

Article **Motorway Traffic Emissions Estimation through Stochastic Fundamental Diagram**

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Abstract: Travel time, or, more generally, level of service, has always been considered the main parameter with which to design roads, particularly in extra-urban areas where geometries and policies, such as speed limits, play a key role in the performance achieved. Unfortunately, this type of approach does not consider the impact on emissions that is obtained when only performance-based goals are pursued. The paper deals with the analysis of the impact on emissions and fuel consumption under different traffic conditions, and we present a new methodology for emission estimation based on the stochastic formulation of the fundamental diagram in a highway environment. The proposed methodology estimates the emissions using a stochastic adaptation of the CORINAIR methodology based on COPERT software on both specific vehicle types and the average Italian vehicle fleet. As expected, due to the convexity of the emission function, accounting for speed dispersion leads to an increase in energy consumption and emissions. Tests show that the stochastic component can lead to an increase in the emission estimation up to 5.5% and, therefore, it should be considered. The methodology has been applied by means of real trajectories, and the results of the application show that performance optimization strategies can contrast with sustainability and emission reduction policies. Results show that for some vehicular classes, emissions or fuel consumption are highly dependent on speed, with different proportionalities. In all cases, the minimum consumption is obtained at speeds ranging from 70 to 90 km/h. The analysis of the curves shows that an increase in speeds, even to reach low speeds, generally leads to an increase in energy consumption and emissions per kilometer traveled and, therefore, is independent of the decrease in travel time.

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Keywords: emissions estimation; stochastic fundamental diagram; speed distribution

1. Introduction

Generally, the main parameters considered to design roads [\[1\]](#page-14-0) are travel times, maximum capacity, and level of service, particularly in extra-urban areas where geometries and policies, such as speed limits, play a key role in the performance achieved. However, this kind of approach does not consider the impact on emissions that is obtained when only performance-based goals are pursued.

The increasing attention focused on environmental aspects requires, in the context of road transport, the estimation of atmospheric emissions due to traffic flows in order to properly identify and evaluate the most effective interventions in terms of their decrease [\[2\]](#page-14-1). With regard to highway sections, currently, the estimation of emissions is mainly conducted with the use of macroscopic models fed by aggregate-type data, such as, for example, the average speed of traffic flow. These types of models, which are easily applied over a wide area, have the limitation that they are unable to take into account the stochasticity of traffic and, in particular, the variation in speed, a quantity that is strongly correlated with emissions. To solve this problem, the research community, as we will see in the literature review, mainly uses micro models in both simulation and emission calculations, increasing model calibration variables and computational effort. The proposed research

aims to close this gap by developing a methodology that can estimate emissions based on macro models calibrated by real disaggregated data that are able to take into account the speed distribution.

The aim is, therefore, to define a methodology for calculating emissions applicable to the observation of aggregate quantities and their stochastic characterization. Specifically, the first step involves the stochastic characterization of speeds with respect to the mean values provided by the fundamental diagram based on the observed trajectories by clustering them. The second step involves a stochastic analysis of emissions. Results of the methodology application show the effect of speed dispersion on emissions based on observed frequencies and modeled probability density functions (pdf).

In [\[3\]](#page-14-2), we propose a methodology to model and calibrate the S-FD to achieve specifications that are consistent with TST applications. In the present paper, we discuss how to specify speed pdf and, thus, estimate energy consumption and emissions. Therefore, in this paper, we suggest a methodology for estimating emissions according to the stochastic fundamental diagram. Moreover, the paper deals with the analysis of the impact on emissions and fuel consumption under different traffic conditions. Furthermore, the analysis has been carried out per vehicle class, e.g., light vs. heavy vehicles, and per type of air pollutants.

The proposed methodology has been applied using real trajectories detected on a highway segment.

The paper is structured as follows. Section [2](#page-1-0) reports the state of the art. Section [3](#page-3-0) describes the proposed methodology. Section [4](#page-6-0) presents the results of the application. Finally, Section [5](#page-12-0) summarizes the conclusions and future developments of this research.

