FROM MONO-CLASS TO MULTI-CLASS PHYSICS-GUIDED TRAFFIC STATE PREDICTION: A COMPARATIVE STUDY OF GAUSSIAN PROCESSES AND LSTM NETWORKS

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ABSTRACT

Accurate traffic prediction is fundamental to effective urban mobility. This paper investigates the shift from mono-class to multi-class traffic modelling and its implications for physics-guided machine learning techniques. We examine two approaches for multi-class highway traffic prediction, encompassing both passenger vehicles and trucks: (i) a physics-regularized Gaussian Process (GP) model that integrates constraints from the multi-class METANET model, and (ii) a Long Short-Term Memory (LSTM) network that incorporates these constraints into its loss function. Beyond evaluating prediction accuracy, computational cost, and implementation complexity, we highlight the challenges introduced by multi-class formulations—particularly the need to account for diverse vehicle dynamics. Our findings provide insights into the trade-offs and feasibility of each approach and assess the impact of transitioning from mono-class to multi-class models on predictive performance.

Keywords: Gaussian Processes, machine learning, LSTM networks, multi-class METANET model, traffic modelling

1. INTRODUCTION

Accurate evaluation and prediction of traffic conditions are essential for improving traffic flow management, reducing congestion, and enhancing safety in Intelligent Transportation Systems (ITS). Traditional physics-based models, such as the METANET model (Papageorgiou *et al*., 1989), offer interpretable representations of macroscopic traffic dynamics. However, they often require extensive calibration and struggle to capture the stochastic nature of real-world traffic. Conversely, machine learning models have demonstrated strong predictive capabilities by leveraging large datasets, yet they may lack physical consistency and generalizability—especially in scenarios with limited data. To address these challenges, we propose two physics-guided machine learning models that integrate the strengths of data-driven approaches with domain knowledge derived from the widely adopted multi-class METANET framework.

The multi-class METANET model (Pasquale *et al*. 2015), an extension of the original METANET framework, incorporates distinct dynamics and interaction terms for different vehicle classes, enabling a more accurate representation of mixed traffic flow. This enhances the realism and precision of traffic state modeling, particularly in scenarios involving heterogeneous traffic composed of both passenger vehicles and trucks.

In this paper, we build upon our previous work on mono-class traffic prediction (Binjaku *et al*. 2024) by extending it to a multi-class context that explicitly accounts for vehicle heterogeneity. In our earlier study, we compared physics-regularized Gaussian Processes and physics-informed LSTM networks within a mono-class traffic setting. However, since real-world traffic comprises multiple vehicle types exhibiting diverse behaviours, mono-class models may fall short in accurately capturing these complex dynamics.

This study addresses two key research questions:

- What are the benefits of extending physics-guided machine learning models from a mono-class to a multi-class traffic setting that explicitly captures vehicle heterogeneity?
- How does the performance of a physics-informed Long Short-Term Memory (LSTM) model compare to that of a physics-regularized Gaussian Process (GP) when both are applied to multi-class traffic prediction?

To answer these questions, we propose and evaluate two multi-class physics-guided models based on the METANET framework:

1. A multi-class physics-regularized Gaussian Process, in which the equations from the multi-class METANET model are incorporated as

a regularization term to guide the GP in learning traffic dynamics, while guaranteeing adherence to basic traffic flow relationships.

2. A multi-class physics-informed Long Short-Term Memory network, which enhances the ability of an LSTM neural network to model temporal dependencies by directly embedding traffic flow physics into its architecture, thereby preserving physically meaningful constraints.

Both models explicitly consider two vehicle classes—cars and trucks—allowing for a more accurate presentation of mixed traffic flow, both of which are critical indicators for evaluating and managing traffic conditions. are explicitly taken into account in both models, enabling a more accurate depiction of mixed traffic flow dynamics. The primary traffic variables predicted are mean speed and traffic flow, both of which are critical indicators for evaluating and managing traffic conditions.

To rigorously evaluate the performance of the proposed models, we compare them across three key dimensions: i) accuracy of predictions, ii) training time, and iii) complexity of implementation.

We perform and a comparative analysis of the physics-informed LSTM and the physics-regularized Gaussian Process models in both mono- and multi-class settings. The inclusion of results from our prior mono-class framework enables a comprehensive and consistent evaluation, allowing us to assess the advantages of incorporating multiple vehicle classes in modelling process.

The reminder of the paper is structured as follows: Section 2 provides an overview of related work on the METANET model, Gaussian Processes, LSTMs, and physics-guided machine learning models for traffic analysis. Section 3 introduces the proposed multi-class physics-based machine learning models and summarizes all models employed in this study. Section 4 details the experimental setup using real-world traffic data. Finally, Section 5 presents the conclusions and outlines directions for future research.5.

