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Investigation of User Behavior in Pedal-Assisted Vehicles: From Field Testing to Driving Cycle †

Adelmo Niccolai, Andrea Raimondi, Lorenzo Berzi * and Niccolò Baldanzini

Department of Industrial Engineering of Florence, University of Florence, Via di S. Marta 3, 50139 Florence, Italy; adelmo.niccolai@unifi.it (A.N.); andrea.raimondi@unifi.it (A.R.); niccolo.baldanzini@unifi.it (N.B.)

* Correspondence: lorenzo.berzi@unifi.it

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Abstract

In recent years, electric cargo (e-cargo) bikes have been increasingly adopted as a sustainable alternative for urban logistics and last-mile delivery, particularly in densely populated areas where traditional vehicles face traffic congestion and access limitations. This study aims to develop a representative driving cycle for e-cargo bikes based on real-world cycling data. An instrumented Long John-type e-cargo bike was used to collect naturalistic data from four different riders covering a total of 50 km along a predefined route in the city center of Florence, selected in collaboration with the Italian postal service provider (i.e., Poste Italiane) to reflect typical delivery operations. The driving cycle was generated using a Markov chain Monte Carlo (MCMC) method, modeling the stochastic transitions of vehicle speed and acceleration values. The resulting driving cycle, defined as the Florence cargo bike driving cycle (FCBDC), achieved an error of 2.1% on the Speed Acceleration Probability Distribution (SAPD) root sum square difference; although minor losses in peak acceleration values were observed due to data smoothing and discretization, the synthesized driving cycle effectively reproduces the dynamic characteristics of e-cargo bike riding. While the study is limited to a single route and is equivalent to simulated postman behavior, it provides valuable insights to guide the future development and optimization of e-cargo bikes for sustainable mobility operations.

Keywords: driving cycle; e-cargo bike; rider behavior

1. Introduction

Over the past few decades, a notable shift has occurred in urban mobility, primarily driven by the introduction of light mobility vehicles. Among these, e-bikes and e-cargo bikes offer a viable solution in urban settings, especially in EU member states [1]. E-cargo bikes are specially modified pedal-assisted bicycles designed to carry different types of loads or passengers, such as children, and are designed with two, three, or four wheels. E-cargo bikes and e-bikes have emerged as feasible alternatives to alleviate or partially resolve the main adverse impacts of transportation systems [2]. The primary application of e-cargo bikes, as discussed in the literature, is centered on commercial transport, primarily for urban logistics and last-mile deliveries [1,3]. E-commerce has increased the demand for smaller volumes of deliveries in urban areas, where conventional vehicles struggle with efficiency due to traffic congestion and parking problems, making e-cargo bikes an attractive alternative [4].

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Although less explored, the literature also discusses the role of e-cargo bikes for personal transport, particularly for shopping and carrying children over short to medium distances [1]. The expected daily miles for e-cargo bikes can vary, with one specific pilot study indicating a range of 19 to 39 km [4]. Overall, the literature on the topic is limited and as a consequence, energy consumption and range assessment estimation methods may be affected by the limited availability of standardized test procedures.

Within the PNRR Next Generation EU program, the National Center for Sustainable Mobility (MOST) aims to contribute to sustainable and active mobility through the design of innovative light pedal vehicles. The goal of the work is to support the proper design and dimensioning of e-cargo bikes using representative real-world usage conditions.

For these reasons, taking inspiration from the methodology proposed by [5], a similar approach was adopted to collect and analyze naturalistic cycling data from four riders, using an instrumented e-cargo bike on a predefined route of a postman within the city of Florence, because the e-cargo bike is well-suited for this type of operation.

In conclusion, the route was selected on the basis of detailed information provided by Poste Italiane. The riding data were then collected and analyzed to extract significant statistics, which led to the development of a driving cycle. The DC can be employed for the design and performance assessment of pedal-assisted vehicles, including energy consumption, range estimation, and powertrain sizing.

2. Materials and Method

2.1. Driving Cycle Development Workflow

The development of a driving cycle typically follows five key steps: selecting the route and vehicle, collecting data, analyzing the data, constructing the cycle using a specific method, and validating the results. The process for DC development is illustrated in Figure 1.

