A traffic-augmented macroscopic model of electric vehicle energy consumption

Marcello Montanino [a, *], Ilaria Natale [a], Chiara Fiori [b], Vincenzo Punzo [a]

[a] Department of Civil, Environmental and Architectural Engineering, Università degli Studi di Napoli Federico II, Napoli, Italy

[b] Department of Civil Engineering, Università degli Studi di Salerno, Fisciano, Italy

[*] Corresponding Author: Ph.: +39 081 7683770

E-mail addresses:
marcello.montanino@unina.it
ilaria.natale@unina.it
cfiori@unisa.it
vincenzo.punzo@unina.it

ABSTRACT

This paper shows that the assumption of constant link speed to predict energy consumption in electric vehicle routing optimisation problem significantly underestimates energy consumption. An analytical investigation proves a dependency between energy consumption and vehicle acceleration variance, while a Monte Carlo simulation quantifies the bias from ignoring this factor, incorporating variability in speed and slope profiles through novel algorithms. A global sensitivity analysis identifies acceleration variance as the most critical input factor affecting prediction accuracy. To correct the bias, a macroscopic energy consumption model is developed which incorporates speed variance as an explanatory variable and links it to measurable macroscopic traffic characteristics, such as link density and flow. The model is validated using laboratory and experimental data, showing improved accuracy compared to the base macroscopic model. These results highlight the importance of accounting for driving and traffic dynamics in energy consumption modeling for electric vehicles.

1. Introduction

Accurate modelling of electric vehicles energy consumption is essential to solve an electric vehicle routing optimization problem. In such problem, the vehicle energy consumption on each network segment must be known in advance to design optimal routes, charging locations and schedules. In the field literature, energy consumption predictions are typically provided by macroscopic models which return vehicle energy consumption on each segment as a function of average inputs, such as average speed and slope on that segment (Othman et al.,2019).

In particular, three macroscopic modelling approaches to simulate energy consumption have been adopted so far: 1- assumed to be proportional to the link length through a constant coefficient (e.g., Wen et al.,2016; Schiffer and Walther,2017; Bongiovanni et al.,2019; Lian et al.,2023; Su et al.,2023); 2- simulated by a macroscopic data-driven model (e.g., Yi et al.,2018; Zhang et al.,2020; Pan et al.,2023); 3- simulated via a simplified version of a microscopic power-based model (e.g., Masmoudi et al.,2018; Basso et al.,2019; Pelletier et al.,2019; Sayarshad et al.,2020; Ma et al.,2021; Avishan et al.,2023). Generally, a microscopic power-based model gives a vehicle energy consumption function of vehicle speed profile, road slope profile, vehicle characteristics and environmental conditions, but since the actual speed profile is unknown when solving a vehicle routing problem, a constant link speed assumption is made to derive a macroscopic energy consumption model.

All the proposed approaches suffer from significant limitations that may jeopardise the robustness of design service operations. While the first approach is unable to adequately describe the variability of consumption across the network, the others lack transferability to different case studies and suffer from potential bias in consumption prediction due to overly simplistic and unrealistic assumptions. In particular, the constant link speed assumption adopted in the last two approaches compromises the prediction accuracy, as it implies neglecting driving dynamics, i.e., the acceleration and deceleration phases.

Therefore, to address limitations of current modelling approaches, several contributions are provided in this work:

1. Mathematical quantification of the inaccuracy resulting from the constant link speed assumption.
2. Generalisation of the theoretical results through a simulation experiment and identification of the model inputs that most affect the variance of the output (i.e. of the SEC error) by means of a variance-based global sensitivity analysis.
3. Proposal of two algorithms to generate speed and slope profiles in a way that emulates their real-world variability.
4. Proposal of an augmented macroscopic energy consumption model whose aim is to eliminate the bias of macroscopic models, relative to microscopic ones.
5. Validation of the augmented model against 1Hz real-world energy consumption data of a fleet of electric minivans, as collected by Fiori and Marzano (2018).

2. Theoretical analysis

In this section the relationship between energy consumption and the standard deviation of vehicle acceleration σ_a is examined. Analysing this aspect is necessary to understand the impact of a constant link speed assumption on energy consumption prediction. The analysis is performed through mathematical steps, starting with a normally distributed acceleration signal $\{a_t\}$, i.e., $a_t \sim i.i.d. \mathcal{N}(0, \sigma_a^2), \forall t \in \{0,1,2,\dots,T\}$, where $T = \mathrm{T}/\Delta t$, T is the signal duration, and Δt is a finite time step. The speed signal $\{v_t\}$ results from the integral of the acceleration signal.

According to Newton's second law of motion, the traction force applied to the vehicle wheels is composed of an inertial component, due to the applied acceleration signal, and a resistance component, due to motion resistances, customarily modelled as a quadratic function of the instantaneous speed, $r_t = \sum_{j=0}^{2} \beta_j v_t^j$.