2. Literature Review

As it is well known, the traffic fundamental diagram (FD) is the basis of traffic flow theory; it relates the three aggregate traffic variables: flow, speed, and density. Starting from the observation that the actual detected data are very dispersed, in recent studies, authors have focused on the study of the stochastic fundamental diagram (S-FD). In [\[4\]](#page-15-0), the authors present a probabilistic graphical approach to modeling the distribution of the parameters of the FD. Wang et al. [\[5\]](#page-15-1) introduce a stochastic speed-density model to recreate the empirical observations. Fan and Seibold propose a methodology for verifying the accuracy of data-fitted macroscopic traffic models by means of vehicle trajectories [\[6\]](#page-15-2). In [\[7\]](#page-15-3), the authors derive the probabilistic macroscopic relations from Newell's car-following model. Nikolic et al., starting from the high dispersion of data, propose a probabilistic speed–density model of pedestrians [\[8\]](#page-15-4). Siqueira et al. [\[9\]](#page-15-5) propose a stochastic two-speed state model to consider the variance of the FD. Qu et al. [\[10\]](#page-15-6) propose a methodology for calibrating the S-FD based on percentiles. Then, the authors propose a framework to correct the unrealistic results obtained by the model application [\[11\]](#page-15-7). In [\[12\]](#page-15-8), the authors consider stochastic headway in order to derive the FD for mixed vehicle traffic flow. In [\[13\]](#page-15-9), the authors present a link-based S-FD that explicitly considers speed heterogeneity in order to study the effects of different drivers and types of vehicles on the macroscopic traffic model.

Concerning the emissions, a major contributor to GHG emissions is road traffic due to its heavy reliance on fossil fuels, and while overall GHG emissions are decreasing, those from transportation continue to increase, according to studies in Europe [\[14\]](#page-15-10). Therefore, the study to estimate emissions with a focus on greenhouse gases is of particular interest. Several methodologies have been proposed in the literature that are mainly differentiated into static and dynamic models.

Static models assume that emission factors are a function, under steady-state flow conditions, of average speed [\[15\]](#page-15-11) and are widely used to estimate road traffic emissions by integrating them with macroscopic assignment models. Such models use aggregate data, such as average vehicular flow speed and traffic volume, to estimate average fleet emissions. The easy application of these aggregate models is the result of a huge amount of work to calibrate the formulations, which, differentiated by vehicle type and technology, require a

large amount of data of a microscopic type [\[16\]](#page-15-12) and have required the implementation of projects specifically dedicated to data collection such as the ARTEMIS project [\[17\]](#page-15-13).

- COPERT: The most widely used static model in Europe is COPERT (Computer Program to calculate Emissions from Road Transport), developed by the European Environment Agency and based on the CORINAIR methodology. This methodology, depending on the level of information available (only fuel consumption, only distance, speed, and distance), defines three different calculation methods: Tier 1, 2, and 3 [\[18\]](#page-15-14). The COPERT model, using the methodology proposed by CORINAIR, estimates the GHG emissions of the fleet of vehicles on the road.
- TEE: TEE (Traffic Energy and Emissions) is an average speed-corrected emissions model developed by ENEA (Italian National Agency for New Technologies, Energy and Sustainable Economic Development). EE offers an alternative to the classical average speed approach for estimating vehicle emissions as a function of their kinematics with an intermediate approach called average corrected speed calculated with a simplified driving cycle model built as a function of flow density [\[19\]](#page-15-15).

The advantages of static models are related to their ease of use, the availability of input data, and the corresponding degree of approximation to the macro-scale of analysis. However, macroscopic models have some limitations because they do not allow for adequate spatial and temporal resolution and are unable to consider the effect of speed distribution within the vehicular flow. TEE tries to overcome this issue by performing an evaluation of the fractions of time spent during cruising, acceleration, deceleration, and idling and hypothesizing the effect of user behavior on emissions. Unfortunately, this approach does not cover the most recent EURO regulations.

To overcome these limitations, dynamic emission models have been developed, which correlate emissions to vehicle operation during short intervals (often 1 Hz), thus defining models based on instantaneous speed and acceleration. Some of the most frequently cited dynamic models are:

- EMFAC: A dynamic model developed by California's EPA (Environmental Protection Agency)-approved transportation agency. The model includes various parameters such as vehicle age, fuel type, speed, and driving patterns and estimates emissions of pollutants such as CO, NOx, PM, and VOC. The latest versions of the model also implement electric and hybrid vehicles [\[20\]](#page-15-16).
- EMPA, derived from international cooperation for HBEFA (Handbook Emission Factors for Road Transport), is a widely used model for estimating exhaust emissions from road vehicles in Europe. In addition to taking speed into account, the model also considers traffic congestion and road section characteristics [\[21,](#page-15-17)[22\]](#page-15-18).
- DRIVE-MODEM: The MODEM model was developed in collaboration with the French research institute INRETS during the DRIVE program of the European Commission. MODEM was developed on the basis of experimental data acquired by laboratory tests on a sample of vehicles representative of the fleet circulating in the countries of the European Community in order to highlight the influence of the construction characteristics of the vehicles on emissions. The emission model was specified discretely and in matrix form using the representative variables of instantaneous speed and instantaneous acceleration [\[23\]](#page-15-19).
- MOVES (MOtor Vehicle Emissions Simulator) is a program developed by the US EPA for the estimation of atmospheric emissions of pollutants produced by mobile sources. It uses a modal approach based on vehicle-specific power measurements (VSP) that allows emissions to be calculated over any driving cycle and estimated from the average speed. The model also depends on weather, vehicle fleet, vehicle activity, fuel, and the U.S. emission control program [\[24\]](#page-15-20).
- PHEM (Passenger car and Heavy-duty Emission Model) is an instantaneous emission model that estimates fuel consumption and emissions based on instantaneous engine power and engine speed for a user-specified driving pattern [\[25\]](#page-15-21).