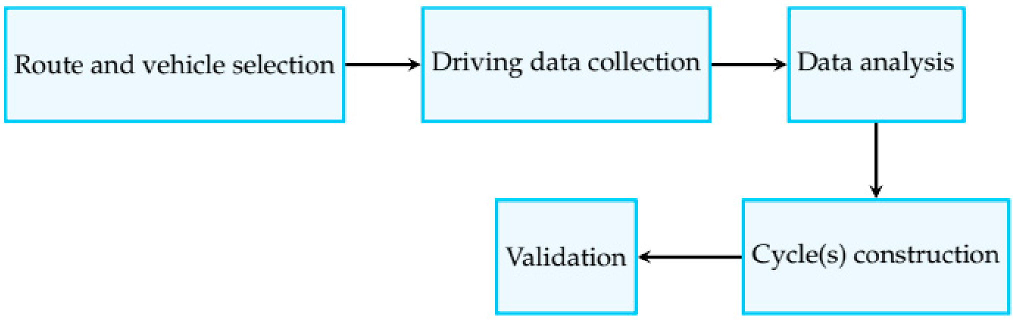


Figure 1. Workflow for driving cycle development.

The selection of route and vehicle is critical, as it defines the scope of data collection. The vehicle and route selection are described in Sections 2.2 and 2.3, respectively. Once data were collected, they were analyzed to extract key metrics and identify typical driving patterns. These insights were then used to build one or more representative driving cycles using constructive methods. The resulting cycles were compared to the original data using characteristic parameters (CPs), which are the key statistics of the DC, such as the average speed. The set of CPs used to compare the developed speed profile with the data is known as the performance values (PVs) [6], and the cycle with the lowest PV is considered the most representative.

The stochastic modal method predicts driving sequences using models like Markov chain Monte Carlo (MCMC). This latter approach effectively captures driving behavior by modeling transitions between different driving states, such as acceleration or cruising. The accuracy of this method depends on the choice of features, including speed, acceleration, or even road slope.

The MCMC approach has previously been used to successfully generate driving cycles, where Markov states were defined based on vehicle speed and acceleration [7]. The MCMC algorithm was implemented using a discrete-time, time-homogeneous Markov chain model (DTHMC). The latter model consists of a series of random variables forming a stochastic process that satisfies the Markov property, commonly referred to as the memoryless property. This implies that the current state contains all the necessary information about the past and is sufficient to predict the future state. Hence, the outcome of the next state is independent of all previous states except the current one, and can be described using the following equation:

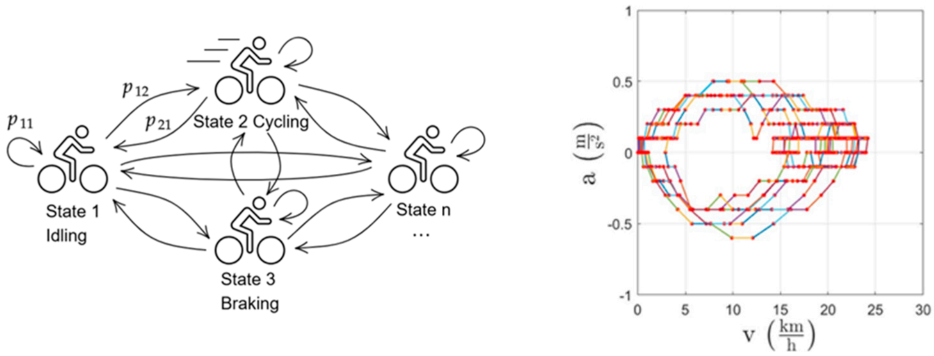
$$P(X_{n+1} = i_{n+1} | X_n = i, X_{n-1} = i_{n-1}, \ldots, X_0 = i_0) = P(X_{n+1} = i_{n+1} | X_n = i) \quad (1)$$

where X_n, $n = 0, 1, \ldots, k$ are the random variables in the time step $t = n$ and the set of all possible values that can be assumed constitutes the state space. This state space is constructed through vehicle dynamics, including speed and acceleration discretization. The transition probability between the states in a time step is defined as follows:

$$p_{ij} = P(X_{n+1} = j | X_n = i) \quad (2)$$

where p_{ij} denotes the transition from state i to state j. These transition probabilities for all state combinations can be organized into a matrix known as the transition probability matrix (TPM). The progression of the Markov chain over time is governed by this matrix.