2. RELATED WORK

The literature on traffic modelling broadly categorizes existing approaches into three groups: data-driven models, physics-based models, and hybrid approaches that integrate domain knowledge into machine learning frameworks. Traditional physics-based models—such as microscopic and macroscopic traffic models—have been widely adopted over the years. Macroscopic models offer a higher-level representation of traffic flow dynamics and include first-order models like the Lighthill-Whitham-Richards (LWR) model, as well as second-order models such as Payne-Whitham (PW) and Aw-Rascle-Zhang (ARZ). Among these, the METANET model has gained particular prominence due to its discrete-time, discrete-space formulation, which enables efficient traffic state estimation and supports practical control applications. Numerous extensions of the METANET framework have been proposed to handle heterogeneous vehicle classes (Pasquale *et al*. 2014; 2015), autonomous and connected vehicles (Shahri *et al*. 2022), and freeway control systems incorporating features such as ramp metering and variable speed limits (Hegyi *et al*. 2005; Chavoshi *et al*. 2023). These enhancements have improved the model's flexibility and applicability in addressing the demands of modern traffic management.

With the increasing availability of traffic data, data-driven models have become powerful tools for estimating and forecasting traffic conditions. Among these, Gaussian Process (GP) models have been widely adopted due to their probabilistic nature and inherent ability to quantify uncertainty. Applications of GP models span a range of tasks, including scalable predictions via infinite mixture models (Sun and Xu, 2011) and queue length forecasting (Kocijan and Přikryl, 2010). Their predictive performance has been further improved through hybrid approaches such as GP ensembles (Zhan *et al*. 2018) and GP-LSTM combinations (Xie *et al*. 2021). On the other hand, Long Short-Term Memory (LSTM) networks are particularly well-suited for capturing temporal dependencies in traffic data. They have demonstrated strong performance in various applications, including multi-step traffic forecasting (Liyong and Vateekul, 2019), imputation of missing data (Tian *et al*. 2018), and graph-based modelling for road link optimization (Liu *et al*. 2020). Moreover, the integration of Convolutional Neural Networks (CNNs) with LSTMs has enhanced the ability to detect spatiotemporal patterns in traffic networks (Chu *et al*. 2021; Lian and Wang 2024).

While physics-based models often struggle to adapt in real time, traditional data-driven models tend to overfit when faced with sparse or noisy data. Physics-guided machine learning (PGML) addresses these limitations by integrating physical laws into data-driven models, thereby enhancing the accuracy and robustness of real-time traffic management systems. PGML enables models to learn from data while remaining consistent with the underlying physical principles or domain knowledge of the system being modelled. In recent years, interest in physics-guided machine learning has grown significantly. This increasing trend is illustrated in Figure 1, which is based on the body of literature identified during our review.

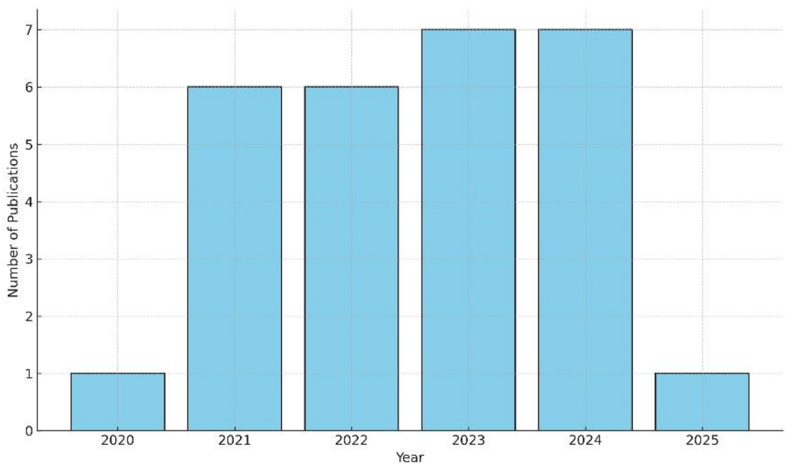

Fig.1: Distribution of publications about physics-based machine learning models for traffic state estimation.

Physics-guided machine learning (PGML) techniques have been applied to a wide range of tasks, from fuel consumption modelling and car-following behaviour to trajectory prediction. For instance, to reduce vehicle emissions, (Das and Tanvir 2024) integrates Vehicle-Specific Power into a physics-informed LSTM model for autonomous vehicles (AVs). To enhance trajectory prediction, several studies—such as (Long *et al*. 2024; Sheng *et al*. 2024), and (Geng *et al*. 2023) —incorporate traffic models like the Intelligent Driver Model (IDM) and vehicle kinematics into deep learning frameworks. In efforts to simulate driver behaviour, hybrid approaches also merge classical physics with machine learning techniques. Liu *et al.* (2023) employ quantile regression within a physics-informed deep learning (PIDL) framework to capture stochastic driving dynamics, while Mo *et al.* (2021) propose variations of PIDL-CF based on four distinct car-following models. Lei *et al*. (2024) utilize NSGA-II multi-objective optimization in conjunction with physical models to address both fuel consumption and battery degradation in plug-in hybrid electric vehicles (PHEVs).