However, these models require disaggregated vehicle speed data that are difficult to obtain systematically.

Other authors have estimated emissions by combining FDs and emission models: ref. [\[26\]](#page-15-22) uses FDs to estimate large-scale emissions by applying them but does not take into account the stochasticity of the phenomenon. On the other hand, ref. [\[27\]](#page-15-23) performs an empirical analysis by analyzing a considerable amount of data and showing a relationship between speeds and emissions calculated with the MOVES micro model. This last study achieves the empirical definition of an e-MDF (emission-macroscopic fundamental diagram) by not defining a replicable analytical formulation. This can also be seen in the work of Mohammad Halakoo, Hao Yang, and Harith Abdulsattar [\[28\]](#page-15-24) who report the use of COPERT in Blacksburg, VA, using e-MDF. As the article reports in their conclusion, they considered some simplifying assumptions that could be relaxed in future research, such as adding different vehicle types and conducting a sensitivity analysis of our model for different vehicle combinations. A network fundamental diagram (NFD) combined with a micro emission model is proposed by [\[29\]](#page-15-25) to estimate the total emissions on heterogeneous vehicular fleets through a first estimation phase realized with micro simulation models. As we will see in the methodology, this study differs by using the formulation of a stochastic fundamental diagram and taking advantage of a macro methodology for emission calculation such as COPERT, which is easier to apply.

The present study proposes a methodology that combines the knowledge of speed variability defined through S-FD with the simplicity of applying established macroscopic emission estimation models such as COPERT.

3. Methodology

This study aims to find a methodology capable of calculating emissions by combining the definition of an S-FD and the COPERT emission model, taking into account the effect of speed variability within the flow on emission assessment. The methodology, which will be described in detail below, is shown in the workflow in Figure [1.](#page-3-1)

Figure 1. Methodology workflow. **Figure 1.** Methodology workflow.

The workflow is split into two streams. The first one analyzes real data, on which two separate studies are carried out: calibration of an FD and statistical speed analysis. The combination of these two studies allows for the definition of the S-FD. The second stream, combining the information on the composition of the vehicular fleet, defines a general COPERT-based emission curve for the whole fleet.

Finally, the results of the two streams, S-FD and emission curve, are combined to calculate total fleet emissions, taking into account the effect of the stochastic speed component and speed (spatial average) do not depend on time instant and are interrelated through α on this evaluation.

Usually, on a road link, flow, density, and speed can be measured or calculated and related to each other. Specifically, flow will depend on the measurement position (abscissa) and measures vehicles per unit time; density is a quantity that is relative to the entire link, depends exclusively on the time instant, and measures vehicles per unit length; and finally, speed can be calculated as a spatial average that depends on the time instant, or alternatively, it can be calculated as a time average dependent on the abscissa.

Under steady-state conditions, flow does not depend on abscissa, and both density and speed (spatial average) do not depend on time instant and are interrelated through the continuity function:

$$
f = k \cdot v \tag{1}
$$

where

f : flow

k : density

v : space average speed

$$
v = v(f) \in [0, v_0] \qquad 0 \le f \le f_{\text{max}} \tag{2}
$$

where

fmax: maximum flow computed as a function of the geometrical characteristics of the infrastructure (HCM, 2016) or calibrated;

 v_0 : free-flow speed computed as a function of geometrical characteristics of the infrastructure, weather, light conditions, or calibrated.

Combining Equations (1) and (2) according to the traffic flow theory and under steady-state conditions, is it possible to describe vehicles following along a road with the Fundamental Diagram as Greenshileds' well-known formulation:

$$
v(f) = v_0 \cdot \left(1 + \left(1 - \frac{f}{f_{max}} \right)^{0.5} \right)
$$
 (3)

or BPR-based stable regime speed-flow function:

$$
v(f) = \frac{v_0}{\left(1 + a\left(\frac{f}{f_{max}}\right)^b\right)}
$$
(4)

The speed given by the stable regime speed-flow function is to be considered the mean of a random variable V, whose dispersion models several sources of uncertainty, leading to the stochastic fundamental diagram (S-FD).

