Digital Twin Implementation for Urban Tram Systems: A Data-Driven Model for Estimating Traction Current

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***Abstract*—The urgent need to decarbonize our cities places the transport sector—responsible for a significant share of greenhouse gas emissions—at the center of global sustainability efforts. Achieving this goal requires not only the electrification of public transport systems but also ensuring their efficiency and effectiveness to encourage widespread adoption over private vehicles. A promising strategy to modernize such systems is the implementation of a Digital Twin (DT), a virtual counterpart of the infrastructure that integrates real-time field data from strategically deployed sensors. This work focuses on tram-based urban transport systems, where one of the most critical parameters for DT applications is the traction current absorbed by each vehicle. However, the deployment of dedicated onboard current sensors is often constrained by economic and time-related limitations. To address this, we propose a transitional solution: a data-driven model capable of estimating tram current consumption using only GPS-based vehicle position data. Specifically, this paper presents a hybrid neural network architecture combining Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models. The network processes speed and acceleration profiles derived from open-access GPS data, eliminating the need for onboard instrumentation. The model was trained and validated with data from a targeted field measurement campaign, achieving a Mean Absolute Error (MAE) of 61.3 A and a Root Mean Square Error (RMSE) of 95.6 A. Given that the maximum absorbed current exceeds 900 A, these error values indicate that the model's predictive performance is within an acceptable range. This methodology provides a robust, low-cost solution for enabling early-stage DT development in Urban Traction Electrification Systems (UTES), supporting simulation and planning in the ongoing digital transformation of public transport.**

***Index Terms*—digital twin, tram, current estimation**

This study was carried out within the "DC smart grids for Next generation Transportation Systems" (NeTS) project – funded by European Union – Next Generation EU within the PRIN 2022 program (D.D. 104 - 02/02/2022 Ministero dell'Università e della Ricerca). This manuscript reflects only the authors' views and opinions and the Ministry cannot be considered responsible for them.

Acronyms

DT	Digital Twin
EPTV	Electric Public Transport Vehicle
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
OCS	Overhead Contact System
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
UTES	Urban Traction Electrification Systems

I. Introduction

The transport sector is responsible for approximately 25% of Europe's total greenhouse gas emissions and represents the leading factor behind air pollution in urban environments. Considering that more than 70% of the European population resides in cities, it is imperative to decarbonize urban mobility systems. Among the various initiatives set in motion to address this challenge, a key one is the enhancement and promotion of public transport, which is widely recognized as the most secure, efficient, and environmentally sustainable mode of mass transit [1].

This study focuses on a particular area within urban public transport: the tramway system, which comprises both electric rolling stock and a supporting electrical infrastructure. This infrastructure, commonly referred to as the Urban Traction Electrification System (UTES), is typically powered by substations containing transformers, AC/DC converters, protection devices, and circuit breakers. Through multiple positive DC feeders, these substations deliver power to the Overhead Contact System (OCS), while the return current flows via the rails and dedicated negative conductors [2]. A UTES is capable of supplying different categories of Electric Public Transport Vehicles (EPTVs), each characterized by specific traction technologies and energy demands.

A promising solution for modernizing tramway systems lies in the development of a Digital Twin (DT)—a dynamic and data-rich virtual counterpart of the physical infrastructure and vehicles, built from mathematical models and real-time information [3]–[6]. For tramway applications, the DT concept includes two core components: a model of the UTES and a model of the in-service EPTVs. To ensure a realistic and functional representation, the two components of the DT (i.e., the infrastructure model and the vehicle model) must be capable of interacting with one another in a dynamic and coherent manner. Moreover, both models must be continuously fed with real-time data acquired from field-deployed sensors, strategically positioned at critical points of the infrastructure (e.g., substations, feeders, and OCS segments) as well as onboard the vehicles. These latter sensors provide fundamental inputs such as vehicle location, and measured values of absorbed current and of voltage of the pantograph.

Unfortunately, the development and deployment of custom on-board sensors is a costly and time-consuming endeavor. These sensors must be specifically designed to achieve a level of accuracy that guarantees sufficient data quality for the intended applications within the DT. Additionally, they need to be equipped with reliable communication capabilities to transmit the collected measurements to a centralized server for further processing and integration.

