This paper describes the extension of the TAPAS-SUMO coupling from functional integration to environmentally sustainable traffic simulation. In addition to travel times, both energy consumption (electricity and fuel) and emissions, estimated by SUMO, can be fed back into the TAPAS database. The framework enables scenarios with different vehicle types and automatic iterative coupling. With these extended features, various metrics can be used to investigate mobility plans, assess resulting energy consumption and emissions at the individual, road, district and/or regional level, and develop environmentally conscious mobility strategies. A case study is carried out for the city of Delmenhorst to validate the model extension and explore changes in electric vehicle energy consumption over time and under different climate conditions.

Keywords: TAPAS-SUMO coupling, energy and emission modeling

1. Introduction

Energy consumption and emissions are increasingly being used as key performance indicators for evaluating the effectiveness of sustainability management strategies. When considered alongside travel time, these indicators influence mode choices and mobility patterns. Moreover, the interdependence between the transport and energy sectors has become increasingly important, especially as electrification, (bidirectional) charging demand and renewable energy integration reshape mobility systems. Improving understanding of these interactions can facilitate optimization of energy management at both district and regional levels. Accordingly, traffic models and microscopic traffic simulation are essential instruments because they reconstruct and capture travel behavior more accurately—such as departure, arrival and stopover locations and times, transport mode choices, and related decision patterns—and estimate energy consumption, energy demand, and resultant emissions while accounting for traffic dynamics.

To address the aforementioned issues, this paper describes how the TAPAS-SUMO coupling (TSC) has been extended from functional coupling to environmentally sustainable integration. An automatic iterative coupling process has been established which yields more realistic travel patterns. The framework is also expanded to accept multiple input files that define distinct vehicle types and their associated energy consumption. A case study is conducted to validate the model extension and to examine how electric energy consumption varies with ambient temperature and over time.

2. Overview of TAPAS-SUMO coupling

The open-source microscopic agent-based travel demand model TAPAS [1] is used to estimate travel demand for cities or regions, covering population generation, activity generation, location and mode choice. The model generates a synthetic population by creating a representative sample of individual residents/travelers with detailed demographic information for each agent.

Afterwards, each person, or agent, is selected from the generated synthetic population, assigned an activity plan, and then matched with appropriate locations and transport modes based on the current situation. The daily plan of each agent is then evaluated for acceptance, with travel time and costs being the major factors. The TAPAS output consists of a daily trip table of the population, with associated activities, locations, transport modes, and estimated travel times and distances. For specific examples of input and output data, as well as further algorithmic details, see Subsec. 4.1, where we describe the TAPAS model for the case study.

To enhance the accuracy of each agent's travel time estimation, the open-source microscopic traffic simulation SUMO [2], [3] is coupled with TAPAS to reflect the influence of traffic dynamics on travel time variations within the road network [4]. The TAPAS-SUMO modeling process is shown in Figure 1. The trip chains, generated from TAPAS, are firstly converted into trips in SUMO-trip format. To avoid unrealistic jams caused by many agents starting or ending at the exact same positions, e.g. university, each agent's departure and arrival positions are further dispersed to nearby road sections surrounding to the original start and end points. Trips are then assigned to the network by SUMO's oneshot assignment algorithm where agents select their best routes based on the traffic conditions at their departure times.