Considering the random variable $\mathbb F$ related to flow, the speed can be defined as below:

$$
v(f) = E[\mathbb{V}|\mathbb{F} = f] \tag{5}
$$

And the probability density function of speed conditioned to flow can be defined as:

$$
p_{\mathbb{V}|\mathbb{F}}(v|f_i) = P(\mathbb{V} = v|\mathbb{F} \in f_i), \qquad f_i \in I \tag{6}
$$

where:

i: a partition of flow in intervals $\{[0, f_1), \ldots, [f_{i-1}, f_i), \ldots, [f_{n-1}, f_n]\}$

 f_i : f_i is *i*-th interval in *I*

 $p_{\mathbb{F}|V}(f_i|v)$: is the conditional probability density function of speed v given flow in f_i

According to the random utility theory used in route choice behavior models, the random variable for speed must be based on the disutility distribution as normal, gamma, or InvGamma.

Using the S-FD and related speed distribution, the evaluation of emissions and energy consumption was carried out using the EMEP/EEA guideline for the estimation of pollutant emissions, which includes the CORINAIR-COPERT methodology [\[1\]](#page-14-0). It is in line with the 2006 IPCC Guidelines for the estimation of GHG emissions and is utilized by the majority of EU Member States. In this methodology, all pollutant emissions and energy consumption were expressed as a function of speed that was parameterized for varying vehicle types, fuel types, engine technologies, road segment types, EURO regulations, etc. The general parametric formulation used by the COPERT methodology is as follows:

$$
E_t(v) = \frac{\alpha_t \cdot v^2 + \beta_t \cdot v + \gamma_t + \delta_t \cdot v^{-1}}{\varepsilon_t \cdot v^2 + \zeta_t \cdot v + \eta_t} \cdot (1 - r_t), \qquad V_{t,min} \le v \le V_{t,max}
$$
 (7)

where *t*: motor and engine technology (fuel, vehicle size, EURO standard, . . .); *v*: speed [km/h]; $E_t(v)$: the emission $\left[\frac{g}{\text{veh-km}}\right]$ or energy consumption $\left[\frac{\text{MJ}}{\text{veh-km}}\right]$ by a vehicle with a specific technology *t* at speed *v*; *α^t* , *βt* , *γt* , *δt* ,*εt* , *ζt* , *ηt* : CORINAIR emission parameters of *t* technology; *r^t* : CORINAIR reduction factor of *t* technology; *Vt*,*min*, *Vt*,*max*: speed bounds of function definition $E_t(v)$ [km/h];

Then, for the estimation of the total emissions of an entire fleet, an average of the E for every technology weighted for the number of vehicles with the specific technology was made according to the following equation:

$$
E(v) = \frac{1}{P} \sum_{t \in T} n_t \cdot E_t(v), \qquad V_{min} \le v \le V_{max} \tag{8}
$$

where *Vmin* and *Vmax* were calculated using the equation shown below:

$$
V_{max} = \min(\{V_{t,max} : t \in T\}), V_{min} = \max(\{V_{t,min} : t \in T\})
$$
\n(9)

where V_{min} , V_{max} : speed bounds of function definition $E(v)$ [km/h]. *T*: all technologies for vehicles as used by CORINAIR; *n^t* : amount of fleet vehicles with technology *t* [veh]; $P = \sum_{t \in T} n_t$: total fleet vehicles [veh]; $E(v)$: total emission $\left[\frac{g}{v \epsilon h \cdot km}\right]$ or energy consumption $\left[\frac{\text{MJ}}{\text{veh}\cdot\text{km}}\right]$ of vehicle fleet.

By combining the S-FD with the COPERT methodology, it was possible to calculate emissions by computing the following integral that combines the emission calculation of Equation (7) for a specific speed with the probability density function of speeds expressed from Equation (6):

$$
\hat{E}_t(f) = \int_{V_{min}}^{V_{max}} E_t(v) \cdot p_{\mathbb{F}|\mathbb{V}}(f_i|v)v \tag{10}
$$

or

$$
\hat{E}(f) = \int_{V_{min}}^{V_{max}} E(v) \cdot p_{\mathbb{F}|V}(f_i|v)v \tag{11}
$$

where $\hat{E}_t(f)$: emission $\left[\frac{g}{\text{veh} \cdot \text{km}}\right]$ or energy consumption $\left[\frac{\text{MI}}{\text{veh} \cdot \text{km}}\right]$ for specific technology *t* when flow is f ; $\hat{E}(f)$: total emission $\left[\frac{g}{\text{veh} \cdot \text{km}}\right]$ or energy consumption $\left[\frac{\text{MI}}{\text{veh} \cdot \text{km}}\right]$ of a vehicle fleet.