Traffic State Estimation (TSE) has been the focus of several studies (Huang and Agarwal, 2020; 2022; 2023a,b; Huang *et al*. 2024). To address challenges such as sparse sensor coverage, noisy data, and complex boundary conditions, these studies iteratively refine their physics-informed deep learning (PIDL) models by incorporating traffic flow models such as the Lighthill-Whitham-Richards (LWR) model, the Cell Transmission Model (CTM), conservation laws, and nonlocal variants of the LWR model. In their later work, fog computing is introduced to improve the real-world applicability and scalability of the models.

Meanwhile, physics-informed neural networks have also been researched by other academics. Aw-Rascle-Zhang (ARZ) is a second-order traffic flow model that was incorporated into the PIDL architecture (Shi, 2021). Shi *et al*. (2022) enhance the model estimation performance under sparse data conditions by extending the PIDL framework with a Fundamental Diagram Learner (FDL). To more flexibly capture traffic dynamics, Di *et al*. (2023) propose a hybrid graph architecture that integrates both physics-informed and physics-uninformed components.

Other notable approaches include the LWR-based PIDL framework proposed by Rempe *et al.* (2021), which integrates multiple sources of traffic data, and the domain-decomposition-based Physics-Informed Neural Network (PINN) developed by Usama *et al*. (2022). Barreau *et al.* (2021a,b) utilize coupled micro–macro PINN models to jointly identify, reconstruct, and predict traffic states using sparse data collected from probe vehicles. Recent advancements include multi-task optimization techniques Wang *et al.* (2023), where auxiliary tasks are used to guide PINNs via the LWR model, and the work of Zhao and Yu (2022), who apply second-order partial differential equation (PDE) models to estimate traffic states both spatially and temporally.

Recurrent neural networks, particularly Long Short-Term Memory (LSTM) models, are frequently used in traffic state prediction due to their ability to capture temporal dependencies in traffic flow. The integration of physics-based traffic flow concepts has been shown to improve the accuracy and interpretability of LSTM models in several studies. For instance, Das and Tanvir (2024) present a physics-informed LSTM framework tailored for self-driving vehicles in mixed traffic conditions. The model employs a multi-objective loss function that incorporates Vehicle-Specific Power (VSP) to balance trajectory prediction with emission reduction. To enhance realistic car-following behaviour, Tischmann *et al.* (2024) combine LSTM with the Intelligent Driver Model

(IDM), using a physics-guided loss function to steer the training process. Fafoutellis and Vlahogianni (2025) employ Granger causality for feature selection and introduce a Traffic Flow Theory-Informed (TFTI) loss function to align LSTM predictions with fundamental traffic flow diagrams. In another study, Pereira *et al*. (2022) integrate the Traffic Reaction Model (TRM) into a physics-informed LSTM to ensure macroscopic consistency in traffic flow predictions.

Physics-guided reinforcement learning (RL) is also emerging as a promising approach in traffic management. Han *et al*. (2022) introduce a physics-informed RL ramp metering method that enhances prediction accuracy by integrating synthetic and real-world data, grounded in polynomial traffic flow models.

To achieve both flexibility and physical consistency, Sheng *et al*. (2024) propose a residual RL framework that embeds domain expertise via the Intelligent Driver Model (IDM) to model core traffic dynamics, while employing neural networks to learn residual patterns beyond those captured by traditional physics.

3. OUR PROPOSED PHYSICS-BASED MACHINE LEARNING MODELS

This section introduces the physics-based machine learning models proposed and developed in this study: the multi-class physics-regularized Gaussian Process (PR-GP) and the multi-class physics-informed Long Short-Term Memory (PI-LSTM) network. These models extend established approaches by integrating components from the Gaussian Process (GP) framework, the multi-class METANET traffic flow model, and Long Short-Term Memory (LSTM) networks, thereby combining data-driven learning with domain-specific traffic flow dynamics.