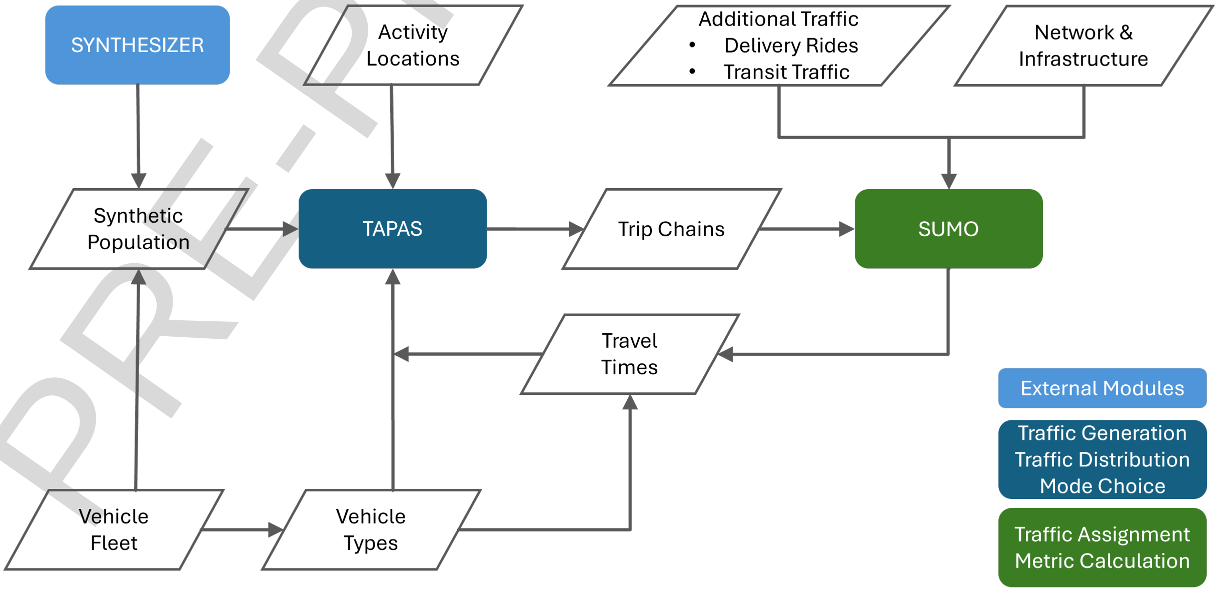


***Figure 1.** The modeling process of the TAPAS-SUMO coupling.*

Consequently, a matrix is generated that contains the travel times between all possible origins and destinations. Based on this matrix, the traffic demand and corresponding mode choices in TAPAS are recalculated. In each iteration, travel times between locations are adjusted using a weighting factor, with 30% assigned to the previous iteration and 70% to the current iteration. This approach determines the travel times used for location selection while reducing oscillation effects. This iteration process continues until the predefined number of iterations is reached.

3. Extension implementation

The main focus of the extension is to integrate simulated emission and energy consumption data into the TAPAS database. To reflect various vehicle settings across scenarios, the TAPAS–SUMO coupling framework enables the integration of scenario-specific vehicle files. Energy consumption and generated emissions are written to the extended trip outputs table, reported in megajoules (MJ) and grams (g), respectively. Moreover, similar to the Origin-Destination (OD) travel time matrix, corresponding matrices for simulated emission pollutants and energy use (fuel and electricity) can also be established, enabling considerations beyond travel time when selecting routes, transport modes, destinations, or travel chains. Figure 2 depicts the standard technical workflow of TSC. The process begins with the user defining and starting simulation scenarios via the graphical user interface. The TAPAS server then generates and distributes travel demand and determines mode choice based on OD-based travel times, initially estimated and later updated from simulation results. The TAPAS–SUMO client converts travel chains into individual trips, runs the simulation, and writes outputs such as trip data and OD-based metric matrices to a database. Individual-level information includes journey characteristics, emissions, and energy consumption, whereas OD-level matrices consist of corresponding average metrics. The watcher component monitors whether updated travel times are available and whether further iterations are required. This loop continues until the predefined maximum number of iterations is reached, at which point the process terminates. More detailed technical information can be found in [5].

Figure 3 illustrates an exemplary layout of the TAPAS graphical user interface, which provides users with information about the loaded scenarios, their locations (IP addresses), as well as their online and execution status, such as CPU usage, the number of cores used, the respective timestamps, completion times, and whether a scenario is running, waiting, or finished. Users can also directly add or remove scenarios through the interface.

4. Case study

The model region for this case study is the city of Delmenhorst, an urban district with about 80,000 residents in northern Germany. It is located 10 km west of the city of Bremen and serves as an urban center for the surrounding region. The respective SUMO simulation network is illustrated in Figure 4. The covered area spans approximately 14 km by 15 km.

This case study had two goals: 1) to validate the TAPAS-SUMO model extension, and 2) to assess energy consumption by electric vehicles (EVs) under different weather