Removing the stochastic component and using the speed as in Equation (5), Equations (10) and (11) can be simplified into:

$$
\hat{E}_t(f) = E_t(v(f))
$$
\n(12)

$$
\hat{E}(f) = E(v(f))\tag{13}
$$

or

4. Application and Results 4. Application and Results

The proposed models in the above section have been calibrated using current data, as The proposed models in the above section have been calibrated using current data, thoroughly explained in [\[1\]](#page-14-0). These data, gathered over a 310 m section of the A51 3-lane as thoroughly explained in [1]. These data, gathered over a 310 m section of the A51 3 highway (Milan urban motorway) between 9:10 a.m. and 1:10 p.m., involve the trajectories of all vehicles traveling in both directions. The acquisition technique, based on video processing, allowed the detection of all vehicles in the stretch with a frequency of 1 Hz. For each trajectory, the time instant of crossing a virtual section located at the center of the section (entry gate) was detected (as shown in Figure [2\)](#page-6-1). of the section (entry gate) was detected (as shown in Figure 2).

̂() = (()) (13)

Figure 2. Area of case study. **Figure 2.** Area of case study.

Within a time interval of ∆t = 15 s, the data were processed and aggregated to produce Within a time interval of ∆t = 15 s, the data were processed and aggregated to produce the following results: the following results:

- Speed as spatial average, Speed as spatial average,
- equivalent density, equivalent density,
- equivalent flow, equivalent flow,
- modeled flow, which is calculated as: speed multiplied by equivalent density. modeled flow, which is calculated as: speed multiplied by equivalent density.

Considering that different sizes of vehicles may have an effect on the calculation flows and densities, as suggested by traffic theory, vehicles were transformed into of flows and densities, as suggested by traffic theory, vehicles were transformed into equivalent vehicles using the following equivalence factors: motorcycle $= 0.3$, bus $= 3$, heavy vehicle = 3, medium vehicle = 1.5 , and car = 1 .

The information from many lanes has been combined, and the figures listed below refer to one (average) lane. Analysis will be distinguished by lane in a subsequent study.

Since observed flows are below capacity and densities are much below maximum values, as well as the very good collinearity observed between predicted flows, $f = kv$ as in Equation (1), and observed flows, all data may be taken to relate to a hypocritical state and a steady-state condition.

The values of the measured flows aggregated over a 15 s time interval have been successively aggregated into flow classes with a step size of 120 veh/h. Figure [3](#page-7-0) shows the observed average speed of the cars for each flow class as a red dot within the range plus/minus one observed standard deviation. The line describes how the model was calibrated.

plus/minus one observed standard deviation. The line describes how the model was cali-

Figure 3. Observed and modeled speed vs. flow class. The observed values are shown with box plot **Figure 3.** Observed and modeled speed vs. flow class. The observed values are shown with box plot representation, where a box is bounded by first and third quartiles (Q1 and Q3) and inside is shown representation, where a box is bounded by first and third quartiles (Q1 and Q3) and inside is shown the median. The whiskers are between the mean +/−1.5 IRQ, where IRQ = Q3-Q1 is the interquartile. the median. The whiskers are between the mean +/−1.5 IRQ, where IRQ = Q3-Q1 is the interquartile. The modeled speed is the BPR-based function calculated for each flow class.

Using the data in Figure [3,](#page-7-0) several BPR-based functions (Equation (4)) have been $\overline{0}$ calibrated, obtaining the best results with these parameters: \mathbf{I}

$$
v_0 = 106 \frac{\text{km}}{\text{h}}, \quad f_{max} = 2589 \frac{\text{veh}}{\text{h}}, \quad a = 0.22, \quad b = 1
$$

Through statistical and stochastic analysis, the dispersion of speed values for each flow α bility density functions (pdf) that best fit that best fit that best fit the different point α of α multiple computed point α and α class has been further studied. The availability of frequencies of real detected speed values differentiated for each flow class (as reported in [\[1\]](#page-14-0)) allows for identifying the probability density functions (pdf) that best fit the real data among the different pdf computed in the previous study.

Performing a comparison between normal, gamma, and invgamma pdf, invgamma has been adopted for the calculation of emissions. A comparison between invgamma pdf and observed frequencies is shown in Figure [4.](#page-7-1)

Figure 4. (**a**) Observed speed per flow class; (**b**) InvGamma speed pdf per flow class. **Figure 4.** (**a**) Observed speed per flow class; (**b**) InvGamma speed pdf per flow class.

Figure [5a](#page-8-0) shows the observed speed frequency distribution and discretization of the Figure 5a shows the observed speed frequency distribution and discretization of the InvGamma (Figure 5b) for the different flow and speed classes. InvGamma (Figure 5b) fo[r th](#page-8-0)e different flow and speed classes.

Figure 5. (a) Observed speed frequency pdf per flow class; (b) discretized speed invGamma pdf per flow class. flow class.

4.1. Application with Respect to Engine Type 4.1. Application with Respect to Engine Type

Applying the COPERT methodology to calculate emissions for different types of hicles, it becomes evident that for some vehicular classes, emissions or fuel consumption vehicles, it becomes evident that for some vehicular classes, emissions or fuel consumption are highly dependent on speed, with different proportionalities (all the parameters used are highly dependent on speed, with different proportionalities (all the parameters used can be found within Appendix A. COPERT Methodology and Parameter). can be found within Appendix [A.](#page-13-0) COPERT Methodology and Parameter).