It is therefore crucial to identify and implement transitional solutions that can provide realistic estimates of tram current consumption, even in the absence of dedicated onboard measurement systems. Such interim approaches would enable the early development and testing of algorithms related to DT applications, such as the evaluation of utilization levels of electrification infrastructure elements.

To estimate the power demand of a tram during its operation, two main classes of modeling approaches can be employed: analytical models and data-driven models.

Analytical models are grounded in physical principles and can be further categorized into forward (also named "cause-effect") and backward (also named "effect-cause") models [7]–[9]. In forward models, the simulation starts from control inputs, such as throttle commands or torque demands, and proceeds to compute the mechanical power delivered to the wheels. Conversely, effect-cause models consider as input the vehicle's speed profile, which can be derived from infrastructure constraints such as segment speed limits, stop locations, and predefined timetables [10]. The required mechanical power is then calculated as the product of torque and angular velocity, where torque is determined from the combined effects of tractive resistance, changes in potential energy, and changes in kinetic energy [3]. Finally, for both model types, the electrical power consumption is estimated by converting mechanical power through the efficiency factors of the drivetrain components [3]. These efficiency values may be considered constant [9], or dynamically estimated based on component-level losses [3].

On the other side, data-driven approaches have gained increasing relevance due to the growing availability of operational data and advancements in machine learning. They allow the calculation of the absorbed current without knowing the several physical parameters required in the analytical physics-based model. These include:

- Neural network models, capable of capturing complex nonlinear relationships between inputs and energy demand [11].
- Interpolation-based models, which estimate consumption based on a mixed physical- and data-driven model [12].
- Lookup table models, where energy consumption is mapped to operating points of the vehicle [13].

Each modeling paradigm presents distinct trade-offs in terms of complexity, generalizability, data requirements, and interpretability.

In this paper, Recurrent Neural Networks (RNNs) were selected as the modeling approach due to their architecture, which is specifically designed to process sequential data—such as text, speech, or time series—where the order and temporal dependencies between elements are essential [14]. In particular, we focused on the RNN types called "Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) [15]–[18].

These models can generate continuous predictions over time while maintaining a low computational footprint. This makes them particularly suitable for real-time applications involving an entire tram fleet. Moreover, given the lack of certain input parameters required by physics-based models, such as detailed vehicle specifications or traction system characteristics, the use of a data-driven model relying solely on data derived from the vehicle's position presents a pragmatic and efficient solution. The chosen architecture allows for scalable deployment and seamless integration within a DT environment, even in scenarios where direct current measurements are unavailable.

To the best of the authors' knowledge, LSTM and GRU-based models have not yet been employed to predict the time evolution of the traction current absorbed by a vehicle using time series derived solely from its positional data. This represents a novel contribution in the field of data-driven modeling for urban transport electrification systems.

The remainder of this paper is organized as follows. Section II illustrates the complete data processing pipeline adopted for current estimation, starting from GPS data acquisition to the application of a hybrid LSTM-GRU model. Section III describes the implementation of the LSTM-GRU network, including the field measurement campaign carried out to get the data for its training and validation, its architecture and assessment. Section IV presents the conclusions of the study and discusses the relevance of the proposed model within the broader context of a UTES DT.

II. Methodology

Fig. 1 describes the end-to-end pipeline used to estimate the electric current absorbed by trams, starting from publicly accessible GPS data to the application of a hybrid recurrent neural network model. Each stage of the process is detailed in the following subsections.

A. Data Collection

Tram positional data are continuously acquired from the dataset "Feed GTFS Real-Time trasporti GTT", available on the City of Turin's open data portal ("aperTO"), which provides real-time information on the positions and movements of public transport vehicles operated by GTT (Gruppo Torinese Trasporti) [19]. The dataset is licensed under the Creative Commons Attribution 4.0 International (CC BY 4.0) license, allowing for broad reuse with appropriate attribution. Data are acquired in real time, polished, and systematically organized within a structured SQL database as reported in