The power signal results from the element-wise product of the traction force signal and the speed signal, while the total energy consumption results by the integral of the power signal over time.

$$EC_T = EC_T^{in} + EC_T^{r} = v_0 T a \Delta t + k a^2 \Delta t^2 + T \Delta t v_0 \sum_{j=0}^{2} \beta_j \sum_{t=1}^{T} \left(\sum_{i=1}^{t} a_i \Delta t\text{^}2 \right)^{j+1} \tag{1}$$

where $k = 0.5T(T+1)$. After several mathematical steps and considering the expected value of the total vehicle energy consumption, the result shows that the expected value of the total energy consumption is a function of σ_a^2:

$$\mathrm{E}[EC_T] = \mathrm{E}\left[EC_T^{in}\right] + \mathrm{E}[EC_T^{r}] = k\sigma_a^2 \Delta t^2 + T\Delta t v_0 \sum_{j=0}^{2} \beta_j v_0^j + \Phi(\sigma_a^4) \tag{2}$$

If speed dynamics are neglected, i.e., $\sigma_a = 0$, (2) becomes:

$$\mathrm{E}[EC_T]_{\sigma_a=0} = \mathrm{E}\left[EC_T^{in}\right]_{\sigma_a=0} + \mathrm{E}[EC_T^{r}]_{\sigma_a=0} = T\Delta t v_0 \sum_{j=0}^{2} \beta_j v_0^j \tag{3}$$

In conclusion, assuming a Gaussian white noise acceleration signal, the percentage error, i.e. the consumption underestimation of assuming $\sigma_a = 0$, is:

$$\frac{\mathrm{E}[EC_T]_{\sigma_a=0} - \mathrm{E}[EC_T]}{\mathrm{E}[EC_T]} = -\frac{k\sigma_a^2 \Delta t^2 + \Phi(\sigma_a^4)}{T\Delta t v_0 \sum_{j=0}^{2} \beta_j v_0^j + k\sigma_a^2 \Delta t^2 + \Phi(\sigma_a^4)} \tag{4}$$

which is not negligible, especially in congested traffic. For example, for a 5.5 ton electric minivan, with a payload of 2.5 ton, an average speed v_0 = 10 m/s, a duration T = 100 s, an acceleration variance σ_a^2 = 2 m^2/s^4, road load coefficients β_0 = 0.0787, β_1 = 5.6·10-4, β_2 = 0.5441, the vehicle energy consumption underestimation ranges from 79% for a constant regenerative braking efficiency equal to 0.3, to 35%, for an efficiency equal to 0.9.

3. Methodological framework

The theoretical findings presented above have been generalised through simulation. To quantify the degree of underestimation of macroscopic model predictions, the consumption distributions by a macroscopic model and its underlying microscopic counterpart are compared under uncertain model parameters, and uncertain inputs (speed and slope profiles).

The impact on the variability of model prediction errors of any uncertain inputs or parameters is quantified through a sensitivity analysis. Results are relevant to identify what inputs or parameters are most influential on the mentioned prediction error. This analysis significantly extends the study by Fiori et al. (2021), also considering uncertain speed and slope profiles.

The whole study is built on the methodology depicted in Figure 1.

In the methodology, non-parametric inputs and model parameters are sampled according to the Sobol' design in a quasi-random Monte Carlo setting, from uniform independent distributions (Table 1 lists all the uncertain factors with the selected lower and upper bounds of each distribution). The speed and slope profiles are then generated through algorithms devised to generate profiles in a way which emulate their real-world variability by sampling values of μ_v, σ_a, μ_θ, σ_θ and L.

The speed profile generation algorithm aims to generate a speed profile with a mean μ_v, a zero-mean first derivative ($\mu_a = 0$) and a given σ_a. Applying the algorithm in a Monte Carlo framework produces a population of speed profiles that incorporates the sought variability of μ_v and σ_a. The slope profile generation objective is to smooth a slope profile $\theta\big(x(t)\big), t \in [0, T]$ resulting from a Gaussian process with mean μ_θ and standard deviation σ_θ (being $x(t)$ the longitudinal vehicle position), without altering the slope values, thus preserving μ_θ and σ_θ. Algorithms are not provided for brevity.

For each generated set of input profiles and parameter values, the microscopic power-based model by Fiori and Marzano (2018) and its macroscopic model counterpart are applied to simulate vehicle energy consumption. The result of such uncertainty propagation is a distribution of simulated energy consumption.