Figure 6 sho[ws](#page-8-1) the PM-exhaust and NOx emission curves for a medium vehicle diesel for 3 different EURO standards: 3, 4, and 6. The figures show that all curves, except for PM-EURO 6d, descend to a point of minimum and then rise again for higher speeds. In PM-EURO 6d, descend to a point of minimum and then rise again for higher speeds. In the case of PM-EURO 3, emissions begin to grow exponentially already after reaching a speed above 50 km/h; similar behavior is observed for EURO 4, but for speeds above 70 km/h and with a smaller growth factor. Pseudo-parabolic behaviors occur for NOx emissions in all vehicular classes. Their comparison shows similar behavior but with different scaling scaling factors, and a minimum value of emission is obtained for speeds close to 70 km/h. factors, and a minimum value of emission is obtained for speeds close to 70 km/h.

 \mathbf{F} **Figure 6.** \mathbf{P} M emission (a) and NO_X emission (b) of same type of vehicle and fuel with different **Figure 6.** PM emission (**a**) and NOx emission (**b**) of same type of vehicle and fuel with different EURO regulations.

Figure 7 compares energy consumption between medium and SUV vehicles powered Figure 7 compares energy consumption between medium [an](#page-9-0)d SUV vehicles powered by diesel and the same vehicles powered by petrol.

This figure again shows a pseudo-parabolic pattern of the curves and a difference in scaling as a function of car size in the comparison between medium and SUV vehicles. Furthermore, a similar difference is observed when comparing diesel and petrol due to the

different efficiency of the engines. In all cases, the minimum consumption is obtained at speeds between 70 and 90 km/h. by bedie between the direction of the same personal

Figure 7. Energy consumption comparison between SUV and medium vehicle. (**a**) Diesel EURO 6; **Figure 7.** Energy consumption comparison between SUV and medium vehicle. (**a**) Diesel EURO 6; (**b**) petrol EURO 6. (**b**) petrol EURO 6.

The analysis of the curves shows that an increase in speeds, even to reach low speeds, state and space of care carried of comparison between medicine medicines of comparison between $\frac{1}{2}$ generally leads to an increase in consumption and emissions per km traveled and, therefore, is independent of the reduction in travel time.

The curves also show a minimum value of emission or consumption when the speed ranges from 50 to 80 km/h, which is much lower than the permitted highway speeds.

Figure [8a](#page-9-1) shows the PM emission estimates given by the curves in Figure [6a](#page-8-1) when Equation (12) (solid line), derived from non-stochastic FD, and Equation (10) (dashed line), derived from the S-FD in which an InvGamma-type speed distribution is assumed, are applied. As expected, due to the convexity of the CORINAIR function, accounting for speed dispersion leads to an increase in EC. $\mathbf{1}$ (solid line), derived from non-stochastic FD, and Equation (10) (dashed from non-stochastic FD, and Equation (10) (dashed from non-stochastic FD, and Equation (10) (dashed from non-stochastic FD, and Equation (10

Figure 8. PM emission for each flow class using the BPR-based fundamental diagram and the BPR-**Figure 8.** PM emission for each flow class using the BPR-based fundamental diagram and the $\frac{1}{2}$ BPR-based stochastic fundamental diagram (**a**) and the only stochastic component calculated as the difference between PM emission of S-FD and FD. (**b**) Emission of EURO 6d was excluded because it was insignificant for the analysis.

Specifically, the figure shows that for each emission curve, the emissions computed considering the stochastic component are higher than those calculated not considering the speed distribution (over +3% for both), and both curves are decreasing (−22% for EURO 3 and −7% for EURO 4). Focusing on the contribution of only the stochastic component, v_{H} and v_{H} are α in α and α vehicles (α Figure [8b](#page-9-1) shows an increase and subsequent decrease (flow > 1000 veh/h) for EURO 3
red: the end subsequent democratic EURO 4 red: the (, , , , , , , , , , , , , , , $\sum_{i=1}^{n}$ when $\sum_{i=1}^{n}$ and $\sum_{i=1}^{n}$ and Equation (12) (defined line) and Equation (10) (defined line) and Equa vehicles and a general decrease for EURO 4 vehicles (−27%).