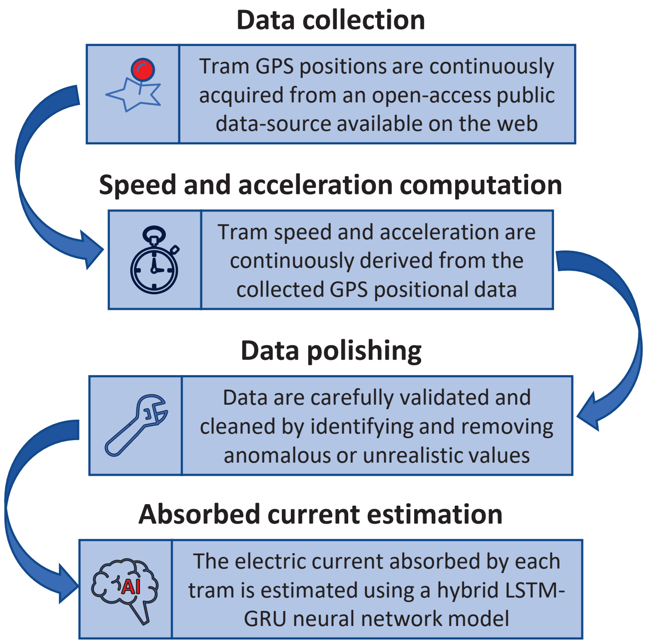

Fig. 1. Logical schema for the tram current estimation process.

the paragraph below. The data conform to the General Transit Feed Specification Real-Time (GTFS-RT) standard [20].

B. Speed and Acceleration Computation

From the collected GPS data, tram speed and acceleration are derived using finite difference methods. These quantities are essential for characterizing the dynamics of tram motion and serve as key features for the subsequent prediction model.

C. Data Polishing

To ensure the quality and reliability of the dataset, a data polishing phase is performed. This process includes the detection and removal of anomalies and outliers, such as unrealistic speed variations, missing values, or sudden position jumps, which may result from sensor noise or transmission errors. Anomalous values are replaced by linear interpolation of the data series of the quantity of interest. Fortunately, in Turin, the stretches of track where the GPS signal is compromised, such as underground tunnels, are negligible. Therefore, the GPS data can be considered a reliable and practical primary source of spatial information.

D. Data Storage

The cleaned dataset is organized and stored in a MariaDB relational database [21]. This structured storage enables efficient data retrieval, supports scalable queries, and facilitates downstream processing for model training and evaluation.

E. Absorbed Current Estimation through an LSTM-GRU Neural Network

The final stage involves estimating the electric current absorbed by each tram. To this end, we adopt a hybrid recurrent neural network model that integrates both LSTM and GRU layers. This hybrid configuration was chosen to leverage the strengths of both models in capturing temporal dependencies of varying lengths while maintaining computational efficiency.

LSTM networks are a well-established extension of standard RNNs, specifically designed to overcome the limitations related to vanishing gradients and short-term memory. They incorporate a memory cell and a set of gating mechanisms (input, forget, and output gates) that regulate the flow of information, enabling the network to preserve relevant features over extended time intervals. This makes LSTMs particularly suitable for modeling the long-range temporal dependencies inherent in vehicle dynamics, such as gradual changes in acceleration or sustained current draw patterns.

GRU networks, on the other hand, offer a more compact and computationally efficient alternative by combining the forget and input gates into a single update gate, and introducing a reset gate. Despite their simpler structure, GRUs have demonstrated competitive performance in a wide range of sequential learning tasks, especially when training data is limited or when low-latency inference is required.

In this work, the LSTM and GRU layers are stacked sequentially, allowing the model to first capture long-term trends and then refine them through more responsive short-term dynamics.

III. RNN IMPLEMENTATION

This section describes the process followed for training and validating the neural network used to estimate the current absorbed by the tram. The model was trained using data collected during a dedicated measurement campaign.

The experimental setup of the measurement campaign is detailed in subsection III-A, followed by a description of the RNN architecture, the input data, and the training and validation procedures, presented in subsections III-B,III-C, and III-D, respectively.

A. Field measurement campaign

Fig.2 represents the measurement setup of the campaign conducted on the tram 8014 of the GTT fleet in Turin. During this campaign, the current absorbed by the tram for traction was registered using a HIOKI MR8880 waveform recorder combined with a current probe, while the vehicle's position was tracked through a smartphone-based application [22].