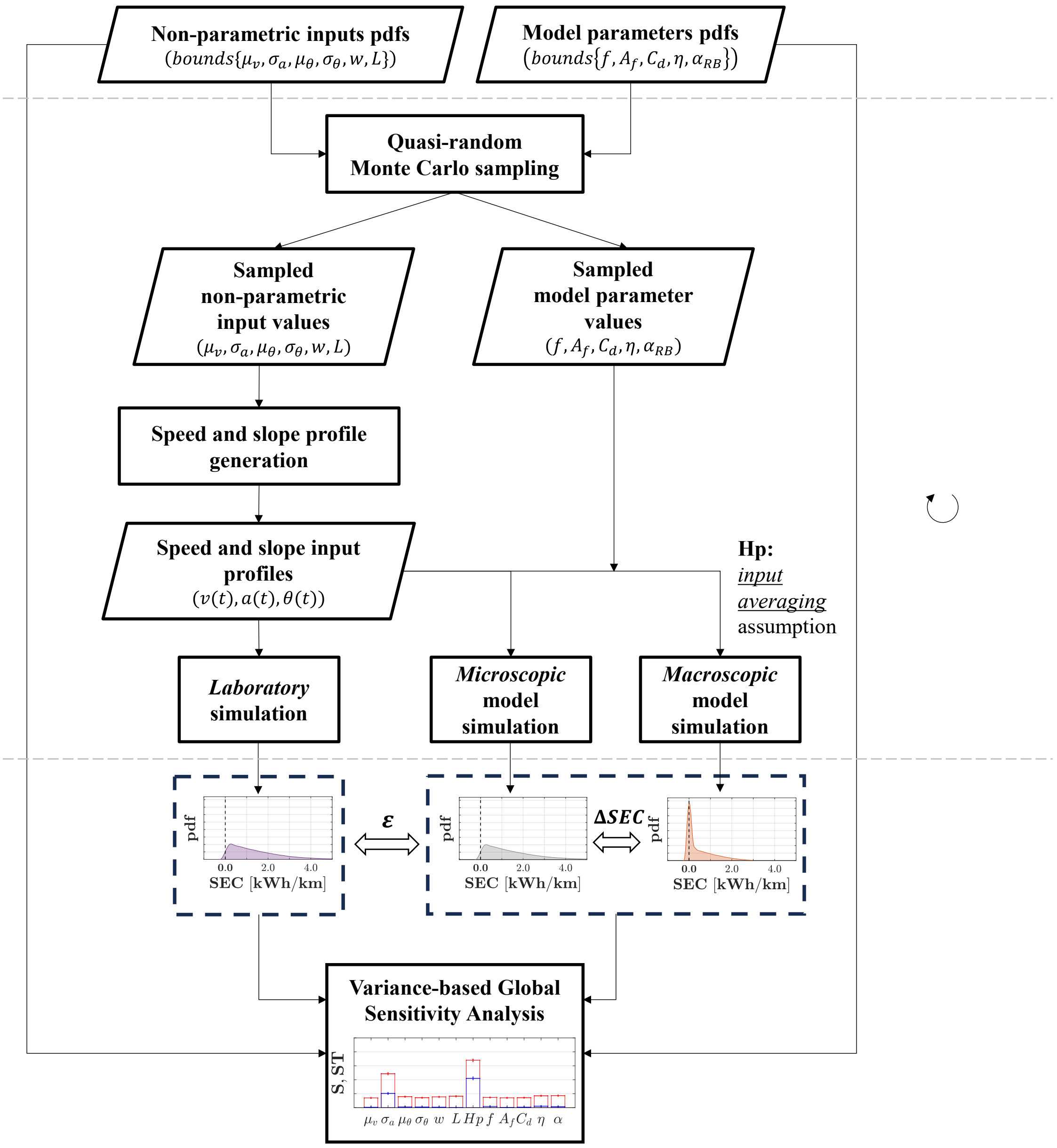

Figure 1 – Methodological framework.

To investigate the impact of the input averaging assumption of the macroscopic model on the variability of the model prediction error, a further uncertain factor is included in the experimental design, a Boolean variable whose values correspond to the model structure – microscopic or macroscopic – applied in SEC computation.

Accordingly, a total number of 1,835,008 model simulations were run to explore the impact of the uncertain factors on consumption error variability and compute the sensitivity indices (1,835,008 = $2^{17} \cdot (K+2)$, where K=12 is the total number of uncertain factors).

To study the accuracy of energy consumption prediction, the difference between a simulated SEC and a laboratory SEC is used as a measure of discrepancy (see ε in Figure 1). Such laboratory consumption is computed by applying the model in Genikomsakis and Mitrentsis (2017) with calibrated parameters.

A variance-based global sensitivity analysis is then applied to disentangle the impact of the two sources of input uncertainty (parameters and speed/slope profiles) on model error variability. This analysis provides also an evaluation of the impact of the input averaging assumption in macroscopic modelling.

Table 1 – List of uncertain factors and corresponding lower (LB) and upper (UB) bounds of uniform distributions.

Non-parametric inputs	**LB**	**UB**
Mean speed, μ_v [km/h]	5.0	130.0
Acceleration standard deviation, σ_a [m/s^2]	0.0	3.50
Mean slope, μ_θ	-0.05	0.05
Slope standard deviation, σ_θ	0.00	0.05
Vehicle load, w [kg]	0	2500
Link length, L [m]	100	2000
Model parameters	**LB**	**UB**
Rolling resistance parameter, f	0.005	0.020
Frontal section area, A_f [m^2]	0.70	0.90
Drag coefficient, C_d	0.10	0.50
Powertrain efficiency, η	0.70	0.90
Regenerative braking coefficient, α	0.00	5.00

Based on a Sobol's variance decomposition (Sobol,2001), the first-order sensitivity index, S_i, and the total sensitivity index, ST_i, of each input factor i, are computed. These indices describe the contribution to the unconditional error variance of a factor, both by the factor alone (first-order effect), and by the factor in interaction with all the others (total effect).