Figure [9a](#page-10-0), similarly to the previous figure, shows the NOx emission estimates given by the curves in Figure [6b](#page-8-1) when Equation (12) (solid line) and Equation (10) (dashed line) are applied. Even in this case, the curve generated using S-FD is always higher than those generated using no stochastic FD (+3.4% for EURO 3 and +5.5% for EURO 4), and a reduction in emission per vehicle is evident when the flow increases (about −8% for both). Focusing on the stochastic component in Figure [9b](#page-10-0), the behavior is similar to an initial cusing on the stochastic component in Figure 9b, the scintter is similar to an increase and a subsequent reduction (−22% for EURO 3 and −21% for EURO 4). Figure 9a, similarly to the previous figure, shows the NOx emission estimates given are applied. Even in this case, the curve generated using S-FD is always h α cand a subsequent reduction (−22% for EURO 3 and −21% fo

Figure 8b shows an increase and subsequent decrease \mathcal{L}

Figure 9. NOx emission for each flow class using the BPR-based fundamental diagram and the BPR-**Figure 9.** NOx emission for each flow class using the BPR-based fundamental diagram and the BPR-based stochastic fundamental diagram (**a**) and the only stochastic component calculated as the difference between NOx emission of S-FD and FD (b). Emission of EURO 6d was excluded because it was insignificant for the analysis.

the constant calculated with the S-FD is always higher than that calculated according \sim Figures [9](#page-10-0) and [10a](#page-10-1),c show the same behavior as shown in the previous figures, where the consumption calculated with the S-FD is always higher than that calculated according to the FD. Some difference is observed in the analysis of the stochastic component alone, where a trend of decreasing consumption is quite evident (Figures [9](#page-10-0) and [10b](#page-10-1),d).

Figure 10. Energy consumption for each flow class using the BPR-based fundamental diagram and the BPR-based stochastic fundamental diagram (**a,c**) and the only stochastic component calculated as $T_{\text{max}} = 1.6$ to $T_{\text{max}} = 1.6$ to $T_{\text{max}} = 4.1$ the difference between S-FD and FD (**b**,**d**).

The stochastic component represents +1.6% to +4.1% and a decreasing range between −7.8% and −2.5%, and it is present in the non-stochastic component.

4.2. Application to a Vehicle Fleet

Both emissions and consumption depend greatly on the vehicular composition of the analyzed fleet, and for this reason, the emission curves for NOx and EC of the 50 most representative vehicle types in the Italian vehicle fleet were identified (more details can be found in Appendix [A:](#page-13-0) Italian Fleet Composition) and the average emission curves were calculated using Equation (8), the results of which are shown in Figure [11.](#page-11-0) In this case, the minimum emission value corresponds to a speed ranging from 50 to 60 km/h, and the minimum consumption value is relative to a speed of about 70 km/h.

Figure 11. NOx emission curve (a) and energy consumption curve (b) for the Italian vehicle fleet.

Using these curves of the Italian vehicle fleet, an evaluation of emission and consumption or flow class has been performed, and the results are shown in Figures 12 and 13 13. per flow class has been performed, and the results are shown in Figures [12](#page-11-1) and [13.](#page-12-1) 13. Using these curves of the nation vehicle fleet, an evaluation of emission and consumpt

Figure 12. NOx emission for each flow class using the BPR-based fundamental diagram and the BPR-based stochastic fundamental diagram (**a**) and the only stochastic component calculated as the BPR-based stochastic fundamental diagram (**a**) and the only stochastic component calculated as the difference between S-FD and FD (**b**). difference between S-FD and FD (**b**). BPR-based stochastic fundamental diagram (**a**) and the only stochastic component calculated as the like the stock of \overline{D}

Specifically, Figure [12a](#page-11-1) shows a high decrease (−11%) in emissions as flow increases in both the non-stochastic and stochastic components (b). The dispersion-related component increases the emission assessment by +3.7%, which decreases as the flow increases by half.

Figure 13. Energy consumption for each flow class using the BPR-based fundamental diagram and the BPR-based stochastic fundamental diagram (**a**) and the only stochastic component calculated as the difference between S-FD and FD (**b**).

Figure 12. NOx emission for each flow class using the BPR-based fundamental diagram and the

Figure [13,](#page-12-1) related to EC, shows similar results for NOx emissions. In fact, in this case, an increase of +3.6% is due to the stochastic component (Figure [13a](#page-12-1)), and this increase halves when the flow reaches over 2000 veh/h (Figure [13b](#page-12-1)), while a decrease of −7% is present in the non-stochastic component (Figure [13a](#page-12-1)).

All tests show a reduction in consumption and emissions as flow increases for both the stochastic and non-stochastic components. The reduction in the stochastic component can be as much as half, and that of the stochastic component can be more than 20% as flow increases.

Considering the proposed formulation, this decrease is due to the reduction of the mean speed and of the speed dispersion within the flow class.

Tests also show that the stochastic component can lead to an increase in the emission estimation up to 5.5% and, therefore, should be considered.

