CPSO for Innovative Transport Planning and Designing

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Abstract. Mobility and transport systems are becoming increasingly complex. In order to make them more efficient and sustainable, it is necessary to promote studies and research that can improve not only the aspects related to data acquisition but also to data processing and simulation. Several studies in the literature focus on the evolution of mathematical models and traffic simulation tools. This allows planners to use available budgets and resources as efficiently as possible when expanding or rebuilding transport systems. Simulation models help to understand the effects that different measures have on traffic volume and flow under different circumstances. Therefore, traffic simulation creates a sound basis for sound and economic decisions, making traffic and mobility safe, sustainable, equitable and resilient. Starting from the acquisition of traffic data on a case study located at the Municipality of Enna in Sicily, this study focused on the use of the aforementioned dataset for the implementation of a Continuous Particle Swam Optimization algorithm to define a Neural Network model and predict the short-term traffic flow of a smart traffic control region. This approach emphasises that the prediction aspect compared to other methods is more accurate, and the prediction results provide a basis for improved vehicle flow management and intelligent regional traffic control.

Keywords: Particle Swarm Optimization · Neural Network · Traffic Flow Prediction · Sustainable Road Network

1 Introduction

Sustainability is a key factor in modern transport planning. Most regulatory instruments such as Sustainable Urban Mobility Plans (SUMPs) focus on the creation of environmentally friendly, socially inclusive and economically viable transport systems. These plans favor public transport, cycling and walking over car-centred models, with the aim of reducing carbon emissions and improving urban liveability. Implementation of SUMPs involves extensive stakeholder involvement to ensure a balance between community needs and environmental objectives, [1,2].

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O. Gervasi et al. (Eds.): ICCSA 2025 Workshops, LNCS 15897, pp. 304–318, 2026.
https://doi.org/10.1007/978-3-031-97660-5_21

These documents often require preliminary baseline studies that can analyse how some solutions reduce vehicular flows (especially private traffic) by favouring collective and public transport such as bus [3] or demand responsive transport [4] or shared mobility [5].

Various technologies and methodologies have been implemented over the years for the evaluation of vehicle flows, starting with the theory of car following models [6] or even traffic simulation models configured as a management system of graphs and matrix assignments, which makes it possible to carry out simulations of transport networks and thus of the road network, by searching for minimum paths and assigning traffic flows to them on the basis of one or more O/D matrices, which makes it possible, on the basis of these minimum paths, to calculate time, cost and distance matrices [7].

Models for simulating traffic flows are generally tools for analysing and predicting traffic effects. They can be used to plan interventions on transport networks, such as the construction of new roads or the renovation of existing ones.

The increasing volume of urban traffic poses significant challenges in terms of road congestion and environmental impact [8]. The ability to accurately predict vehicle flow is essential for implementing effective management strategies and improving mobility quality. With other words, an accurate prediction of urban traffic is essential for optimizing mobility and reducing pollutant emissions.

In recent years, recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have demonstrated excellent performance in modeling complex time series, making them ideal tools for traffic forecasting [9].

However, the effectiveness of LSTM networks heavily depends on parameter selection, such as the number of neurons in hidden layers and the learning rate, which affect predictive performance and training time [9,10]. To address this issue, in this study, we propose an optimization approach based on Continuous Particle Swarm Optimization (CPSO) [16,17], a technique inspired by the collective behavior of swarms, to determine the optimal network parameters.

In this paper an original approach based on Deep Neural Networks (DNNs) for modeling vehicle traffic is proposed. In details, for the analysis, a LSTM network optimized through Continuous Particle Swarm Optimization (CPSO) has been implemented in order to select the number of neurons in hidden layers and the learning rate. The efficiency of this approach in traffic analysis and its ability to predict traffic flow have been investigated and applied to a real test-case. It has been shown that the optimization improves the algorithm's performance due to cut of the number of parameters and decreasing the computational cost. It means that the computational efficiency enhance thanks to the lower number of neurons, without compromising predictive performance. In particular, the results reveal a significant reduction in loss and Root Mean Squared Error (RMSE), highlighting the potential of the proposed approach for innovative prediction applications in urban traffic.