3.1. Uncertainty and sensitivity analysis results

The scatter plots in Figure 2 show the simulation errors of the macroscopic and microscopic models. For each simulation i, the error ε_i has been computed as follows:

$$\varepsilon_i = \frac{EC_{model}(\boldsymbol{u}_i, \boldsymbol{\beta}_i) - EC_{synthetic}(\boldsymbol{u}_i)}{L_i} \quad (5)$$

where EC_{model} is the simulated total energy consumption on the link of length L_i by the microscopic/macroscopic model fed with the model parameters $\boldsymbol{\beta}_i$ and the speed/slope profiles generated by the proposed algorithms according to the non-parametric inputs $\boldsymbol{u}_i$; and $EC_{synthetic}$ is the laboratory energy consumption computed by means of the reference model fed with the same input profiles. A positive error means that the model overestimates consumption, a negative value implying an underestimation.

In the scatter plots, the simulation errors are plotted against each analysis factor. Results show that the macroscopic model significantly underestimates consumption in most of the simulations, see the bottom rightmost plot. Conversely, the microscopic model has the same probability of overestimating or underestimating consumption. Given a factor, the higher the variance of light grey and yellow points over that factor, the higher the influence of that factor on the variation of the average SEC error of microscopic and macroscopic model, respectively.

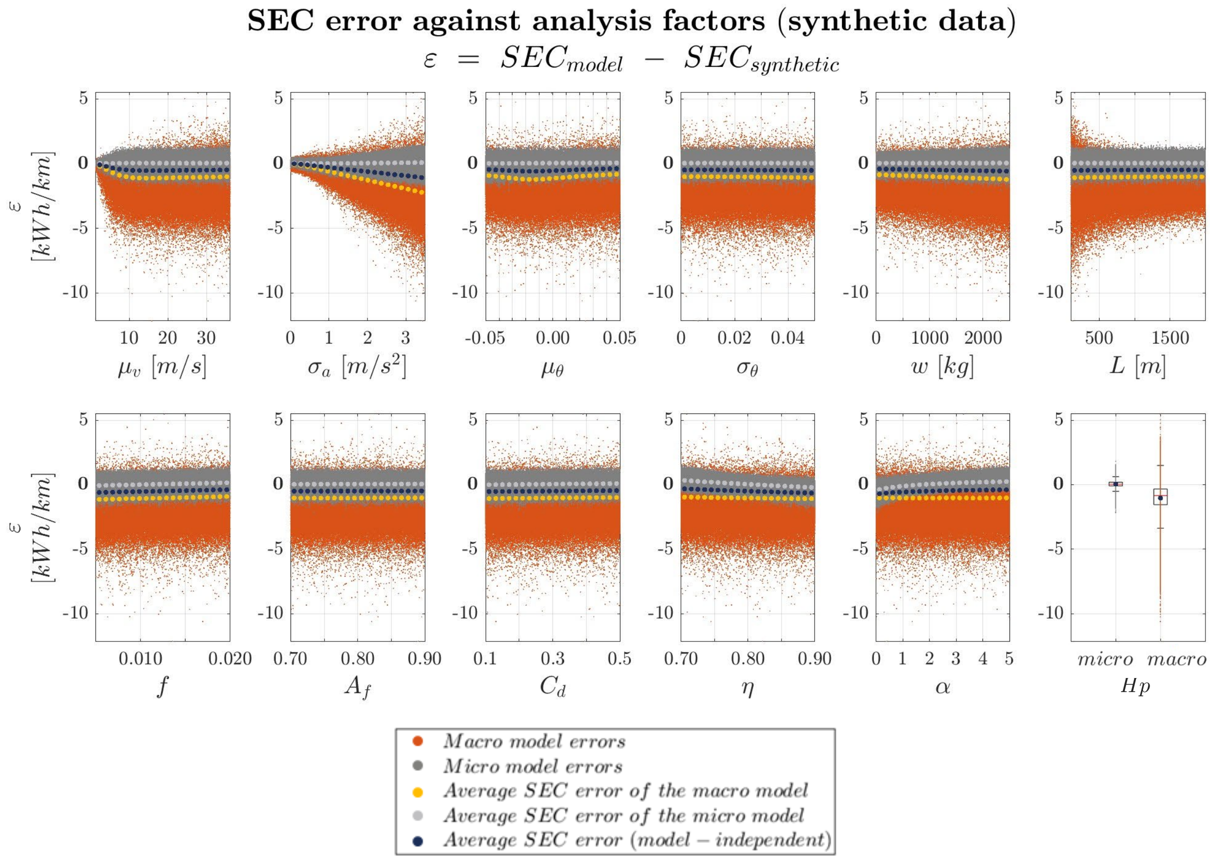

Figure 2 – Scatter plots of the microscopic and macroscopic models *SEC errors* relative to the laboratory ground-truth.