3.1The physics-regularized Gaussian process

The multi-class physics-regularized Gaussian Process (PR-GP) model developed in this study is based on the integration of the multi-class METANET traffic flow model and Gaussian Processes (GPs). GPs are a powerful and flexible non-parametric framework used for regression and classification tasks, where relationships between data points are modelled probabilistically (Su and Zhang 2017). To ensure that the GP model remains consistent with fundamental traffic flow principles, a regularization term is incorporated into the objective function. This regularization component is derived from the governing equations of the multi-class METANET model, initially introduced in (Pasquale *et al.*, 2015), which extends the original METANET framework (Papageorgiou *et al.*, 1989) by incorporating the dynamics of multiple vehicle classes. Specifically, the regularization term is formulated based on the multi-class METANET equations for traffic density, mean speed, and traffic flow (Equations 1, 2, and 3 in Pasquale *et al.*, (2015)), and is computed as follows:

$$g_{1,c} = \widehat{\rho_{i,c}}(k+1) - \widehat{\rho_{i,c}}(k) - \frac{T}{L_i\lambda_i}\left[\widehat{q_{i-1,c}}(k) - \widehat{q_{i,c}}(k) + \widehat{r_{i,c}}(k) - \widehat{s_{i,c}}(k)\right] \qquad (1)$$

$$g_{2,c} = v_{i,c}(k+1) - v_{i,c}(k) - \frac{T}{\tau_c}\left[V_{i,c}(k) - v_{i,c}(k)\right] - \frac{T}{L_i}v_{i,c}(k)\left(v_{i-1,c}(k) - v_{i,c}(k)\right) + \frac{v_c T\left(\rho_{i-1}(k) - \rho_i(k)\right)}{\tau_c L_i\left(\rho_i(k) + \chi_c\right)} - \delta_{on} T\,\frac{v_{i,c}(k) r_i(k)}{L_i\left[\rho_i(k) + \chi_c\right]} \qquad (2)$$

$$g_{3,c} = \widehat{q_{i,c}}(k) - \widehat{\rho_{i,c}}(k)\cdot\lambda_i\cdot\widehat{v_{i,c}}(k) \qquad (3)$$

where $\hat{\rho}$, $\hat{v}, \hat{q}$ denote the estimated values of traffic density, speed, and flow, respectively.

Gaussian Processes are employed to estimate these quantities. To enhance the physical consistency of predictions, a set of pseudo-observations (Z,ω) is introduced. These pseudo-observations (Z,ω) have the same structure as the original input-output pairs (X,Y), where X represents the input features and Y the observed outputs. The pseudo-inputs Z are selected from the spatial-temporal domain to represent regions within data distribution. The corresponding pseudo- outputs ω are not directly, but are instead inferred from GP model and are used to evaluate adherence to physical constrains. The selection of pseudo-inputs Z is performed using a clustering-based approach, specifically the k-Means algorithm (Ikotun *et al.* 2023) to ensure good coverage of the spatial-temporal data domain.

Importantly, the pseudo-observations are selected to represent the input space in a realistic and data-representative manner. The locations Z are determined using a clustering-based technique, specifically the k-Means algorithm (Ikotun *et al.* 2023). This approach ensures that the pseudo-observations effectively cover the spatiotemporal domain, reflecting the underlying structure of the dataset. As a result, the model is able to evaluate and enforce physical constraints across a diverse range of traffic conditions.

At the selected pseudo-observation points, the model evaluates the predicted values of traffic density, speed, and flow, which are then used to assess the degree to which the multi-class METANET equations are satisfied. This evaluation enables the computation of physics-based residuals corresponding to each governing equation.

These residuals are used to derive the terms $g_{1,c}$, $g_{2,c}$, and $g_{3,c}$, which represent the deviations from the expected physical relationships for each vehicle class ccc. These terms are incorporated into the regularization strategy of the model. By embedding them into the Gaussian Process objective function, the model is guided to generate predictions that not only fit the observed data but also conform to the underlying physical traffic flow dynamics. This physics-based regularization, made possible through the use of pseudo-observations, enhances the model's generalization capabilities—particularly in regions with sparse or noisy data—while ensuring that the learned relationships remain consistent with established traffic flow theory.

Consistency with traffic flow dynamics is enforced through the inclusion of a physics-based regularization term, which enhances the Gaussian Process (GP) marginal likelihood. This augmented likelihood forms the basis of the final objective function. As a result, the model is trained not only to fit observed data but also to remain consistent with known physical laws governing traffic dynamics.

The posterior distribution of the GP model, incorporating both observational data and physics-based constraints, can be expressed as:

$$p(Y, \omega, g, \hat{f}, Z| X) = p(Y|X)\, p(\omega, g, \hat{f}, Z| X, Y)\,] \qquad (4)$$

However, computing the log marginal likelihood log $p(Y| X)$ directly is often intractable. To address this, the model is trained by maximizing the Evidence Lower Bound (ELBO), a variational approximation of the true marginal likelihood. We denote this objective function by L, and it integrates both the data likelihood and the regularization imposed by the physics-based constraints. This ELBO-based approach was first formalized in the context of sparse Gaussian Processes by Titsias (2009).