2 State of the Art

2.1 Traffic Models

The requirement of making cities more sustainable for the lives of citizens is a major issue in our time, as well as the need of reducing the pollution or minimizing the time wasted in traffic jams. Thus, in accordance with 2030 agenda [29], the research in the filed of sustainable local mobility models held a great appeal and many scientists proposed original ideas in order to support the integration of sustainable mobility into future global policy.

In this context, mathematical models play a key role due to their intrinsic ability in describing the phenomenon under study in a realistic, suitable but also rigorous way. With other words, they have a predictive feature that can be applied, for example, in order to analyze the effect of possible urban planning interventions. Moreover, such mathematical models can be adjusted for the purpose of fitting real data collected from street experiment, that is defining the dynamics of the involved variables (i.e. vehicles and/or pedestrian) and their interactions. It also means that they can simulate realistic scenarios, assess benefit and risk of any kind of approach.

Literature is reach in mathematical models for description of traffic flow, usually classified in microscopic, macroscopic, and kinetic models (see [30]).

The macroscopic mathematical models arise form the fluid dynamics equations or rather are systems of partial differential equations. The microscopic mathematical models are the agent based models, that include for example the cellular automata model and the force based models. They respectively simulate the behavior of vehicles or pedestrians and the timing evolution of the traffic in a road or the crowd in a room. The last ones are the mesoscopic models which are mainly based on the equations of the kinetic theory for gas dynamics.

In this paper an original approach based on DNN is proposed for modeling vehicle traffic. Namely, a LSTM network has been optimized by means of CPSO with the aim of select the minimum number of neurons in hidden layers and the learning rate.

2.2 Deep Learning Approaches for Traffic Flow Prediction

DNNs are a class of artificial neural networks distinguished by the presence of multiple hidden layers between input and output. This architectural depth enables them to model highly complex and non-linear relationships, making them particularly effective in domains such as image recognition and natural language processing. A key strength of DNNs lies in their ability to perform hierarchical feature extraction: lower layers capture basic patterns, while deeper layers progressively learn more abstract representations.

In the context of traffic dynamics modelling, this capacity translates into the ability to detect intricate temporal and spatial dependencies in traffic patterns—relationships that traditional models or shallow networks may fail to capture. Among DNN architectures, RNNs, and specifically LSTM networks, have shown

strong performance in time series prediction tasks such as traffic flow forecasting, thanks to their ability to retain long-term dependencies in sequential data.

However, the effectiveness of these models heavily relies on the careful tuning of hyperparameters, including the number of neurons, learning rate, and network depth. Given the high dimensionality of the parameter space, manual optimization is often impractical, leading to the adoption of heuristic and nature-inspired optimization techniques.

In this regard, several studies have explored the integration of algorithms such as Particle Swarm Optimization (PSO) to automatically search for optimal network configurations. For instance, a PSO-Bi-LSTM model has been proposed for short-term traffic flow prediction, achieving improved accuracy and stability compared to conventional approaches [18]. Similarly, PSO-based optimization of LSTM architectures has been shown to enhance forecasting performance and generalization capability [19].

These contributions form the theoretical foundation for the approach proposed in this work, which employs a continuous variant of PSO (CPSO) to optimize both the architecture and hyperparameters of an LSTM network, with the objective of developing an efficient and reliable predictive model suitable for simulating real-world urban traffic scenarios.

2.3 The Evolution of Traffic Data Acquisition

Recent decades have witnessed a profound structural change in transport demand patterns, both for the movement of people and for goods [32]. These phenomena, undoubtedly linked to economic development and the ever-increasing number of vehicles in transit, have led to a gradual increase in vehicle congestion. This has also led to an increasing increase in journey times, road accidents and environmental problems related to pollution, especially around large cities where urban traffic often combines with goods transport and long-distance journeys [33].

In recent decades, various mathematical models have been developed that can support engineers in the delicate task of carrying out accurate analyses on the evolution of traffic flows [34]. These models, the development of which is also attributable to the sudden and unstoppable technological development of sensors and software that make it possible to perform both simulative and predictive analyses.