Clearly, σ_a and the modelling assumption *Hp* are the two factors with the highest first-order effect on the error variance (see the variance of the *blue* points). The first-order impact of σ_a on the error variance materializes only when the macroscopic model is used and this consideration suggests that the modelling bias of the macroscopic model is an increasing function of σ_a.Therefore, neglecting the variability of the input speed profile significantly affects model accuracy.

For the microscopic model, despite σ_a has no impact at the first-order on the model error variance, the conical pattern of the *dark grey* points suggests that σ_a still retains some influence on the error variance, due to the interaction with other factors. In general, interaction effects are captured by the total sensitivity index ST_i that, for any factor i, quantifies the total contribution of that factor to the output variance (in this case, to the SEC error variance).

First-order and total sensitivity indices are reported in Figure 3 for all factors. Sensitivity indices confirm that all factors but σ_a and *Hp*, have an impact on the error variance only in interaction with other factors. Therefore, σ_a and *Hp* are the only factors that have a first-order impact on the SEC error variance, and when considering also the interaction effects (see the red bars) they are by far the factors that mostly influence the SEC error variance and the bias.

In conclusion, as macroscopic models neglect traffic dynamics by imposing a constant speed profile, i.e., $\sigma_a = 0$, and this causes a significant bias on consumption, and much higher errors than considering $\sigma_a \neq 0$, the robustness of any service based on consumption predictions by a macroscopic model is seriously questioned. The goal of the next section is to remedy this modelling deficiency.

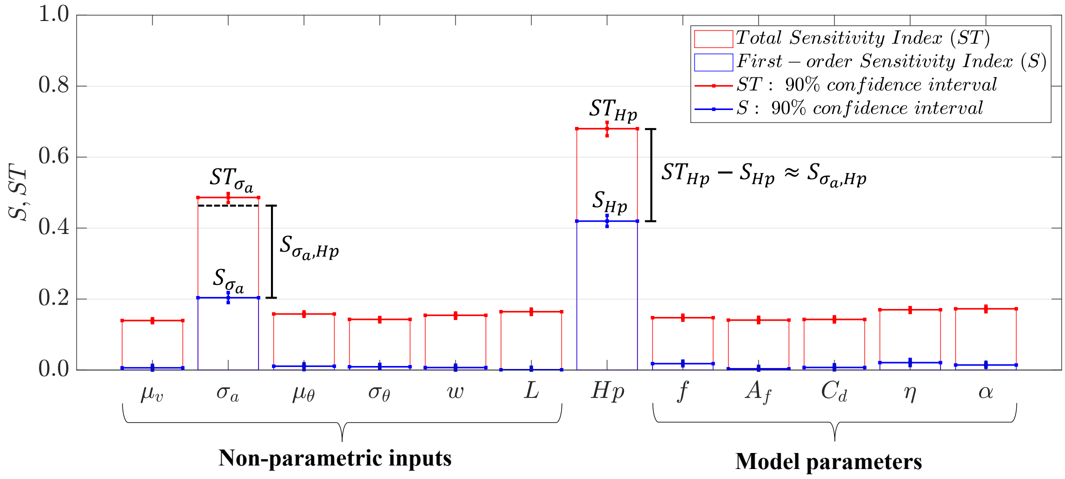

Figure 3 – First-order and total sensitivity indices of the analysis factors.

4. Traffic-augmented macroscopic model

A model augmentation, guided by the uncertainty and sensitivity analyses, is performed to correct the prediction bias of macroscopic energy consumption models of electric vehicles, i.e., the underestimation of consumption. As such bias is primarily caused by neglecting traffic dynamics, a model component is added to explain the 'average' variability of consumption due to prevailing traffic conditions.

To make the macroscopic model unbiased (relative to the microscopic one), a model component ε equal to the bias is added to the model itself (Eq.(6)). To find ε expression, ΔSEC is plotted against the non-parametric input factors $\boldsymbol{u_i}$, and σ_v (Figure 4).

$$SEC_{macro}^{aug} = SEC_{macro} + \varepsilon \tag{6}$$

In accordance with the theoretical findings, the scatter plots highlight that σ_a explains the systematic consumption underestimation of the macroscopic model. As expected, being σ_v directly linked to σ_a, also this factor significantly affects ΔSEC. The best fitting curves of ΔSEC for σ_a or σ_v and the two expressions for the model components are depicted in the figure, respectively, in green and blue.