Figure 2 shows the block diagram of the algorithmic workflow, that we have implemented to predict traffic flow and speed, for the multi-class physics-regularized Gaussian Process. The model input X is the position of the sensor and the time where the data are measured, while the output Y are the real values for flow and speed. L is the objective function, and the execution ends when a predefined number of iterations has finished, set to 500, or the value of the objective function does not change for more than 10 iterations. We have implemented the algorithm in Tensorflow framework and to update the parameters, ADAM optimizer is used.

Figure 2 presents the block diagram of the algorithmic workflow we have implemented for traffic flow and speed prediction using the multi-class physics-regularized Gaussian Process model. The model input X consists of the sensor location and time stamp at which traffic measurements are recorded, while the output Y corresponds to the observed values for flow and speed. The training process optimizes the objective function L and terminates either when a predefined maximum number of 500 iterations is reached, or when the value of L has not changed for more than 10 consecutive iterations. The algorithm is implemented using the TensorFlow framework, and parameter updates are carried out using the ADAM optimizer.

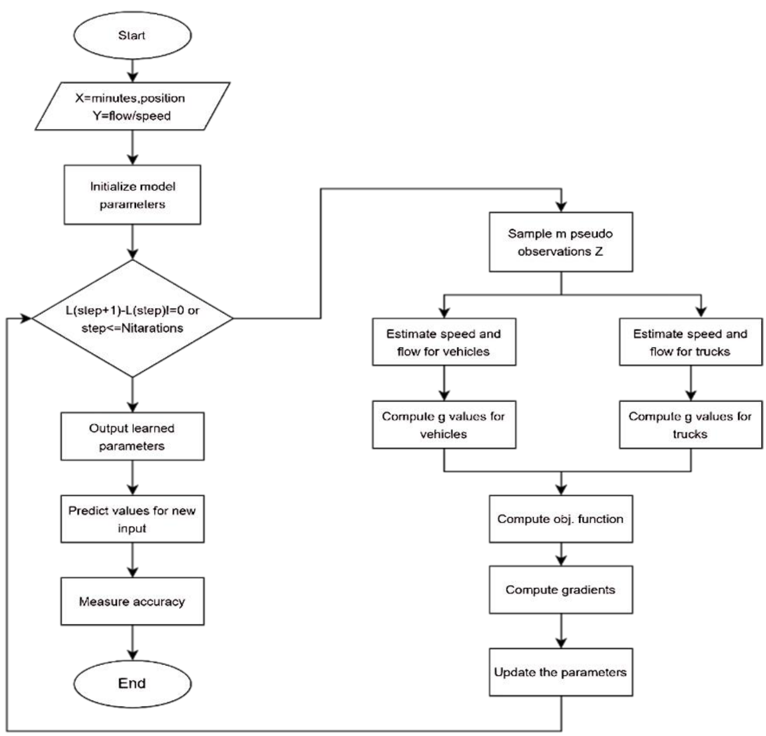

Fig. 2: Workflow of the multi-class physics-regularized Gaussian Process for traffic flow and speed prediction.

3.4.1 The physics-informed LSTM model

The physics-informed LSTM model extends the concept of incorporating physical constraints into machine learning, specifically for sequential data. Long Short-Term Memory (LSTM) networks are an advanced class of Recurrent Neural Networks (RNNs) designed to capture long-range dependencies in time-series data (Hochreiter and Schmidhuber, 1997). Unlike standard RNNs, which struggle with long-term memory due to vanishing gradients, LSTMs introduce memory cells and gating mechanisms that regulate the flow of information, enabling them to retain relevant context over extended sequences.

In contrast to the physics-regularized Gaussian Process, which enforces physical consistency through an external regularization term, the physics-informed LSTM model directly embeds the multi-class METANET equations into the network's temporal architecture. This makes it particularly well-suited for traffic flow modelling, where time-dependent dynamics play a critical role.

The model balances data-driven learning and physical consistency by incorporating a physics-based loss term into its training objective. The overall loss function consists of two components: (1) the standard mean squared error (MSE) between the LSTM predictions and observed traffic data, and (2) an additional term that penalizes discrepancies between the LSTM outputs and the physics-based estimates derived from the multi-class METANET model:

$$\mathcal{L} = \alpha \cdot \mathrm{MSE}(y, \hat{y}) + (1 - \alpha) \cdot \mathrm{MSE}\left(\hat{y}, \widehat{y'}\right) \quad (5)$$

where $\alpha \in [0, 1]$ balances physical laws with data-driven learning. While the parameters of the multi-class METANET model are pre-calibrated using real traffic data, the parameters of the LSTM network are optimized during training using gradient-based methods, specifically Stochastic Gradient Descent (SGD) and the Adam optimizer. Figure 3 illustrates the block diagram of the algorithmic workflow implemented to predict traffic flow and speed using the multi-class physics-informed LSTM model. The input to the model is a time series of past values for a single traffic state variable (either speed or flow) across consecutive time steps. Training proceeds for a maximum of 500 iterations, or until the objective function L shows no significant improvement for more than 10 consecutive iterations. The entire algorithm is implemented in the TensorFlow framework.