The first type, the simulative one, analyses how the model behaves when it is stressed by particular external conditions, without these necessarily having to occur in reality. This aspect is of particular interest to a road section manager who needs to know what would happen if, for any reason beyond the everyday, the section in question were temporarily subjected to conditions quite different from the steady state. The second, i.e. the forecasting type, can be achieved by monitoring traffic conditions and, therefore, through it is also possible to make predictions about the occurrence of critical phenomena such as traffic jams or slowdowns, and possibly prevent them, or, if it is not possible to remain in an

acceptable flow condition, equip oneself to deal with the criticality in the best possible way.

In this context, traffic models play an active role in the identification of traffic states and critical situations in the system, make it possible to determine which particular measures to take in order to take due account of exceptional situations (an accident or the temporary closure of a lane) and finally to assess the effects of the countermeasures that can be adopted [35,36]. Traffic simulation models can generally be subdivided into

- microscopic models, which describe traffic behaviour at a high level of detail and consider individual vehicles by describing their movements as the result of individual choices and interactions with other vehicles and the road environment [37];
- macroscopic models, which use ensemble relationships and identify global properties and state variables in which traffic is generally described as a flow defined by behavioral rules that are based primarily on the interaction of vehicles with each other and with the infrastructure [41];
- mesoscopic models, which are at an intermediate level of detail between the previous ones, examine the behaviour of groups of vehicles, thus allowing a simplification of the study compared to the micro but a greater level of detail compared to the macro-simulation [38].

Among the models in the literature that are capable of individually representing the movement of each vehicle on the basis of driver behaviour are, for example, those based on the:

- pursuer theory – Car Following,
- lane change theory – Lane Change,
- minimum access interval theory – Gap Acceptance.

Any road traffic flow estimation model requires a road flow survey phase to determine the actual traffic conditions of the network. The collection of traffic data is therefore of fundamental importance for all activities that may affect the complex mobility system in a more or less direct way, both in small areas, such as a single intersection, and in large areas, such as long-distance roads. In particular, the surveys of certain quantities, both quantitative and qualitative, characterising the vehicular flows passing over a road section contribute to the definition of the analytical framework of mobility and, thanks to their continuous and constant updating, may constitute an element of fundamental importance for the development of the territory [39]. Over the years we have witnessed the evolution of survey methods from manual ones to those with advanced sensors or the use of Big Data [40].

Manual traffic data collection methods are based on the use of one or more operators who record certain traffic data such as the number and type of vehicles passing through a given time interval. The recording of traffic data can be carried out using paper forms or using hit counters. There is no doubt that the use of observers has natural limitations that may not guarantee the correctness and accuracy of the information recorded [42].

The need to continuously and accurately collect traffic data has led technological research in the sector to produce increasingly refined instruments and detection systems. Over the years, data acquisition techniques with various technologies and sensors such as inductive loop, pneumatic tubes, triboelectric cables, piezoelectric sensors and others have become widespread.

While traditional automatic vehicle traffic detection technologies offer the undoubted advantage of allowing measurements to be taken over a long period of time and with a good level of reliability, they have the disadvantages of being suited to the measurement of only a few specific flow parameters (mostly flow rate and speed) and of having a rather limited spatial domain of analysis (represented only by the road sections where the detection sensors are positioned).

Since the Second World War, the use of technology in the management and processing of information has become increasingly strategic for organisations and citizens. Since the 1990 s, in conjunction with the internet boom, the term Information and Communication Technology (ICT) has entered common parlance to refer to that complex of sciences, methodologies, criteria, techniques and tools, capable of collecting, processing and transmitting information of various kinds. These types of applications are also used in the transport sector, both with regard to the transport of goods and the movement of passengers [43].

Aerial photography can be considered a particular technique for observing and analysing the traffic flows of a territorial portion, even a very large one, through which it is possible to trace the main parameters of the vehicular flow of each section of the study area.