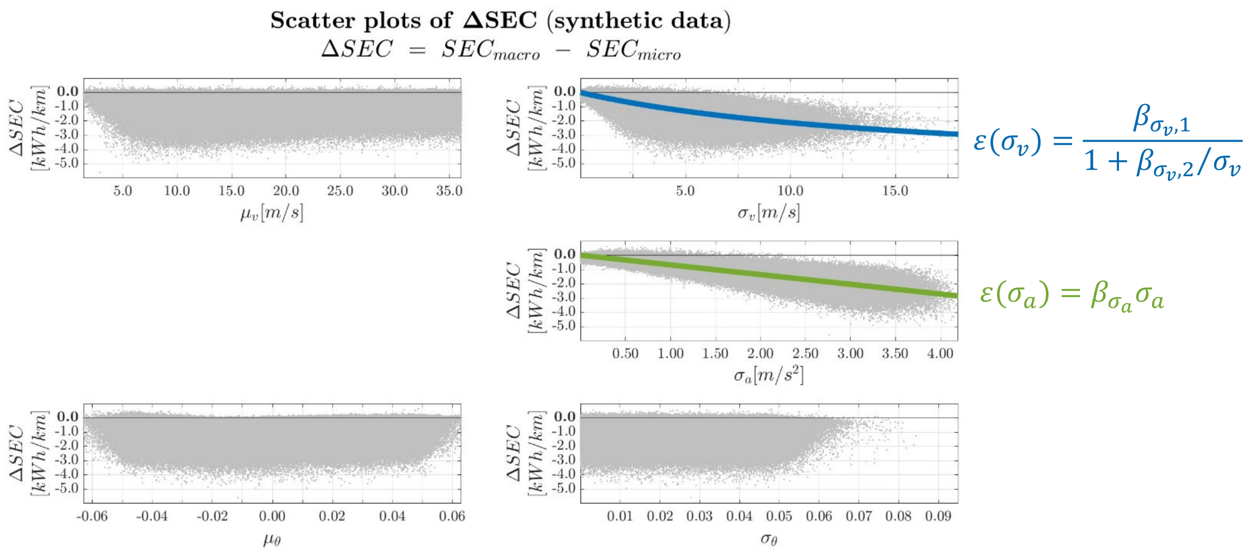

Figure 4 – Scatter plots of the difference between the SEC values returned by the macroscopic and microscopic models, relative to non-parametric model inputs.

Figure 5 depicts the distributions of ΔSEC returned by the base macroscopic model (orange curve), and by the two augmented models. The negative bias of the macroscopic model is corrected by both the proposed models.

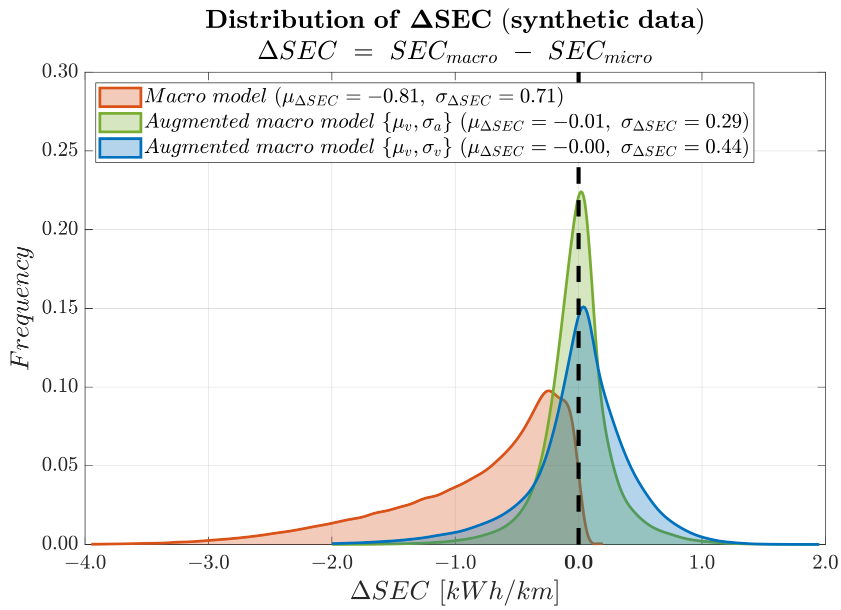

Figure 5 – ΔSEC distributions of the macroscopic model (orange), the σ_a-based (green) and the σ_v-based (blue) augmented models.

Among the proposed augmented models, the σ_a-based formulation is the best but is hardly applicable as vehicle accelerations are not usually available. On the contrary, there exists a relationship among σ_v and the traffic density, k, and the flow, q, on a link (measurable macroscopic traffic characteristics). Figure 6 shows the relationship among these quantities obtained by processing the reconstructed NGSIM I-80 vehicle trajectory dataset.

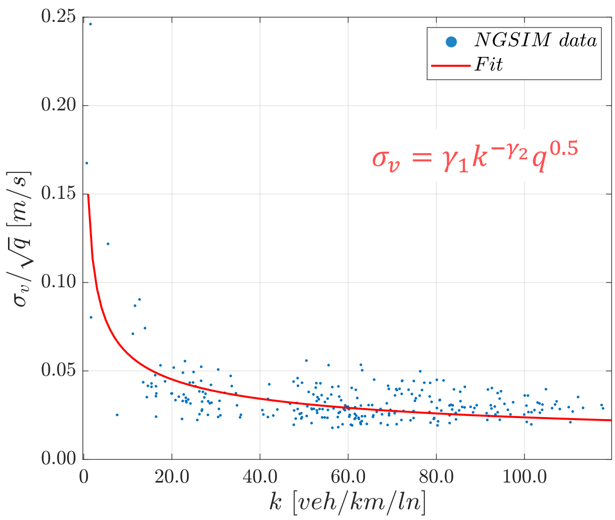

Figure 6 – Empirical relationship among σ_v, k and q, in the reconstructed NGSIM I-80 vehicle trajectory data.