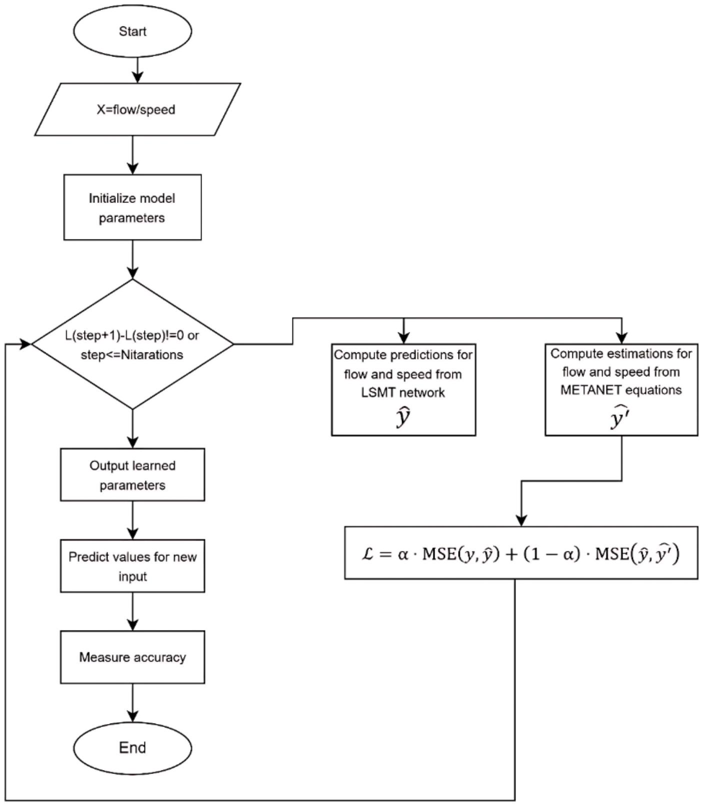

Fig. 3. Workflow of the multi-class physics-informed LSTM model for traffic flow and speed prediction.

4. CASE STUDY APPLICATION

We evaluated the proposed physics-guided models using data from the Caltrans Performance Measurement System (PeMS). The selected freeway segment and the corresponding sensor locations are depicted in Figure 4. In the figure, green labels indicate mainline sensors used for training the models, blue and purple labels represent sensors that provide on-ramp and off-ramp flow measurements, and the red label marks the location where predictions are performed. Traffic data were collected at 5-minute intervals over a 5-day period from each sensor. This data collection strategy is based on findings from a prior study (Binjaku *et al*. 2025) in which we analysed the effect of training data size on the performance of a multi-class physics-regularized Gaussian Process for traffic state prediction. That study showed that using two weeks of training data yielded the highest prediction accuracy, but at the cost of significantly increased computational time. In contrast, using 5 days of data provided an optimal trade-off between prediction accuracy and computational efficiency, and was therefore adopted in the present study.

Fig. 4: The considered freeway stretch.

Figure 5 illustrates the traffic data distribution for both cars and trucks over a five-day period at sensor S2. As shown in the plots, vehicle volumes increase significantly during peak hours and decline sharply—almost to zero—during night time. The speed distribution along the corridor similarly indicates congestion during rush hours, characterized by reduced average speeds. This traffic pattern is observed consistently across the entire study segment, confirming the temporal regularity of congestion during peak demand periods.

The Pearson correlation coefficient between the flow of vehicles and trucks is −0.06, and between their speeds is −0.09, indicating negligible linear correlation in both cases. These low correlation values suggest that vehicles and trucks exhibit distinct flow and speed patterns across the dataset. As a result, it is justifiable and appropriate to model the two vehicle classes separately, particularly in the context of multi-class traffic flow modelling.