Once the TPM was established, speed time series were generated by simulating the progression of states within the Markov chain, essentially performing a random walk as a sequence of Markov states. These were carried out in MATLAB R2024b using a Monte Carlo simulation framework based on a uniform probability distribution, an example is shown in Figure 2b. To build the TPM, it was necessary to define the states or classes based on measurable physical variables; an example of state definition is shown in Figure 2a.



(**a**) States definition example (**b**) Random walk

Figure 2. (**a**) States definition example; arrows indicate the transition probability and (**b**) random walk result in the speed–acceleration plot, where each point represent a state and each line a transition. Different colors are used to highlight transitions from point to point.

In this study, the classes were determined by the discretization of longitudinal speed (v) and acceleration (a) using fixed steps (i.e., values Δ) for each respective vector. Specifically, the velocity space was discretized with a step size (Δv) of 0.1 m/s, covering the range from 0 to 35 m/s. Similarly, a step size (Δa) of 0.1 m/s^2 was set for acceleration, covering values from -1 to 1 m/s^2. This process enabled the definition and sampling of the Markov process over a constructed finite space, facilitating the probabilistic modeling of dynamic systems where transitions depend on both current velocity and acceleration states.

To define the PV, the Speed Acceleration Probability Distribution (SAPD) root sum square difference was used. The SAPD describes the driving data probability to be of a certain speed and acceleration class [8], and it was discretized as the Markov states. Values lower than 1 km/h were excluded to avoid long vehicle idling time.

Among the 100 developed DCs, the final DC was the one with the lowest SAPD root sum square difference. Furthermore, other CPs were analyzed in the study to describe the data collected, the comparison between data and the DC developed here, and for future comparison with other data or DCs.

2.2. Vehicle Selection and Instrumentation

The instrumented e-cargo bike used for this study was designed by BCARGO, an Italian cycling company located in Florence (see acknowledgement). It is equipped with a mid-drive motor and a front-loading cargo box that has a volume capacity of 50 L and a weight capacity of 80 kg, as shown in Figure 3. This layout is commonly known as 'Long John' [9], and the commercial name is "BCARGO Professional".

Figure 3. BCARGO e-cargo bike employed for the naturalistic study.

This pedal-assisted vehicle is excluded from the type approval system defined by Regulation EU 168/2013 [10], and classified as a 'cycle' by Italian legislation in Legislative Decree 285/1992 [11] and subsequent amendments, as it satisfies the following requirements:

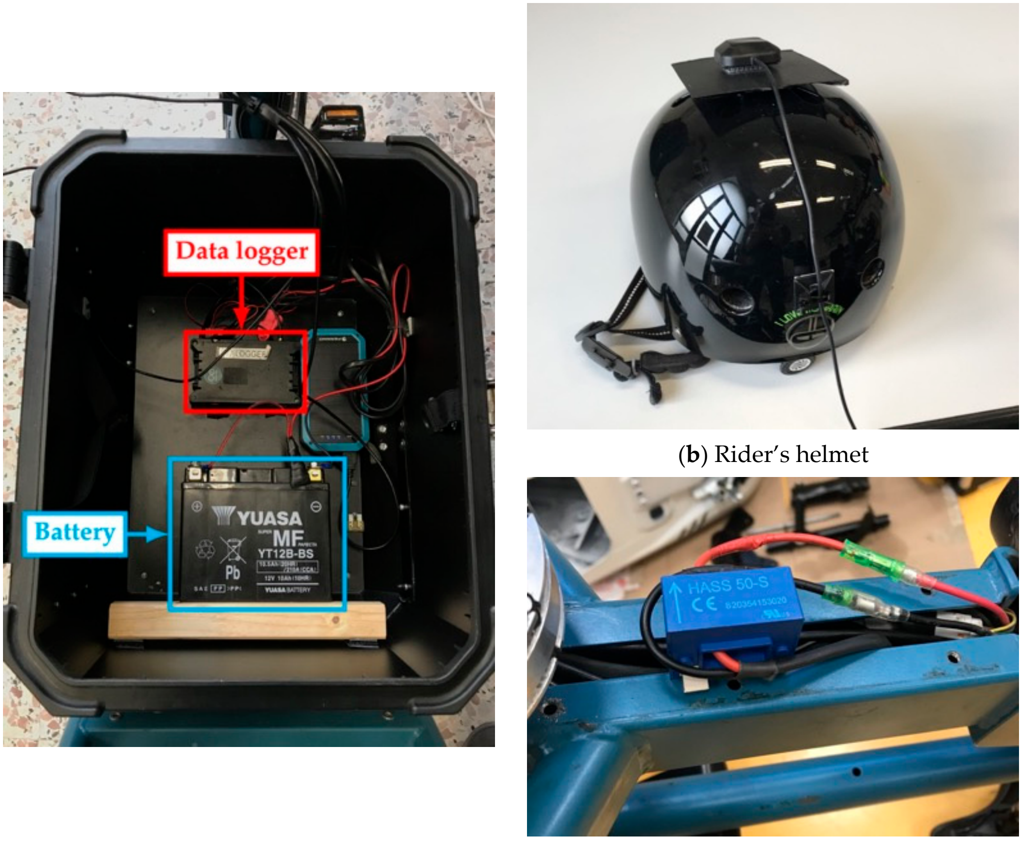
- maximum continuous rated power less than or equal to 250 W;
- electric assistance switched off when the cyclist stops pedaling;
- electric assistance progressively reduced and finally switched off before the vehicle reaches a velocity of 25 km/h.

As a result, several benefits arise, including the absence of demand for a license plate and the possibility to access several infrastructure areas where other vehicles are not allowed to circulate, which are bicycle lanes, pedestrian areas, and shared paths [9]. Ultimately, insurance for damages resulting from vehicle use is not required.

The e-cargo bike was equipped with a data logger and different sensors. The data logger was the DL1 CLUB model produced by Race Technology, which comprises the following features:

- built in GPS unit with GPS3 technology and outputs position, speed, position accuracy, and speed accuracy at 5 Hz with no interpolation;
- GPS 3.3 V active antenna with a magnetic base and SMA connector;
- built in a three-axis accelerometer with 2 g full scale and a resolution of 0.005 g;
- built in single-axis yaw rate gyro with a maximum rate of 300 degrees/s;
- twelve external analogue inputs, all 12-bit resolution with a 0–25 V range. All inputs are protected and filtered.

The described instrumentation architecture is shown in Figure 4.



(**b**) Rider’s helmet

(**a**) Instrumented box

(**c**) Current transducer

Figure 4. E-cargo bike instrumentation setup: (**a**) data logger and battery, (**b**) GPS antenna, and (**c**) current transducer.

The device was secured to the internal base surface of the box using a special tape, allowing a resealable mounting system. In addition, it was necessary to squarely position the data logger with the button facing the back of the vehicle and set the appropriate configuration with its own software.

A 12 V motorcycle battery was used for the power supply. The battery has a capacity of 10.5 Ah and a weight of 4.1 kg. Due to the chamfered edges between the horizontal and vertical faces of the box, to prevent the battery from detaching during potential hard braking, a wooden spacer was inserted between the battery and the vertical face of the box.

The GPS antenna was mounted on the rider's helmet using tape and a metal plate to amplify the GPS signal, as shown in Figure 4b. The chosen position allowed for a clear view of the sky in all directions and a reduced level of vibrations and electrical noise. In addition, the battery current was collected through the data logger and recorded using a current transducer fixed to the lower part of the frame with a clamping screw. The cable pins that connect the battery to the electric motor were disconnected and then reconnected, after being inserted into the transducer, as shown in Figure 4c.