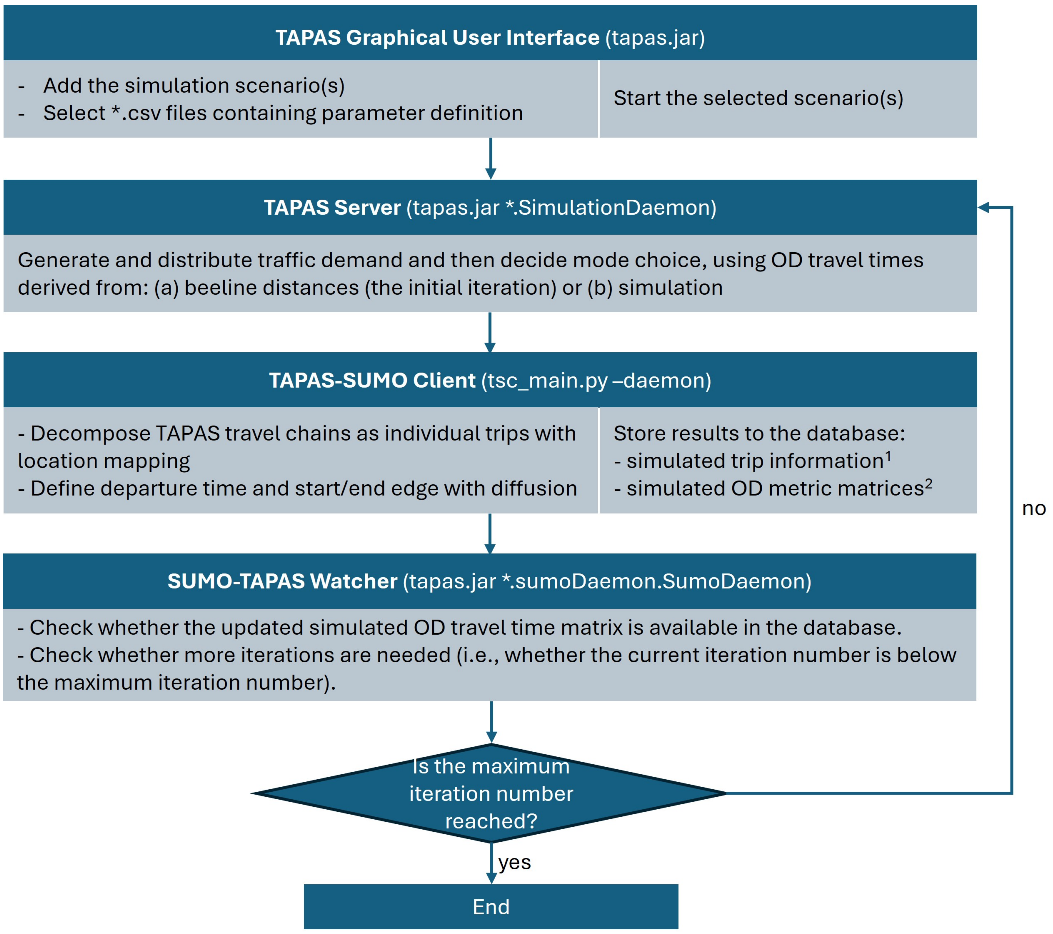
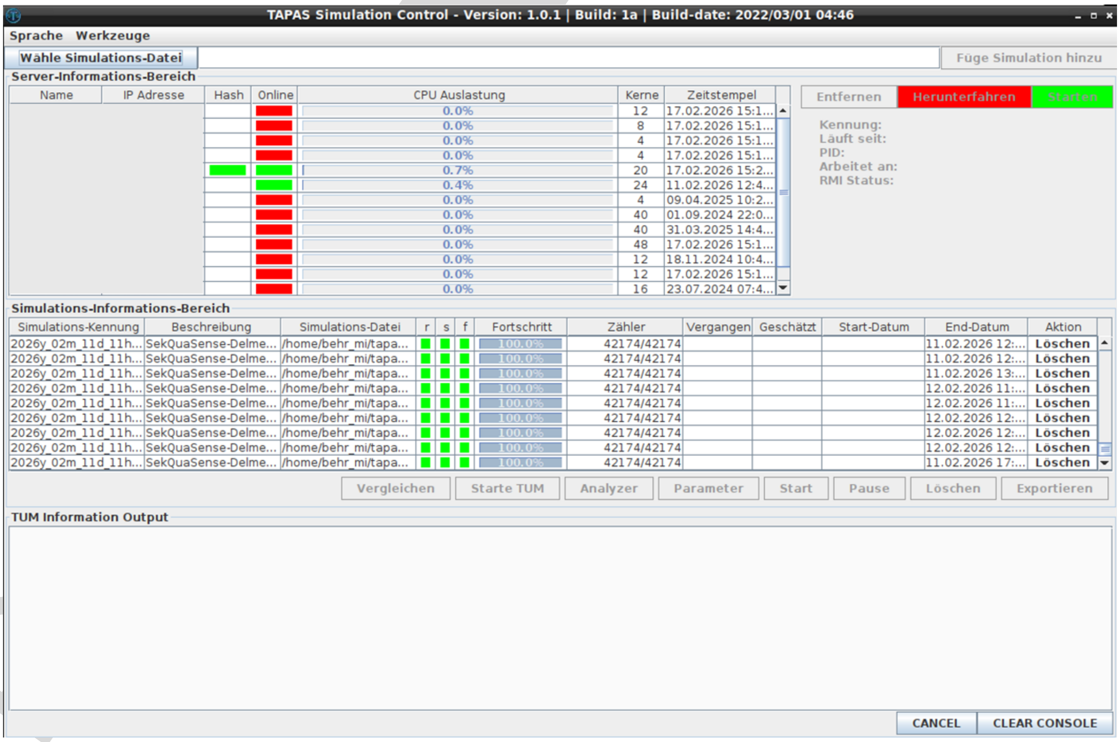


Figure 2. *Iterative TAPAS–SUMO coupling with independently (re)startable components that remain on standby pending completion of tasks by other components.*



Server-Informations-Bereich

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Simulations-Informations-Bereich

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TUM Information Output

Figure 3. *Overview of the TAPAS user interface.*

conditions, i.e., seasonal variations, as well as under various projections of the EV share into the future (see Subsec. 4.2).