Traffic monitoring through the use of video cameras is a non-intrusive procedure that, since its first applications in the 1970 s, has made it possible to more accurately analyse the dynamics and evolution of traffic flows over time. A further new traffic monitoring technique developed consists in the use of probe vehicles, i.e. vehicles equipped with GPS (Global Position System) devices capable of detecting the satellite positioning of the vehicle. This detection technique, also known this detection technique, also known by the acronym FCD (Floating Car Data), presents itself as a 'mobile sensor' in the vehicle flow as it does not require any type of installation along the roadway, is cheaper than other monitoring techniques and requires less maintenance [44]. Moreover, it provides the advantage of being able to cover the entire road network, provides more reliable information on journeys in terms of route lengths and travel times, allows the evaluation of origin-destination flows and, finally, gives the possibility of automatically detecting abnormal traffic delays, such as those caused by accidents. In contrast, there are limitations associated with the instruments used in this monitoring technique, i.e. the accuracy of position determination can also be very poor, as in the case of urban canyons or in tunnels where GPS reception is interrupted [45].

In recent years, in conjunction with the sudden spread of web use, both through the use of PCs and mobile devices (smartphones, tablets, etc.), a series of applications have been developed that, although providing in most aggregate

or often qualitative data, can be useful for finding information, such as in the case of traffic congestion levels (e.g. google maps and/or waze), [46].

3 Methodology

3.1 Optimization Algorithms

Optimization is a fundamental concept in computer engineering and plays a crucial role in solving a wide range of complex problems. Among the various approaches to address these challenges, heuristic optimization methods inspired by natural processes or social phenomena, proved to be particularly effective in determining optimal solutions in complex research spaces. Heuristic methods are based on general algorithms, i.e. problem-independent, in which the components and their interactions achieve an optimal solution on the strength of practical experience and knowledge. Among others, we can mention for example Tabu Search [20–22], Genetic Algorithm [25,28], Ant Colony Optimization [23,24] and Particle Swarm Optimization (PSO) [26,27].

A stochastic optimization technique inspired by swarm movement was first proposed in 1995 by Eberhart and Kennedy [12]. The latter belongs to the family of evolutionary algorithms and finds application in different areas varying from training of neural networks, from clustering methods for the analysis of large volumes of data to intrusion detection systems.

The PSO simulates the social behavior of a flock of birds flying synchronously in searching for food. The algorithm therefore proposes a cooperative dynamics in which each particle (bird of the flock) moves influenced not only by its own experience (learning of itself) but also by the other members experience. Since 1995, numerous variants of the original method have been introduced to improve quality and efficiency, such as [13–15].

Among these variants, Continuous searching for Particle Swarm Optimization (CPSO) stands out [16,17]. Designed to accelerate the convergence of the swarm towards the optimal solution, that is the search for the maximum or minimum of an assigned function, called objective function, the CPSO uses continuous functions to update the position and speed of the particles. The formulation is derived from the integration of a Cauchy problem associated with a second order differential equation that describes the motion of a damped harmonic oscillator known the angular frequency and damping coefficient. In details, let us denote with $\mathbf{p}(t) = [x_1(t), x_2(t), \ldots, x_n(t)]$ the vectorial function representing the position of each particle of the swarm in a *n-dimentional* space and, analogously, $\dot{\mathbf{p}}(t)$ its velocity and $\ddot{\mathbf{p}}(t)$ its acceleration, then, they are updated in CPSO by the integration of the following Cauchy problem

$$\begin{cases} \ddot{p}(t) + 2\zeta(t)\omega(t)\dot{p}(t) + \omega^2(t)p(t) = f(t) \\ p(0) = p_0 \\ \dot{p}(0) = \dot{p}_0 \end{cases} \tag{1}$$

with $t \in [0,\ T]$.

The previous problem describes the dynamics of a damped harmonic oscillator with ω the undamped angular frequency of the oscillator and ζ the damping ratio.