2.3. Route Planning and Data Collection

In the context of urban logistics, data collection plays a crucial role in evaluating the performance and feasibility of e-cargo bikes. Reliable and context-specific data enable researchers and stakeholders to analyze operational efficiency, identify infrastructural challenges, and optimize delivery routes, particularly in dense urban settings. In this study, data collection was carried out along a typical urban route of a postman within the historical city center of Florence, Italy. The route was defined based on a list of delivery addresses provided by Poste Italiane, reflecting realistic logistics operations, and is shown in Figure 5. To ensure variability and robustness in the dataset, four different riders completed the route. This approach allowed for the collection of data under a range of real-world conditions, capturing the impact of different riding styles and external factors such as road traffic and potential road hazards.

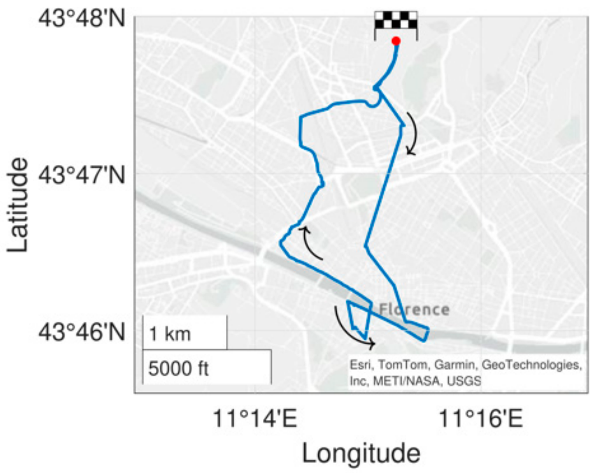
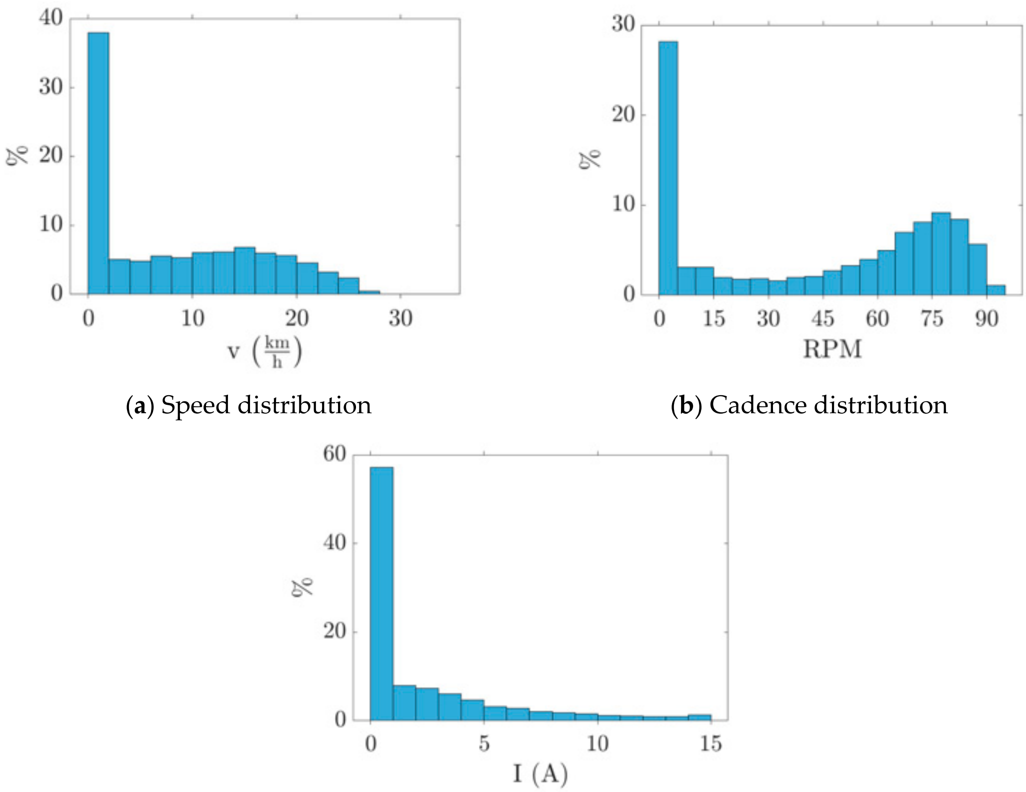


Figure 5. E-cargo bike route through the city of Florence (a clockwise loop). The red marker identifies the starting point, coinciding with the finish line. Blue line represents the main route, and arrows represent the riding direction.