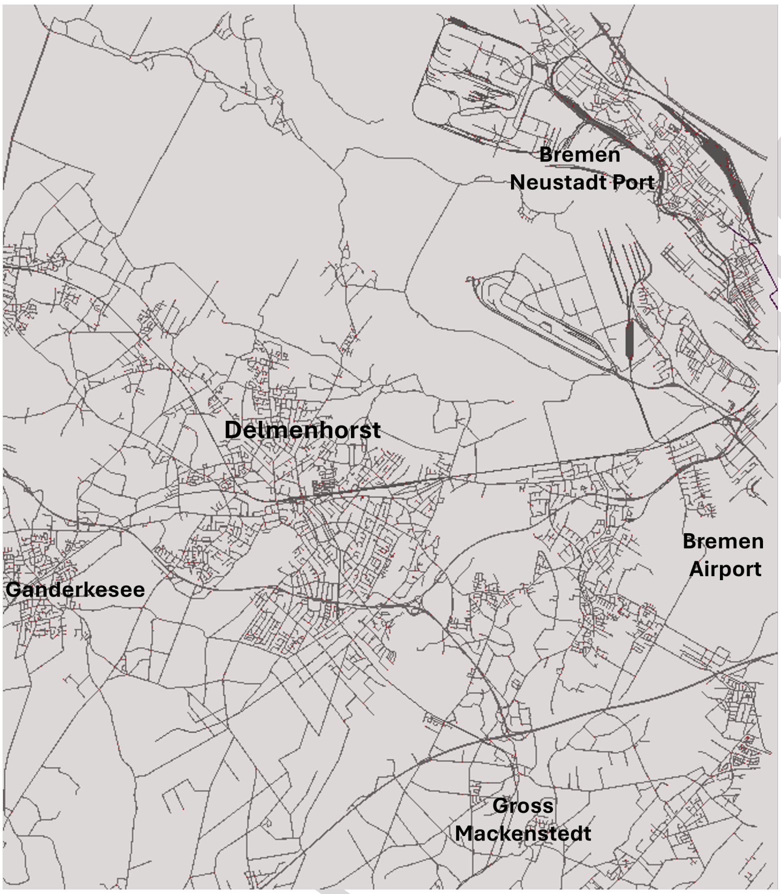

Figure 4. *Overview of the Delmenhorst simulation network.*

4.1 Traffic demand generation and calibration

Buildings, including activity locations, are extracted from OSM. The synthetic population is generated based on socio-demographic characteristics and is assigned to buildings and households according to the data provided by the German Federal Agency for Cartography and Geodesy (BKG) [6]. Activity plans are selected from “Mobilität in Deutschland” [7]. Initial estimates for travel times are computed using the open source tool *”Urban Mobility Accessibility Computer”* (UrMoAC) [8]. We account for commuter travel to the city of Bremen and Ganderkesee based on data from “Pendleratlas” [9].

Activity locations are selected using a gravity model [10], and mode choice relies on a multinomial regression model. The calibration process involves adjusting the model parameters to ensure the reproduction of real-world observed metrics. Specifically, these metrics include: 1) the average distances traveled for each trip purpose, and 2) the modal split, representing the distribution of different transportation modes used for the trips. For the traveled distance data, the “Mobilität in Städten” mobility study [11] for Delmenhorst is used as reference, while the data from the “Mobilität in Deutschland” study [7] are used for modal split. To achieve outcomes that closely mirror reality, model parameters related to the above-mentioned metrics were iteratively adjusted until the optimal alignment with observed values was achieved.

Table 1 compares the model results with the real-world data. Larger discrepancies are observed, particularly with regard to underestimation of commuting distances. We suspect that these deviations originate mainly from the spatial limitation of the study area (see Figure 4), not allowing for long distance trips. Although the main commuting routes to Bremen and Ganderkesee are explicitly modeled, this approach appears insufficient to accurately replicate the observed distances. The deviations in the modal split, e.g. the higher share of cycling, are likely a consequence of this limitation, too.