Considering the specifications and experimental conditions, the measurement errors for the quantities of interest were:

- Current absorbed by the tram: $\pm$ 2.0 % of the reading value $\pm$ 48 A.
- Position: ± 7 meters.

The maximum current measured is 934 A.

In the analysis, only the horizontal components of the position (longitude and latitude) were considered. Vice versa, altitude was disregarded in the present analysis, as the route traveled by the tram was entirely located within a flat urban area, and altitude variations were considered negligible for this study.

In order to simulate realistic load conditions, the tram was ballasted to approximately 30% of its maximum payload capacity. This configuration was chosen to approximate typical operating scenarios while maintaining a controlled and repeatable test environment.

The current signal was sampled at 20 Hz, whereas the GPS-based position data was acquired at a variable frequency, adaptively adjusted according to vehicle motion. Time synchronization between the smartphone and the HIOKI MR8880 waveform recorder was performed prior to the measurement campaign. Nonetheless, to enhance the accuracy of the analysis, a manual alignment between the absorbed

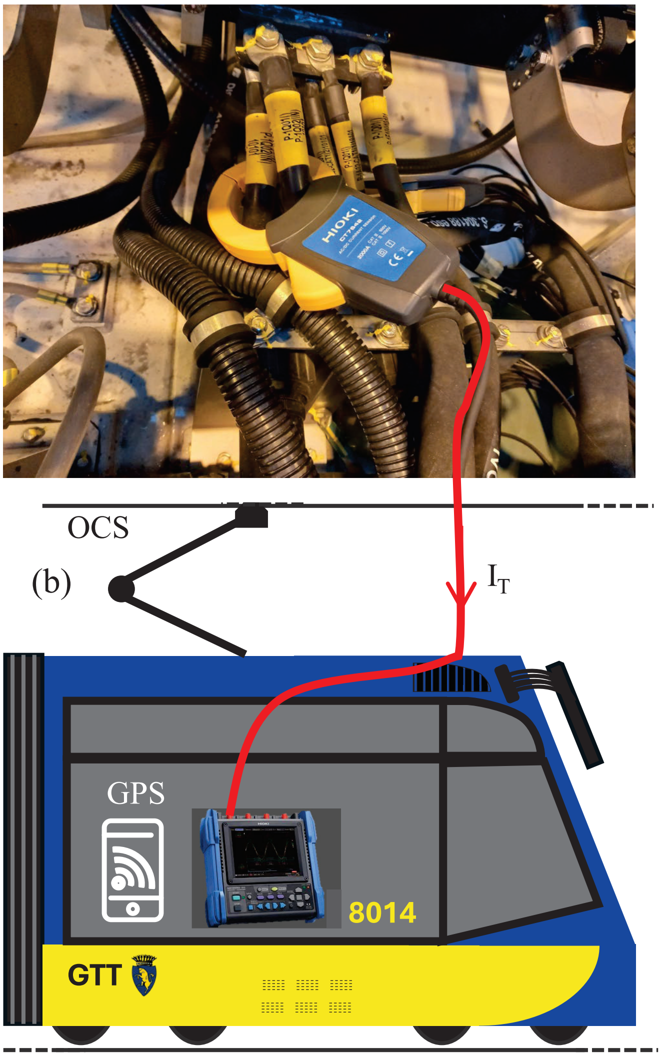

Fig. 2. Measurement setup: Traction current was recorded with a HIOKI MR8880, while vehicle position was tracked via a smartphone application.