By considering this relationship, we obtain:

$$SEC_{macro}^{aug(k,q)} = SEC_{macro} + \varepsilon(k,q) = SEC_{macro} + \frac{\beta_{\sigma_v,1}}{1+\beta_{\sigma_v,2}/(\gamma_1 k^{-\gamma_2} q^{0.5})} \quad (7)$$

Eq.(7) depicts the energy consumption of an electric vehicle in response to prevailing traffic conditions, and this augmented version of macroscopic energy consumption model is implementable in real-world because it only depends on measurable macroscopic traffic characteristics.

The augmented model is validated using data from Fiori and Marzano (2018). Each trajectory was segmented in elements of different lengths and the results, depicted in Figure 7, show that the accuracy of the augmented macroscopic model is very close to that of the microscopic model, regardless of link length.

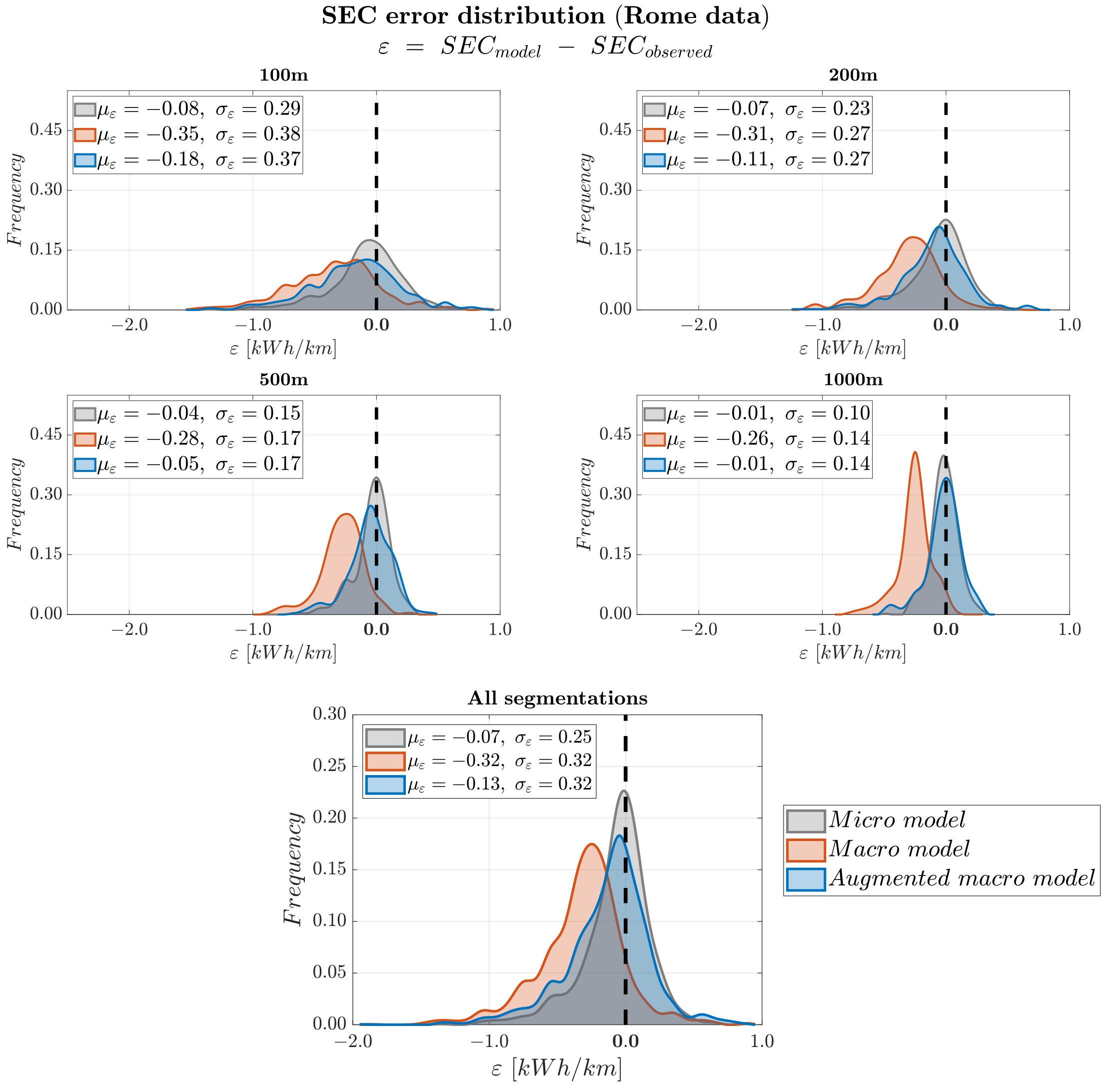

Figure 7 – SEC error distributions relative to the experimental data.