3. Results

3.1. Data Analysis

The dataset collected revealed distinct patterns in the operational characteristics of the e-cargo bike. As shown in Figure 6a, the speed distribution showed a predominantly low-speed operational profile, with the highest frequency occurring at speeds below 10 km/h. The cadence distribution (Figure 6b) showed a bimodal pattern, with significant concentrations at both low and high RPM ranges, suggesting pedal assistance due to high frequency at high RPM. The battery current distribution (Figure 6c) showed a skewed profile, with the majority of operations occurring at low current draw levels, with occasional peaks corresponding to high-demand scenarios, such as acceleration. The battery current remained positive, as it only supplies power from the battery to the motor due to the lack of regenerative braking according to the system layout. The electric powertrain in fact is connected to the wheel by a typical chain and freewheel system, so no torque is regenerated during deceleration due to freewheeling.



(**a**) Speed distribution

(**b**) Cadence distribution

(**c**) Current distribution

Figure 6. (**a**) GNSS vehicle speed distribution, (**b**) cadence distribution in rpm, and (**c**) output battery current distribution.

The descriptive statistics presented in Table 1 provide quantitative insight into these distributions, with speed values ranging from 0 to 31.22 km/h (mean = 6.43 km/h, median = 6.81 km/h), cadence values spanning 0 to 90.91 RPM (mean = 43.09 RPM, median = 51.83 RPM), and current measurements extending from 0 to 14.90 A (mean = 2.24 A, median = 0.69 A).

Table 1. Descriptive statistics of the speed, cadence, and battery current.

	Mean	**Median**	σ	**Min**	**Max**
$v\left(\frac{\text{km}}{\text{h}}\right)$	8.43	6.81	7.99	0	31.22
ω (RPM)	43.09	51.83	32.13	0	90.91
I (A)	2.24	0.69	3.27	0	14.90

3.2. Driving Cycle Synthesis

The constructed synthetic cycles were processed to remove the “staircase” values introduced by discretization. Among the synthesized cycles, the speed profile shown in Figure 7 was chosen as a valid driving cycle, named the Florence cargo bike driving cycle (FCBDC), due to the final speed equal to zero, a reasonable duration, and an error on the RPA really low. The FCBDC is 1641 s long, accounting for 7.6% of the entire dataset’s duration, and spans a total of 3.96 km. The maximum speed is 26.1 km/h, the maximum acceleration is 0.43 m/s^2, the minimum acceleration is -0.46 m/s^2, and the RPA value is 0.25 m/s^2. These latter indicators, along with others, are reported in Table 2.

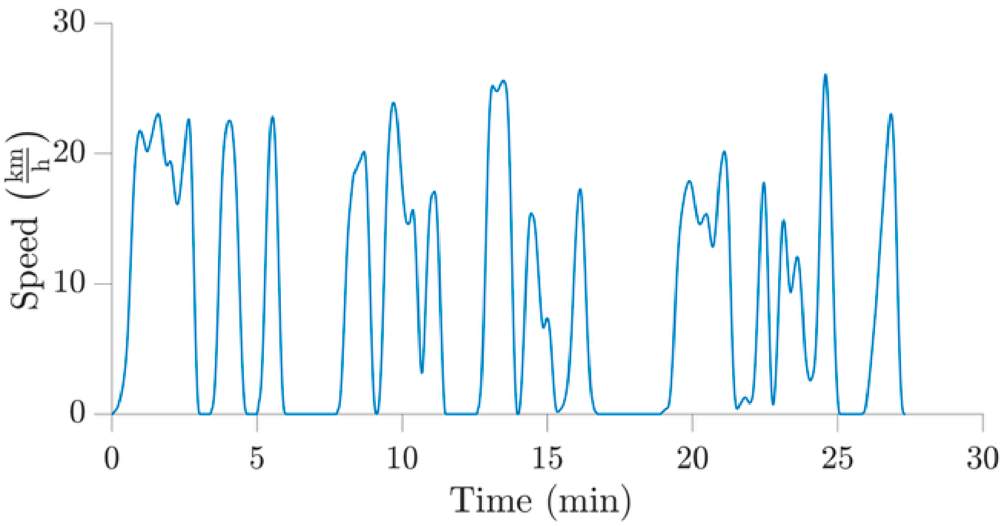
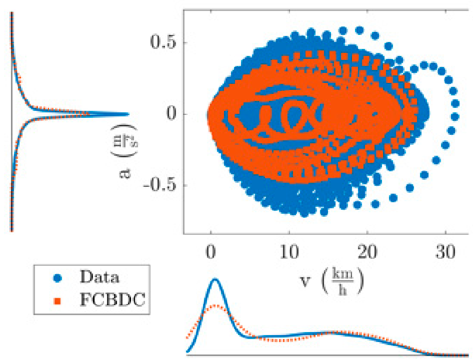