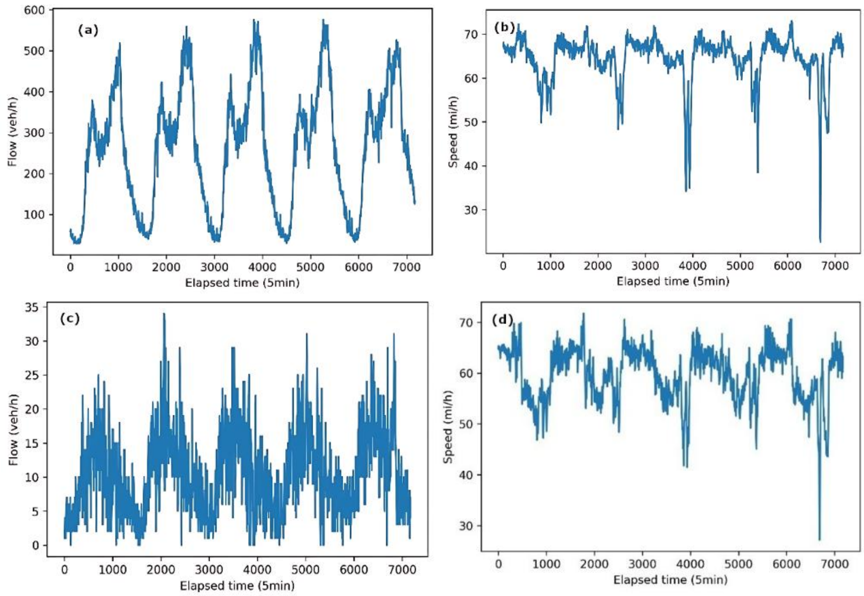

Fig.5: Flow and speed distribution during 5 days, for cars (5a and 5b) and trucks (5c and 5d).

The multi-class physics-regularized Gaussian Process (PR-GP) model was configured with two restarts and optimized using the L-BFGS-B optimizer. The multi-class physics-informed LSTM (PI-LSTM) model was implemented using three stacked LSTM layers, each comprising 50 units, followed by a Dropout layer with a dropout rate of 0.2 to mitigate overfitting. The Adam optimizer was employed for gradient-based parameter updates.

Both models were trained for 500 epochs, with a learning rate of 0.1 and a batch size of 32. Model predictions were generated for sensor S4, focusing on peak traffic hours over a single day.

The fixed parameters of the multi-class METANET model are listed in Table 1, while the remaining parameters were calibrated using the initial values provided in Table 2.

Table 1. METANET parameters with fixed value.

Parameters	**Values**
T	1/12 h
L_i	1.2 mi
λ_i	5

Table 2. METANET parameters initial values.

Parameters	**Values**
v_{free}	100 km/h
ρ^{cr}	59.4 veh/mi
χ	20.97 veh/mi
τ	0.005 h
α	1.5
ν	13.5 mi^2/h

Figures 6 and 7 present the predicted speed and flow for cars and trucks, respectively, using the multi-class physics-regularized Gaussian Process and the multi-class physics-informed LSTM models.

The corresponding Mean Absolute Percentage Error (MAPE) values for speed and flow predictions are reported in Tables 3 and 4, respectively. Additionally, Table 5 summarizes the training time required by each model. Training time was recorded on a standard laptop equipped with 16 GB of RAM, a 2.0 GHz quad-core CPU, and running the Windows operating system.

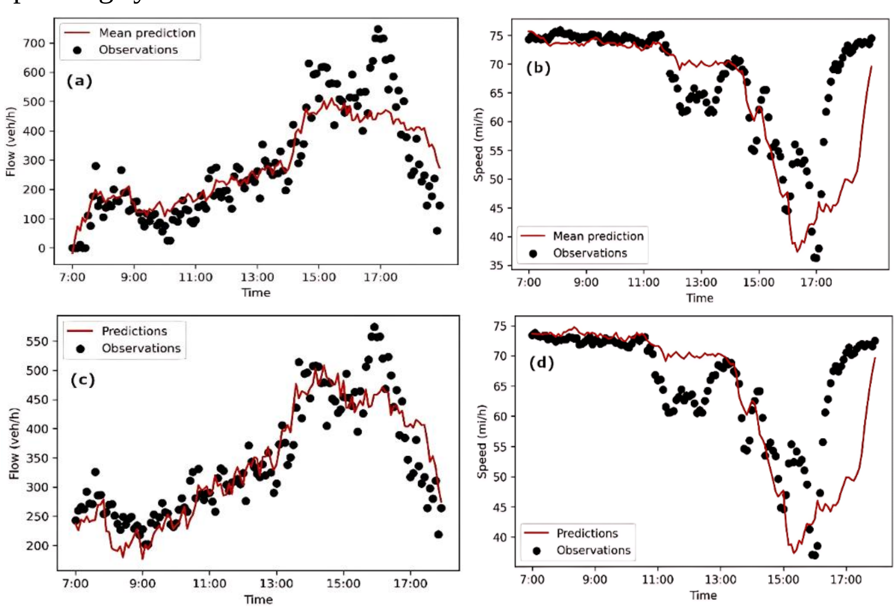

Fig. 6: Flow and speed predictions for cars, with the mono-class physics-regularized Gaussian Process (6a and 6b) and with the multi-class physics-regularized Gaussian Process (6c and 6d).