If $\zeta(t) = \overline{\zeta}$, $\omega(t) = \overline{\omega}$ and $f(t) = \overline{f}$, $\forall t \in [a, b] \subset [0,\ T]$, then,

$$p(t) = c_1 e^{\lambda_1 t} + c_2 e^{\lambda_2 t} + \frac{\overline{f}}{\overline{\omega}},\ \ \forall t \in [a, b] \tag{2}$$

where, λ_1 e λ_2 denote the solutions of the characteristic equation associated to the homogeneous form of 1 in the case of underdamped or overdamped system (i.e. $\lambda_1 \neq \lambda_2$).

Otherwise, if the system is critically damped, i.e. $\lambda_1 = \lambda_2 = \overline{\lambda}$, then

$$p(t) = (c_1 + c_2 t)\, e^{\lambda_2 t} + \frac{\overline{f}}{\overline{\omega}},\ \ \forall t \in [a, b] \tag{3}$$

The values of constants c_1 and c_2, as well as the form for λ_1 and λ_2 are detailed in [16] and [17].

3.2 LSTM Network

For traffic analysis and forecasting, we employed a DNN, leveraging the LSTM's ability to model complex time series. The goal is to provide reliable traffic estimates to prevent congestion and reduce pollutant emissions.

Numerical optimization plays a fundamental role in selecting the network parameters. An incorrect configuration could compromise network performance and significantly increase training time. In this work, we designed a LSTM network to forecast traffic flow based on historical data, with the objective of enabling congestion mitigation and emission reduction strategies. The novelty of the proposed approach lies in the application of the Continuous Particle Swarm Optimization (CPSO) algorithm for hyperparameter tuningan optimization technique that, to the best of our knowledge, has not been previously applied to neural network optimization.

Unlike traditional PSO, the CPSO operates in a continuous domain with a well-defined analytic formulation, allowing for smoother convergence and finer control in the search space. We leveraged CPSO to optimize two crucial aspects of the LSTM architecture:

- The number of neurons in each of the hidden LSTM layers.
- The initialization value of the learning rate.

These parameters play a critical role in determining the network's ability to generalize from data and converge efficiently during training. Poorly chosen values can result in underfitting, overfitting, or excessive training time. CPSO was employed to explore these parameter spaces in a fully automated fashion, minimizing the mean square deviation between predicted and observed values.

The resulting LSTM model consists of three LSTM layers followed by two fully connected layers. Each LSTM layer uses the hyperbolic tangent (tanh) activation function, and the final output layer is linear to support continuous value prediction.

This contribution introduces CPSO as a novel and effective optimization method for neural architectures. The integration of CPSO with LSTM enables a more adaptive and performant prediction model, with potential applications beyond traffic forecasting.

4 The Case Study Analysis

With the aim of validate the proposed procedure, the method has been applied for the traffic prediction in a real case study; namely, the data used to train the neural network were collected on Via Boris Giuliano in Enna, an area characterized by various traffic attraction poles.

The data collection period ran from 3 to 9 February 2025, with acquisitions made from 6:00 am to 12:00 pm. Each hour was divided into 15–min slots to obtain a detailed time series of vehicle flow. In detail, the traffic data was acquired by means of a camera–supported manual count, which was carried out during the aforementioned period from which the peak week emerged.

Through the detection it was possible to validate the hourly peak flows corresponding in the real case to the greatest vehicular flows during the hours of start and end of work and school activities.

The investigated area included two survey stations positioned at the beginning and end of the road arch.

The definition of the O/D matrices was also validated using floating car data (FCD) available on a platform related to the use of Big Data. In particular, the research interrogated a specific 'self-service' web portal with an O/D approach, defining some customized queries, namely:

- the selection of the study area
- the definition of the analysis section
- the survey period (two weeks)
- Times (from which to deduce the peak hours)

The comparison of the acquired data and the interrogation of the portal confirms the choice of the analyzed time period, the object of this study.

5 Simulation and Results

In this section, the presented procedure has been adopted with the aim of traffic prediction in the aforementioned real case study. Namely, the CPSO has been implemented over the time interval $[0,\ T] = [0,\ 10]$.

The integration parameters has been chosen as follows:

- Number of particles: 10;
- Sub-interval of integration: 100;
- Integration step: $dt = 0.1$;
- Maximum number of stalls: 5.