Table 1. *Comparison between estimated and real-world mobility data.*

	Real-world data	**Model**
Distances traveled (km)	**SrV 2013** [11]	**TAPAS**
Vocational training or school	3.6	3.7
Work	13.6	8.0
Shopping	3.8	3.8
Modal split (%)	**MiD 2017** [7]	**TAPAS**
Walk	18.9%	21.4%
Bicycle	12.6%	19.4%
Car	45.6%	40.1%
Car passenger	15.5%	9.6%
Public transport	7.4%	8.9%

4.2 Scenarios

The scenario framework focuses on the evolution of EV energy demand over time, 1) due to the gradual increase of the share of electric vehicles, and 2) because of seasonal variations due to temperature conditions, particularly extreme cold and heat. From the travel demand perspective, both total population and modal split are assumed to remain constant.

In total, nine scenarios are developed by combining three time periods (2025, 2030 and 2050) with three ambient temperature conditions: cold ($\sim$ -5℃), mild (15 – 22℃) and warm (30 – 40℃). The corresponding number of simulated vehicles in each scenario is indicated in Table 2; the share of EVs rises from 4% in 2025 to 20% in 2030 and then reaches 75% by 2050. The fluctuations in the number of trips are not the result of structural changes in population, modal split, or scenario assumptions, but rather stem from the stochastic nature of the demand generation process within TAPAS. As a consequence, minor year-to-year differences in total demand and trip distribution are expected and remain within a statistically reasonable range.

As the primary objective is to validate the proposed model extension while minimizing potential confounding effects, the scenario analysis focuses only on medium-sized vehicles. The MMPEVEM model [12] and the HBEFA4 model [13], embedded in SUMO, are used to calculate electric energy consumption, emissions and fuel consumption. A comprehensive description and comparative analysis of the electric energy consumption models in SUMO are provided in [14]. With the MMPEVEM model, electric energy consumption for propulsion, including overcoming road and aerodynamic resistance, as well as for on-board auxiliary systems, e.g. air conditioning and heating, can be computed. It also considers potential power losses, e.g. those arising from battery

Table 2. *Number of simulated vehicles and proportions of electric vehicles in the analyzed scenarios.*

Scenario	**Number of vehicles**	**Fraction of EVs**
2025-cold	109,701	4%
2025-mild	113,179	4%
2025-warm	112,189	4%
2030-cold	110,177	20%
2030-mild	114,287	20%
2030-warm	112,515	20%
2050-cold	110,652	75%
2050-mild	114,097	75%
2050-warm	113,260	75%

chemistry, and the energy recovered during deceleration. The ambient temperature conditions and the years in the scenarios mainly influence the values set for the model parameter "constant power intake", reflecting the average power required by heating, ventilation and air conditioning (HVAC), on-board auxiliary systems, continuous battery thermal management (heating and cooling), vehicle technology, mainly related to possible improvement on heat pump adoption and insulation, and climate change effects (milder winters and hotter summers).

The interactive effects of ambient temperature, vehicle technology and global climate on energy consumption are complex and difficult to quantify. By drawing on findings from some recent studies, including [15]–[19], the constant power intake for each scenario is assumed and shown in Table 3. It is assumed that a heat pump is employed for cabin heating and that no battery preconditioning is required, while overall power demand is expected to decrease due to continued technological advancements. Although battery heating is energy-intensive under cold conditions, warm conditions can be similarly demanding. In warm environments, active thermal management is required to prevent battery overheating, resulting in simultaneous cooling of both the cabin (HVAC) and the battery. As a result, the average power demand is comparable to or even slightly higher than that under cold conditions over the same time period. The mean value of the lower and upper bounds of the power range is used for each scenario.

Table 3. *The estimated constant power intakes in the scenarios.*

Scenario	**Power average (kW)**
2025-cold	3.6 - 4.9
2025-mild	1.5 - 1.8
2025-warm	4.4 - 5.4
2030-cold	3.3 - 4.8
2030-mild	1.4 - 1.8
2030-warm	3.9 - 4.6
2050-cold	3.0 - 4.0
2050-mild	1.3 - 1.6
2050-warm	3.4 - 4.1

4.3 Results

The maximum number of iterations for the TAPAS-SUMO iterative simulation coupling is set to 5. When considering the overall population, the distributions of the number of trips remain nearly unchanged across all iterations, for the scenario 2025-mild, where the median is 2 trips per person, the mean is 3 trips and the standard deviation is 1.4. Outliers with up to about 12–13 trips are present, but their occurrence is consistent across iterations.