Figure 7. Florence e-cargo bike driving cycle (FCBDC) developed within the city of Florence.

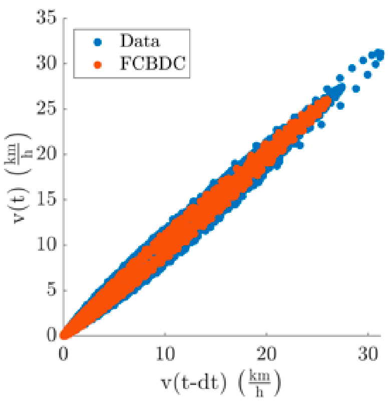
Table 2. Characteristics parameters of the FCBDC.

	$\mathbf{v}_{avg}\left(\frac{\mathbf{km}}{\mathbf{h}}\right)$	$\mathbf{v}^{+}_{avg}\left(\frac{\mathbf{km}}{\mathbf{h}}\right)$	$\sigma_v\left(\frac{\mathbf{km}}{\mathbf{h}}\right)$	$RPA\left(\frac{\mathbf{m}}{\mathbf{s^2}}\right)$	$D(\mathbf{km})$
FCBDC	8.69	13.14	8.43	0.246	3.96
Data	8.43	12.45	7.99	0.243	50.41
Δ %	3.10	5.55	5.51	1.23	−92.14

Figure 8a shows a comparison between the experimental data and the FCBDC in terms of the speed and acceleration distribution. As depicted in Figure 8b, the correlation between speed and speed one second before was maintained by the MCMC model, similar to the reference data.



(**a**) Speed acceleration distribution



(**b**) Time correlation

Figure 8. FCBDC and data comparison: (**a**) speed acceleration distribution and (**b**) time correlation between past and current speeds, with 1-s delta time.

The difference in the SAPD is shown in Figure 9. The SAPD root sum square difference was 2.12%, omitting speed values lower than 1 km/h.

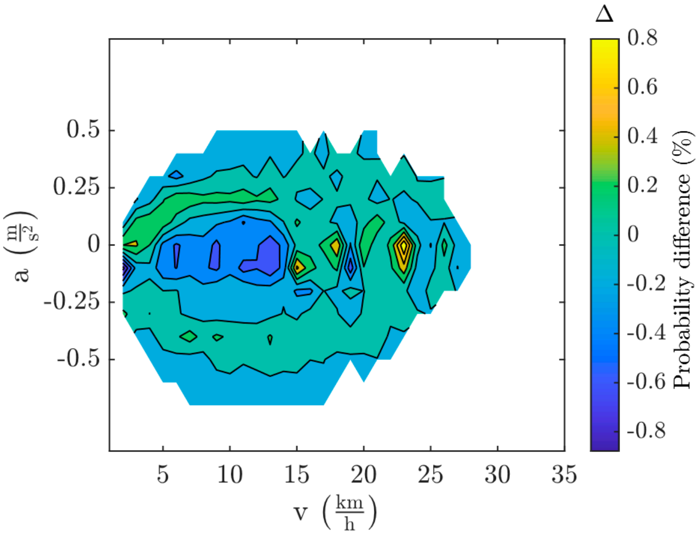


Figure 9. Probability difference between FCBDC and the original data. The values lower than 1 km/h were neglected.