5. Conclusions

Currently, the estimation of emissions is mainly conducted with the use of macroscopic models fed by aggregate-type data. However, these models do not allow for adequate spatial and temporal resolution, and they are unable to consider the effect of speed distribution. The dynamic emission models overcome these limitations. Nevertheless, they require disaggregated vehicle data that are difficult to obtain systematically.

Therefore, in this paper, we propose a methodology capable of estimating emissions based on macroscopic models fed by disaggregated data, such as speed distribution, inferred from the reconstruction of the measured trajectories of individual vehicles. The suggested methodology is applicable to the observation of aggregate quantities and their stochastic characterization. This paper deals with the evaluation of emissions and consumption using a stochastic adaptation of the CORINAIR methodology based on COPERT software. The proposed methodology is based first on the definition of a stochastic fundamental diagram. Next, by means of real detected trajectory data, the S-FD has been calibrated. Then, through statistical and stochastic analysis, the dispersion of speed values for each flow class has been further studied. After combining the S-FD with the COPERT methodology, the emissions are computed for a specific speed considering its probability density function, so it has been possible to define a stochastic component.

Finally, the emissions have been computed for different types of vehicles, such as SUVs and medium vehicles, according to different EURO standards and different fuels.

The proposed methodology has been applied using real trajectory data for a highway segment. As expected, due to the convexity of the CORINAIR function, accounting for speed dispersion leads to an increase in energy consumption.

Results show that for some vehicular classes, emissions or fuel consumption are highly dependent on speed, with different proportionalities. Concerning EURO standards, their comparison shows similar behavior characterized by different scaling factors.

The comparison of energy consumption between medium and SUV vehicles shows a pseudo-parabolic pattern of the curves and a difference in scaling as a function of car. Additionally, comparing vehicles with diesel and petrol, a difference in energy consumption is observed due to the dissimilar efficiency of the engines. In all cases, the minimum consumption is obtained at speeds ranging from 70 to 90 km/h.

The analysis of the curves shows that an increase in speeds, even to reach low speeds, generally leads to an increase in energy consumption and emissions per kilometer traveled and, therefore, is independent of the decrease in travel time.

The main contribution of this research is the formulation of a methodology for calculating emissions according to the stochastic fundamental diagram, whose results may appear at odds with reality. In fact, increased flow leads to reduced emissions and consumption per vehicle. However, it should be emphasized that the study was carried out entirely on a dataset containing only data from stable regimes.

Future developments of this research concern the evaluation of the methodology in the unstable regime; we will also study an analytical flow-dependent formulation of the stochastic component. Moreover, the methodology could be applied by defining the stochastic component as the amount of the speed dispersion of individual vehicles and not the dispersion of speeds within the entire flow.

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Appendix A

1. COPERT Methodology and Parameters

The general formulation of consumption/emission curves [\[17\]](#page-15-13) has the following structure:

$$
COPERT[V] := \frac{\alpha * V^2 + \beta * V + \gamma + \delta * V^{-1}}{\epsilon * V^2 + \zeta * V + \eta} * (1 - rf)
$$

And it is valid between a minimum and maximum speed limit.

The COPERT site [\(https://www.emisia.com/utilities/copert/download/](https://www.emisia.com/utilities/copert/download/) accessed on 31 May 2023) provides the parameters for all 52,000 formulations to travel 1 km given the speed and the resulting pollution and EC, as shown in Figure [A1.](#page-14-3)

Figure A1. Extracted from COPERT database.

The choice of engine type parameters for the emissions and energy consumption The choice of engine type parameters for the emissions and energy consumption show with the article is consistent with the composition of the component with the component of the Italian It flexible the composition of the majority of the Italian shown within the article is consistent with the composition of the majority of the Italian $2.$ Italian Fleet Composition Fleet Comp fleet.

2. Italian Fleet Composition **Shown With the article is consistent with the majority of the majority of the Italian Fleet Composition**

(https://opv.aci.it/WEBDMCircolante/ accessed on 31 May 2023)*,* a database developed by The fleet composition has been established using Open Parco Veicolare [\(https://](https://opv.aci.it/WEBDMCircolante/) opv.aci.it/WEBDMCircolante/ accessed on 31 May 2023), a database developed by *ACI* (Automobile Club d'Italia—Italian Car Driver Association accessed on 31 May 2023), with the following entry: **ACI** *(AUTOROBILE CLUB DETERMINA)*

- Year (Anno): 2021 ;
- *Euro Type Other Petrol Petrol & LPG Petrol & Methane Electric Diesel Hybrid Petrol Hybrid Diesel Methane Not Defined* Capital (Solo Comuni Capoluogo) [Rome]. • Column Names (Dimensioni): Fuel (Alimentazione), Euro Type (Euro), Only Provincial P Provincial Capital (Solo Comuni Capoluogo) [Rome].

Figure A2. Extracted and translated from ACI database.

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