In the current version of TAPAS, the trip generation, distribution, and mode choice are updated in each iteration. Individuals may therefore forgo trips or choose different destinations, activity chains, or transport modes across iterations. This makes direct person-specific comparisons across iterations challenging. Due to the aforementioned limitation, travel time improvements over the course of the iterative traffic assignment and simulation process cannot be assessed on an individual basis. Accordingly, the distributions of overall travel times, used by person-trips in TAPAS, are compared. In Figure 5, for the 2025-mild scenario, Iteration 0 represents the initial assignment, based on an empty network, and shows the highest median travel time (662 s), mean (838 s), and variability (standard deviation = 710 s), reflecting inefficient routing conditions. The corresponding travel time dispersion has reached roughly 8,000 s. From Iteration 1 onward, travel times decrease notably. The median travel time drops to 352 s and stabilizes around 333 – 334 s in Iterations 2 – 4. The mean and standard deviation also decline markedly after the first iteration and remain relatively stable in subsequent iterations, indicating that the assignment procedure quickly improves network performance and converges toward a stable traffic pattern. Such rapid convergence can be attributed mainly to the moderate traffic density in the study area and the use of mesoscopic simulation, which does not model traffic lights and traffic interactions in great detail. This result also applies to the other scenarios, as the main variation between them is the share of EVs.

Furthermore, the comparison between the EV electricity consumption on road segments under the different temperature conditions and across different years is conducted. The metric of normalized electricity consumption is used because the number of trips varies to a certain degree across the scenarios. As shown in Figure 6, the time-series electricity use closely follows daily mobility activity patterns, with a sharp increase starting around 6 - 7 o'clock and a clear peak in the late afternoon, around 16 - 17 o'clock. After 18 -19 o'clock electricity consumption declined rapidly. The increase in electricity consumption corresponds to the EV share specified in each scenario. The relatively marginal difference in electricity consumption between winter and summer conditions can be explained by the modeling approach and related parameter settings mentioned in Section 4.2. In SUMO, energy consumption is primarily simulated during vehicle movement, whereas both hot and cold ambient conditions increase auxiliary energy demand. Since summers become hotter and winters milder over time, the increased cooling demands in summer are largely balanced by reduced heating needs in winter. This offset leads to comparatively small differences in total electricity consumption during vehicle operation in the future. Cold-start energy consumption is not yet included in the model, which would increase winter demand. In high electrification scenarios (2050), electricity demand could substantially increase pressure on distribution grids, particularly during late afternoon hours.

In addition, the changes in CO_2 emissions due to different EV shares across the scenarios are also compared and illustrated in Figure 7. Again, like electricity con-

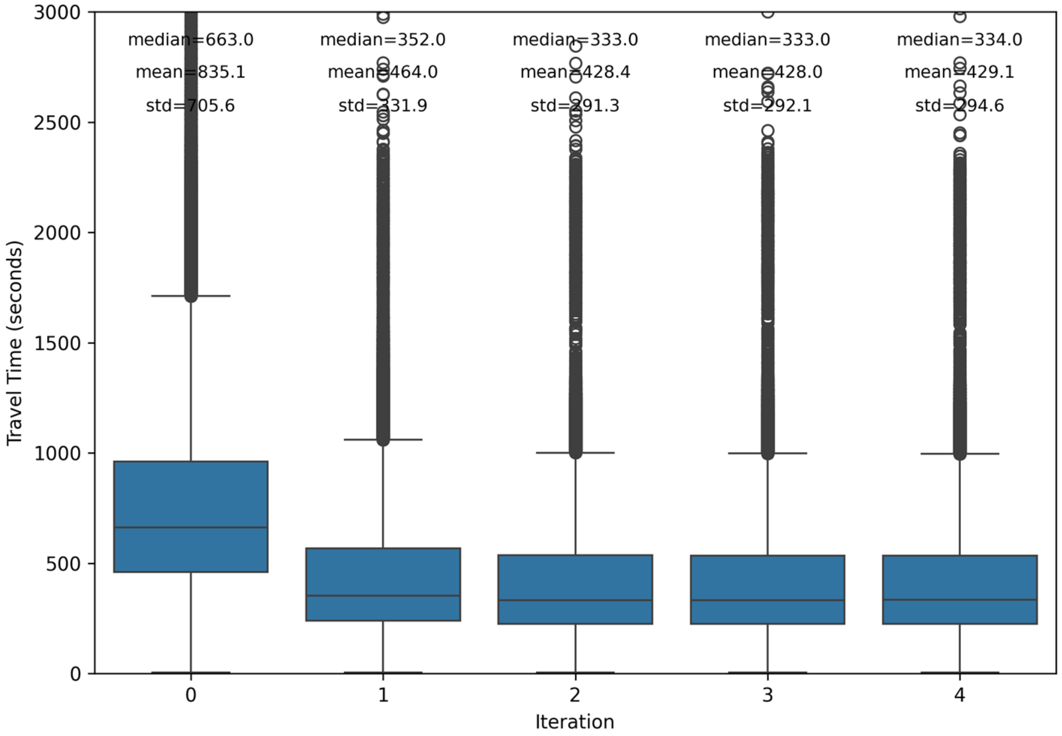

Figure 5. *The distribution of travel times used in TAPAS over iterations in Scenario 2025-mild.*