As an objective function for optimization, we used the neural network training process, focusing on minimizing the Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

Once the optimal parameters were determined, the network was re-executed with the optimized configurations provided by CPSO.

The following figures, Fig. 1 and Fig. 2, show the trend of loss and RMSE error without applying the optimization process.

The optimization led to a significant reduction in the number of neurons in the hidden layers compared to the initial configuration (from 200, 100, and 50 down to 125, 63, and 35). Moreover, the optimized learning rate was initialized at 0.0537.

This configuration improved computational efficiency while maintaining nearly unchanged predictive performance, enhancing the convergence of the neural network.

In Fig. 1 and Fig. 2 a comparison in terms of performance of the neural network is presented with the aim of underline the improvement gained by introducing the optimization process. Such performance is measured by means of Loss error and RMSE error.

In details, the Fig. 1 illustrates the standard LSTM network training process over 200 epochs.

The Fig. 2 shows the LSTM network training process over 300 epochs when the CPSO is introduced.

A reduction in loss below 0.2 can be appreciated, while the RMSE error, initially above 1, decreases below 0.4.

Finally, Fig. 3 shows the neural network's prediction compared to real data. A good correspondence between estimated and observed values is noted, confirming the model's ability to effectively learn traffic dynamics.

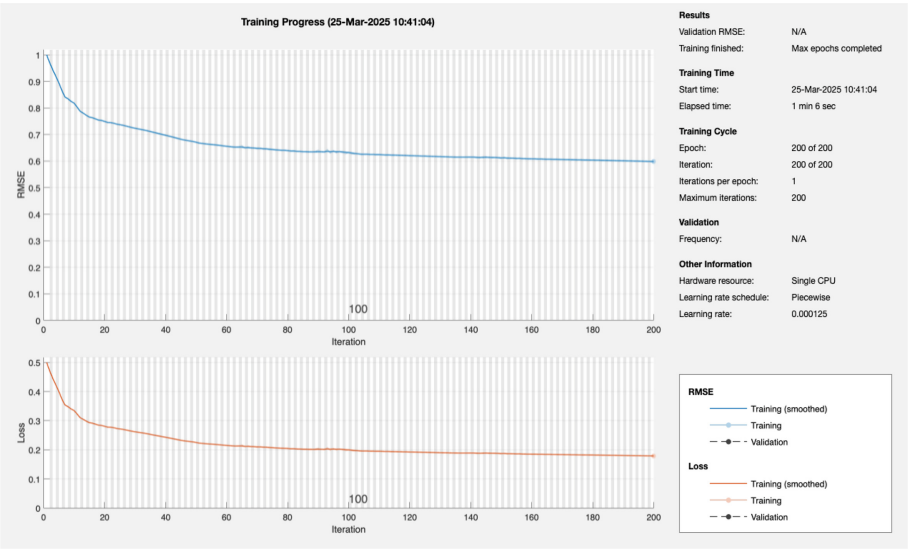

Fig. 1. Loss error and RMSE error trend without optimization process.