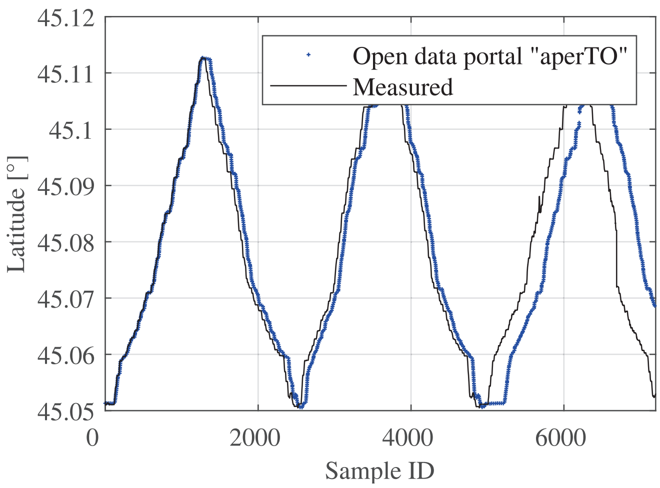

Fig. 3. Qualitative comparison between the latitude measured and collected from the open data portal “aperTO” [19]

current and the derived acceleration signal was subsequently carried out.

The neural network was trained using positional data obtained from the GPS signal recorded by a smartphone installed on board the tram, which is characterized by a higher sampling frequency. However, since the implemented neural network will be fed with data from the publicly available “aperTO” dataset, as described in subsection II-A, a comparison was conducted between the position signals acquired by the smartphone and those provided by the aperTO dataset. Fig. 3 presents a comparison between an extraction of the latitude signal, which is used here as a representative example, measured during the field campaign, and the corresponding data retrieved from the open data portal “aperTO”. From a qualitative standpoint, it can be concluded that the signal provided by “aperTO” is sufficiently reliable within the context of this study.

The speed, acceleration and jerk profiles of the tram were obtained from the position data using incremental ratios (finite differences), calculated over discrete time intervals to approximate the first, second and third derivatives of position.

B. RNN architecture

The architecture combines 4 LSTM layers and 1 GRU layer, stacked sequentially, to exploit both long-term and short-term dependencies. The forward pass at time t is defined as reported in eq. 1 - eq. 3.

$$(h_t^{\text{LSTM}}, c_t) = \text{LSTM}(X_t, h_{t-1}^{\text{LSTM}}, c_{t-1}) \tag{1}$$

$$h_t^{\text{GRU}} = \text{GRU}(h_t^{\text{LSTM}}, h_{t-1}^{\text{GRU}}) \tag{2}$$

$$\hat{i}_t = W_{\text{out}} \cdot (h_t^{\text{LSTM}} + h_t^{\text{GRU}}) + b_{\text{out}} \in \mathbb{R}^2 \tag{3}$$

where:

- X_t is the input data array.
- h_t^{LSTM} is the LSTM hidden state.
- c_t is the LSTM cell state.
- c_{t-1} is the LSTM cell state at time $(t-1)$.
- h_t^{GRU} is the GRU hidden state.
- h_{t-1}^{GRU} is the GRU hidden state at time $t-1$.
- W_{out} is the output weight matrix.
- b_{out} is the output bias vector.
- $\hat{i}_t$ is the predicted current.

To address the problem of overfitting, enhancing the generalization ability of the RNN, a dropout probability of 0.3 was applied between the stacked LSTM layers to prevent the model from relying too heavily on specific neurons. Furthermore, an additional dropout layer with a rate of 0.4 was incorporated after the GRU module to introduce further regularization.

C. RNN input data

Based on the available measurements described in subsection III-A, the first, second, and third derivatives of the tram’s position signal were computed to extract meaningful dynamic features. The calculation of these time derivatives aimed to enhance the model’s ability to capture dynamic behaviors during tram operation, particularly during acceleration, deceleration, and steady-state motion. The data are normalized by removing the mean and scaling to unit variance.

To investigate the influence of different input signal combinations on the neural network’s performance, multiple linear combinations of the available signals were evaluated. Each combination was tested to determine which provided the most accurate and stable predictions. Additionally, several neural network configurations were tested in which the input