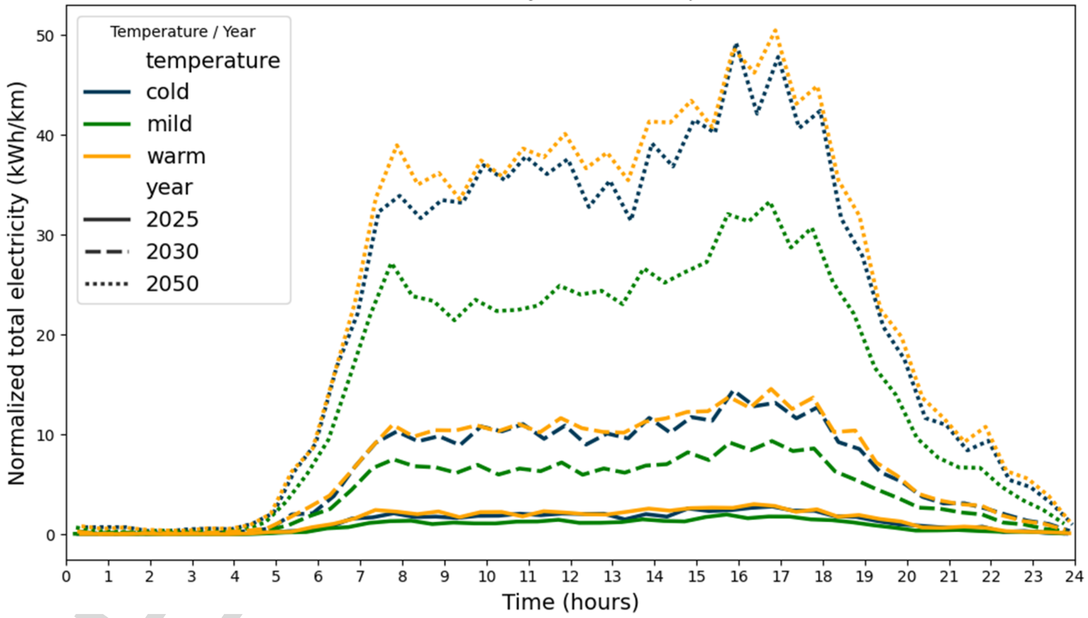

Figure 6. *Comparison of time-series electricity consumption across all scenarios.*

sumption, the normalized metric is used for CO_2 as well. The emission pattern also closely follows the traffic demand pattern with morning and afternoon peaks. Over time, technological advancements and fleet changes significantly reduce total emissions. In contrast, the impact of climate-related temperature variations on emissions is relatively minor, which is mainly due to the applied modeling approach. In the emission models HBEFA and PHEMlight, emission classes are not further subdivided by different temperature conditions. As a result, the corresponding effects cannot be captured in the simulation.