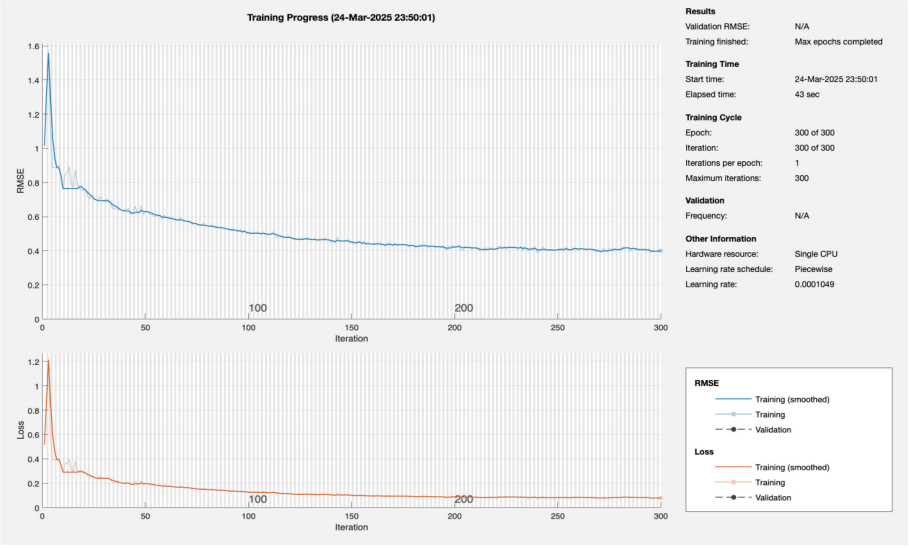

Fig. 2. Loss error and RMSE trend during LSTM network training after CPSO optimization.

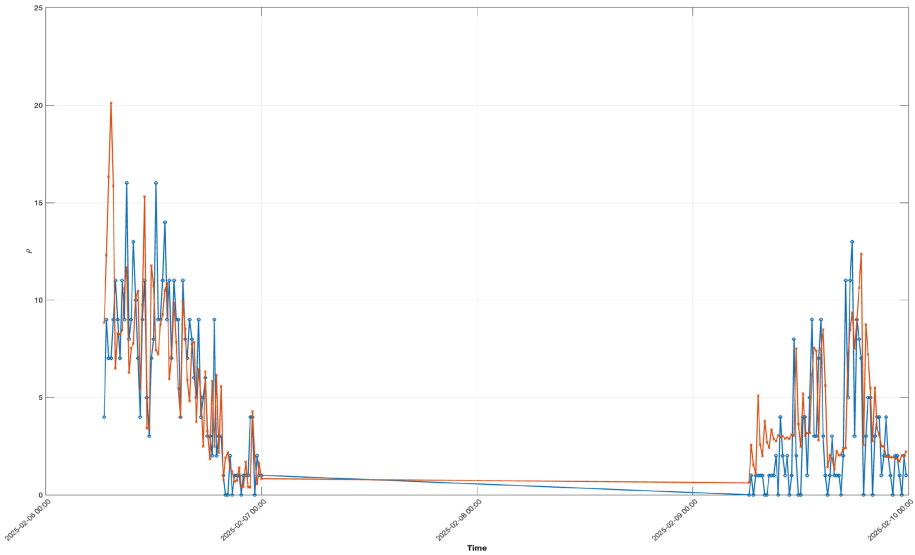

Fig. 3. Neural network prediction compared to real data.

6 Conclusion

The accurate prediction of urban traffic is essential for optimizing mobility and reducing pollutant emissions. In this study, an approach based on DNNs for modeling vehicle traffic on Via Boris Giuliano in Enna has been presented. Data were collected between February 3 and February 9, 2025, with a temporal resolution of 15 min. For the analysis, an LSTM network optimized through CPSO to select the number of neurons in hidden layers and the learning rate has been adopted.

It has been shown that the optimization improves computational efficiency by reducing the number of neurons without compromising predictive performance. The results detail a significant reduction in loss and RMSE error, highlighting the potential of the proposed approach for traffic prediction applications.

The obtained results confirm the effectiveness of CPSO optimization in configuring the LSTM network for urban traffic forecasting. The optimization allowed for a reduction in the number of neurons in hidden layers, improving computational efficiency without compromising prediction quality. The RMSE error, which initially exceeded 1, was reduced to less than 0.4, while the loss dropped below 0.2, demonstrating good model learning capability.

The prediction analysis highlighted a strong correlation between estimated values and real data, confirming the network's ability to model traffic dynamics.

Future developments could include the integration of additional contextual variables, such as weather conditions and special events, to further improve the accuracy of the predictive model.

Acknowledgement. This research was granted by PNRR-M4C2- I1.1 – MUR Call for proposals n.104 of 02-02-2022 - PRIN 2022 – ERC sector SH7- Project title: MOVING StEPS - MOVING from Street Experiments to adaptive Planned Solutions - Project Code 2022BLK9TS - CUP Code J53D23009280008 - Funded by the European Union – NextGenerationEU. The authors A. R., M. R acknowledge the support by G.N.F.M. of I.N.d.A.M.

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