5. Conclusion

Macroscopic energy consumption models are crucial for solving electric vehicle routing optimization problem, but they face limitations that affect prediction accuracy. A theoretical analysis demonstrated that the common assumption of constant link speed significantly underestimates energy consumption, due to the dependency of vehicle energy consumption on acceleration variance, which increases with traffic congestion.

These theoretical results are validated through simulations that quantify the impact of input uncertainties (i.e., speed and slope profiles) on prediction accuracy. To this aim, two algorithms are devised to generate speed and slope profiles in order to emulate their real-world variability. Variance-based sensitivity analysis revealed that the variability of speed profiles - namely σ_v and σ_a – is mainly responsible for consumption variability. Ignoring traffic dynamics results in biased predictions.

To increase the macroscopic models accuracy, a regression component (based on σ_v or σ_a) that corrects the underestimation by incorporating the effects of traffic dynamics is added to the model. Furthermore, the link between standard deviation of vehicle speed and the density and flow of a link resulted in the additional term being expressed as a function of only measurable macroscopic traffic characteristics, making the model easily implementable in real-world applications. Validation with actual data showed that the augmented macroscopic model accuracy is always close to that of microscopic model, regardless of link length.

REFERENCES

Avishan,F.,Yanıkoğlu,İ.,Alwesabi,Y.,2023.Electric bus fleet scheduling under travel time and energy consumption uncertainty. Transportation Research Part C:Emerging Technologies,156,104357.

Basso,R.,Kulcsár,B.,Egardt,B.,Lindroth,P.,Sanchez-Diaz,I.,2019.Energy consumption estimation integrated into the electric vehicle routing problem. Transportation Research Part D:Transport and Environment,69,141-167.

Bongiovanni,C.,Kaspi,M.,Geroliminis,N.,2019.The electric autonomous dial-a-ride problem. Transportation Research Part B:Methodological,122,436-456.

Fiori,C.,Marzano,M.,2018.Modelling energy consumption of electric freight vehicles in urban pickup/delivery operations: analysis and estimation on a real-world dataset. Transportation Research Part D:Transport and Environment,65,658-673.

Fiori,C.,Marzano,V.,Punzo,V.,Montanino,M.,2021.Energy Consumption Modeling in Presence of Uncertainty. IEEE Transactions on Intelligent Transportation Systems,22(10).

Genikomsakis,K.N.,Mitrentsis,G.,2017.A computationally efficient simulation model for estimating energy consumption of electric vehicles in the context of route planning applications. Transportation Research Part D:Transport and Environment,50,98-118.

Lian,Y.,Lucas,F.,Sörensen,K.,2023. The electric on-demand bus routing problem with partial charging and nonlinear function. Transportation Research Part C:Emerging Technologies,157,104368.

Ma,B.,Hu,D.,Chen,X.,Wang,Y.,Wu,X.,2021.The vehicle routing problem with speed optimization for shared autonomous electric vehicles service. Computers & Industrial Engineering,161,107614.

Masmoudi,M.A.,Hosny,M.,Demir,E.,Genikomsakis,K.N.,Cheikhrouhou,N.,2018.The dial-a-ride problem with electric vehicles and battery swapping stations. Transportation Research Part E:Logistics and Transportation Review,118,392-420.

Othman,B.,DeNunzio,G.DiDomenico,D.,Canudas-de-Wit,C.,2019.Ecological traffic management: A review of the modeling and control strategies for improving environmental sustainability of road transportation. Annual Reviews in Control,48,292-311.

Pan,Y.,Fang,W.,Zhang,W.,2023.Development of an energy consumption prediction model for battery electric vehicles in real-world driving:A combined approach of short-trip segment division and deep learning. Journal of Cleaner Production,400,136742.

Pelletier,S.,Jabali,O.,Laporte,G.,2019.The electric vehicle routing problem with energy consumption uncertainty. Transportation Research Part B:Methodological,126,225-255.

Sayarshad,H.R.,Mahmoodian,V.,Gao,H.O.,2020.Non-myopic dynamic routing of electric taxis with battery swapping stations. Sustainable Cities and Society,57,102113.

Schiffer,M.,Walther,G.,2017.The electric location routing problem with time windows and partial recharging. European Journal of Operational Research,260(3),995-1013.

Sobol',I.M.,2001.Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Mathematics and Computers in Simulation,55,271–280.

Su,Y.,Dupin,N.,Puchinger,J.,2023.A deterministic annealing local search for the electric autonomous dial-a-ride problem. European Journal of Operational Research,309(3),1091-1111.

Wen,M.,Linde,E.,Ropke,S.,Mirchandani,P.,Larsenet,A.,2016.An adaptive large neighbourhood search heuristic for the Electric Vehicle Scheduling Problem. Computers & Operations Research,76,73-83.

Yi,Z.,Smart,J.,Shirk,M.,2018.Energy impact evaluation for eco-routing and charging of autonomous electric vehicle fleet: Ambient temperature consideration. Transportation Research Part C:Emerging Technologies,89,344-363.

Zhang,J.,Wang,Z.,Liu,P.,Zhang,Z.,2020.Energy consumption analysis and prediction of electric vehicles based on real-world driving data. Applied Energy,275,115408.