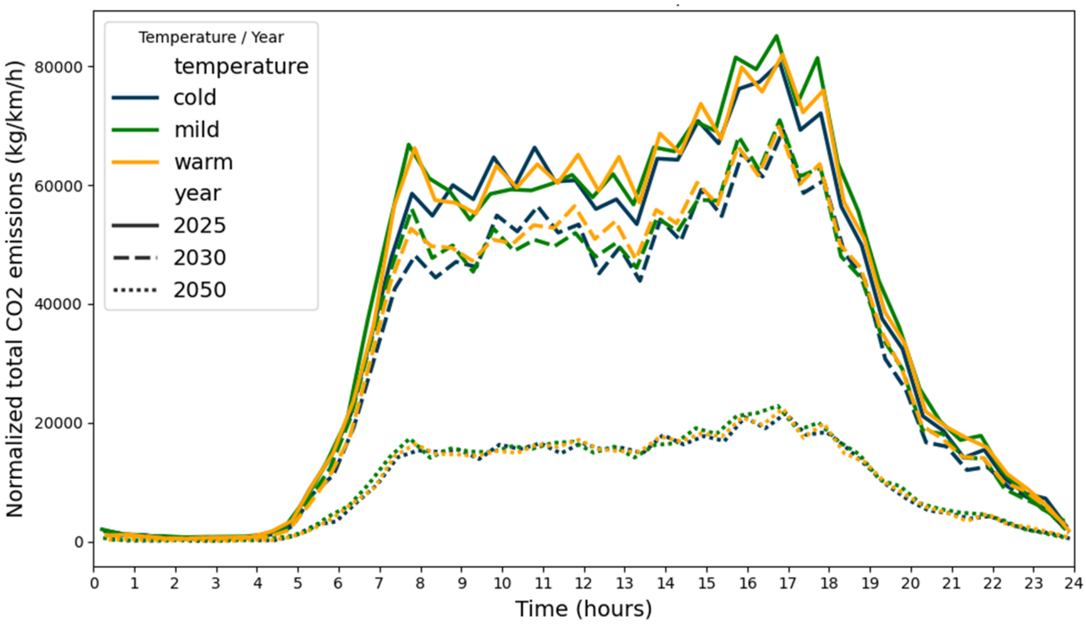

Figure 7. *Comparison of time-series CO_2 emissions across all scenarios.*

5. Remarks and perspectives

This paper has extended the TSC framework to incorporate not only travel time but also environmental and energy-related metrics, thereby providing the opportunity to evaluate environmentally conscious traffic management strategies within the transport planning process. The proposed extension is demonstrated through a selected case study, which further examined the potential impacts of temperature variations and changes in EV fleet composition on electricity consumption and emissions.

The energy and MMPEVEM models embedded in SUMO mainly focus on power consumption associated with vehicle motion and the continuous energy demand of auxiliary systems during operation. The energy model applies basic parameters to calculate energy consumption and the state of charge (SoC). In contrast, the MMPEVEM model incorporates a broader range of battery characteristics, such as internal battery resistance, nominal battery voltage, motor power losses, and losses due to battery chemical reactions. Propulsion efficiency and recuperation efficiency are also taken into account, but in a more physically detailed manner, using additional parameters such as gear efficiency, maximum torque, and maximum recuperation torque and power.

However, several battery characteristics are not yet considered. For example, battery aging and degradation are not explicitly modeled, which may lead to an underestimation of long-term temperature effects on energy consumption. Moreover, the influence of ambient temperature on increased energy demand for propulsion, caused by factors such as higher mechanical friction, increased rolling resistance, reduced regenerative braking efficiency, battery heating losses in cold conditions, and overheating of powertrain components in warm conditions, is not yet accounted for. Currently, temperature influences only the NOx calculation within the PHEMlight5 model. Further corresponding enhancements to the energy models in SUMO can help achieve a more comprehensive assessment of electricity consumption. Moreover, the constant power intake component of SUMO's electric energy consumption models accounts only for traction-related electricity consumption during driving and neglects battery heating energy during cold starts. With current technological standard, battery preconditioning can typically last 20 – 45 minutes or even longer depending on ambient conditions. Incorporating this aspect into SUMO's models would also allow for more accurate calculation of energy consumption, better estimate of charging demand and improved simulation of charging behaviors.

With regard to the sector coupling between energy grid and transportation system, the locations and activity chains of TAPAS trips are spatially diffused and disconnected in SUMO. Accordingly, mapping the simulated result of each agent back to their original locations/buildings can facilitate applications such as district energy management and district emission control.

Finally, the generated metric matrices for travel times, emissions and energy can already be differentiated by vehicle type. However they cover the entire analysis period and are not yet time-dependent. Extending the matrices to incorporate temporal resolution would enable more informed choices regarding destination, departure time, trip chain and modal mode. As TAPAS2 is currently under implementation and testing. It is necessary to assess whether adjustments or more extensions are required to ensure that the existing TSC framework remains compatible with TAPAS2.

Data availability statement

The data are currently accessible only internally and will be made available upon request.

Underlying and related material

N/A

Author contributions

- Conceptualization: Y.-P. Flötteröd, M. Behrisch, K. Heidemann
- Data curation: K. Heidemann, Y.-P. Flötteröd
- Formal Analysis: Y.-P. Flötteröd, K. Heidemann
- Investigation: Y.-P. Flötteröd, M. Behrisch
- Methodology: Y.-P. Flötteröd, M. Behrisch, K. Heidemann
- Software: M. Behrisch, K. Heidemann
- Validation: Y.-P. Flötteröd, M. Behrisch, K. Heidemann
- Visualization: Y.-P. Flötteröd
- Writing – original draft: Y.-P. Flötteröd, K. Heidemann, M. Behrisch
- Writing – review and editing: Y.-P. Flötteröd, K. Heidemann, M. Behrisch

Competing interests

The authors declare that they have no competing interests.

Funding

This research work was supported by funding from the DLR projects SekQuaSens^3 and MoDa.

Acknowledgements

We gratefully acknowledge the valuable discussions on TAPAS–SUMO coupling provided by our colleagues, Alain Schengen and Matthias Heinrichs, which significantly strengthened this work.

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