4. Discussion

The developed e-cargo bike driving cycle captured the key aspects of the experimental data. Analysis of the key parameters, including average speed (v_{avg}), acceleration, and relative positive acceleration (RPA), demonstrated that the generated driving cycle closely approximated the empirical dataset, with discrepancies generally below 6% and generally acceptable error ranges from 5 to 10%. Although the results were satisfactory, the maximum and minimum accelerations were lower, up to -33.2%, indicating that some information was lost during discretization and speed smoothing. Despite this limitation, riding behavior was successfully captured, as shown in the speed and acceleration distribution in Figure 8a. The RPA describes the amount of work needed to increase the unitary mass of the vehicle speed normalized by the distance traveled. Thus, the low error between the RPA data and FCBDC indicates a good representation of the kinetic work. With speeds above 1 km/h, the SAPD root sum square difference between the data and FCBDC was 2.12%, as illustrated in Figure 9.

The time dependence between the past and the current speed was included using the Markov chain method, as shown in Figure 8b. In fact, the speed at the next time step is strongly correlated with the current speed, which makes it possible to predict the next value with high accuracy. This suggests that the methodology used can effectively support the design and optimization of e-cargo bikes, particularly in drivetrain sizing, battery management strategies, and control algorithm development.

The skewed speed distribution reflects urban e-bike riding, characterized by frequent stops and low-speed maneuvers. This operational pattern suggests that optimization strategies should prioritize start–stop cycles and support high current peaks. Additionally, the RPA value of 0.243 m/s^2 indicates considerable dynamic behavior, aligning with frequent braking and acceleration. The current distribution indicates that the vehicle operates primarily in low-demand conditions with intermittent periods of higher energy consumption, which is again consistent with typical urban e-bike usage patterns, with frequent starts and stops. Finally, the battery power can be obtained by multiplying the estimated current with its nominal voltage.

5. Conclusions

In this study, a representative driving cycle for e-cargo bikes was developed based on real-world riding data, representative of the urban last-mile delivery condition. These were collected using an instrumented Long John-type e-cargo bike tested by four different riders along a predefined route in the city of Florence. The Italian delivery company Poste Italiane supported the definition of a typical last-mile delivery route, which was then adopted to simulate the working shift of a postman riding an e-cargo bike. The Markov chain Monte Carlo method was successfully implemented to generate a driving cycle of the e-cargo bike, named the Florence cargo bike driving cycle; such cycle is, at the current moment, an early example of standardized time–speed sequences suitable for e-bikes.

This synthetic driving cycle successfully mimicked the empirical data, particularly in terms of characteristic parameters such as average speed, average driving speed, and relative positive acceleration, with discrepancies generally below 6%. These insights indicate that the FCBDC can effectively guide the design of e-cargo bikes to promote health and sustainable mobility, especially in urban environments.

Although the study provided valuable insights into the riding behavior of e-cargo bikes, it also presents certain limitations. The analysis was based on riding data from a small sample of non-professional riders using a single vehicle along a predefined route in a limited urban area. As a result, the derived driving cycle cannot be fully generalized to different rider profiles, delivery contexts, or urban environments. In addition, the exclusion of professional delivery personnel and the restriction to one e-cargo bike layout further reduce the applicability of the experimental findings. Future research should therefore extend the methodology by considering a larger and more diverse sample, multiple bicycle layouts, a variety of routes and urban environments, as well as the inclusion of commercial users, to better capture the heterogeneity of real-world e-cargo bike operations.

In conclusion, despite these limitations, the proposed driving cycle provides significant hints for more efficient development and purpose-designed e-cargo bikes, particularly for urban logistics and sustainable transportation initiatives.

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Data Availability Statement: The dataset and FCBDC are publicly published at this GitHub repository: https://github.com/A-Niccolai/E-cargo-bike-driving-cycle (accessed on 29 September 2025).

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Abbreviations

The following abbreviations are used in this manuscript:

CP	Characteristic parameter
DC	Driving cycle
FCBDC	Florence cargo bike driving cycle

MCMC	Markov chain Monte Carlo
PV	Performance value
RPA	Relative positive acceleration
SAPD	Speed Acceleration Probability Density

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