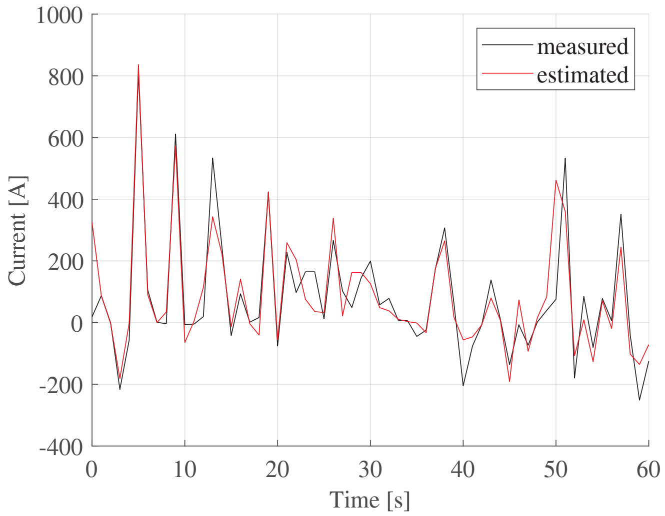

Fig. 4. Comparison between the measured tram current and the current estimated by the LSTM-GRU RNN model over a 60-second excerpt of the test dataset.

variables were transformed through nonlinear operations, such as squaring, to evaluate their impact on the model's learning capability and predictive performance.

One of the most promising model receives the 3-dimensional feature vector $\mathbf{X}_t$ reported in eq. 4 at each discrete time step t.

$$\mathbf{X}_t = \begin{bmatrix} s_t \\ a_t \\ j_t \end{bmatrix} \in \mathbb{R}^3 \tag{4}$$

where:

- s_t: Instantaneous velocity of the tram [km/h],
- a_t: Acceleration [m/s^2],
- j_t: Jerk (third derivative of position) [m/s^3].

D. RNN training and validation

The measured current and voltage signals were utilized both for training and validating the neural network. A standard split of 85% for training and 15% for testing was adopted, ensuring a balanced and statistically significant evaluation of the model's predictive capabilities across different operating conditions.

Fig. 4 shows a qualitative comparison between the measured current absorbed by the tram and the corresponding values estimated by the RNN model based on a hybrid LSTM-GRU architecture. The comparison is conducted on a 60-second excerpt from the test dataset. Although the figure depicts only a portion of the test data, it is representative of the model's performance over the entire test set. The estimated current follows the measured signal, both in terms of magnitude and waveform, confirming the model's ability to generalize effectively within the tested operating conditions.

The model's performance was quantitatively evaluated using the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), yielding values of 61.3 A, 95.6 A, and 0.8, respectively.

These results demonstrate that the proposed model is capable of providing sufficiently accurate estimates of the traction current absorbed by the tram, relative to the research objectives. Consequently, it offers a practical and effective technological solution for constructing and analyzing realistic operational scenarios, aligned with the goals of the tramway network's DT. This approach is especially valuable as a transitional tool, pending the full deployment of dedicated smart meters across the vehicle fleet.

IV. Conclusion

This work presented a novel data-driven methodology for estimating the traction current absorbed by electric trams, leveraging only vehicle speed profiles derived from publicly available GPS data. A hybrid neural network architecture combining LSTM and GRU layers was developed and trained using real-world measurements collected during a dedicated field campaign.

The proposed model successfully captures the complex temporal dependencies inherent in tram dynamics, offering accurate and continuous current estimations without the need for on-board current sensors. The evaluation results, with a Mean Absolute Error (MAE) of 61.3 A, Root Mean Square Error (RMSE) of 95.6 A, and a coefficient of determination (R^2) of 0.8, demonstrate the robustness and reliability of the approach. To improve the results, it would be beneficial to conduct an extensive measurement campaign and design multiple neural networks, each tailored to a specific pair of tram line and vehicle model. In this way, it would be possible to account for the variability in the data due to different driving styles of tram operators, as well as the peculiarities of the route and the tram model itself. By adopting this strategy, the model could better account for variations in operational conditions, ultimately enhancing the performance and reliability of the digital twin in representing the real-world tramway system.

This solution provides a valuable interim tool for supporting digital twin applications in urban traction electrification systems, especially during the transition phase prior to the widespread deployment of smart meters. By enabling realistic simulations and infrastructure analysis, the model facilitates data-driven planning, monitoring, and optimization of electrified public transport networks, thus contributing to the broader goals of sustainable and intelligent urban mobility.

Acknowledgment

We would like to thank "Gruppo Torinese Trasporti (GTT S.p.A.)" for their support during the planning and development of this research work, particularly Daniele Chiesa, Marianna Costa, Salvatore Gaudiello, and Andrea Vaj.

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