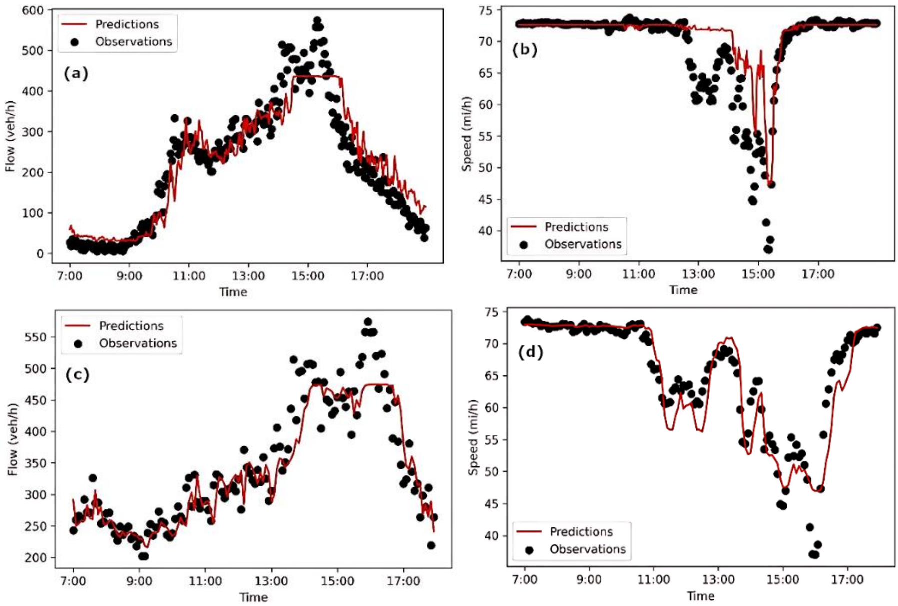

Fig. 7: Flow and speed predictions for cars, with the mono-class physics-informed LSTM (7a and 7b) and with the multi-class physics-informed LSTM (7c and 7d).

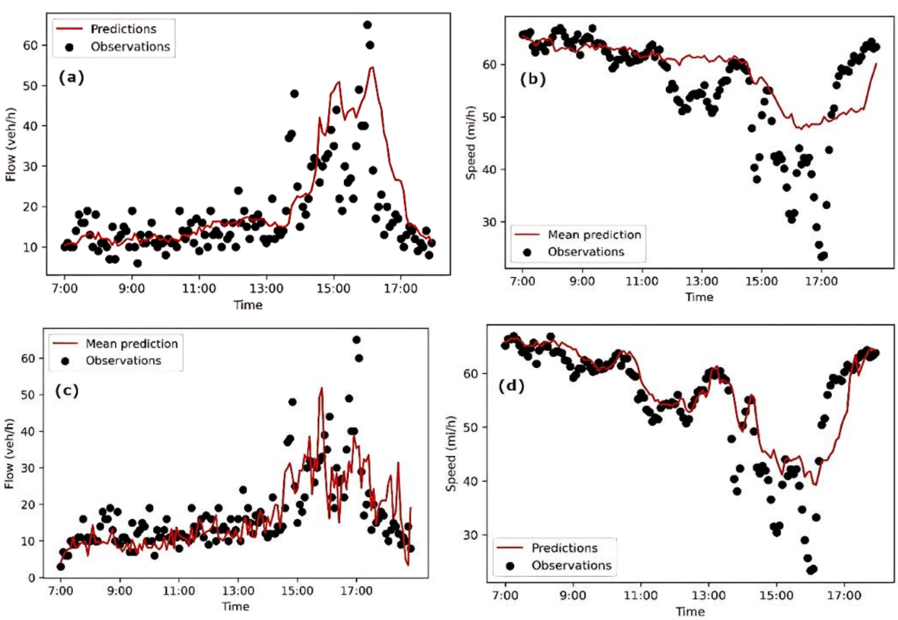

Fig. 8: Flow and speed predictions for trucks, with physics-regularized Gaussian Process (8a and 8b), and physics-informed LSTM model (8c and 8d).

Table 3. Mean Absolute Percentage Errors in flow and speed for cars, with physics-regularized Gaussian process and physics-informed LSTM models

	Traffic flow	**Traffic speed**
Mono-class physics-regularized Gaussian process	0.23	0.17
Mono-class physics-informed LSTM	0.18	0.15
Multi-class physics-regularized Gaussian Process	0.21	0.16
Multi-class physics-informed LSTM	0.17	0.11

Table 4. Mean Absolute Percentage Errors in flow and speed for trucks, with physics-regularized Gaussian process and physics-informed LSTM models

	Traffic flow	**Traffic speed**
Multi-class physics-regularized Gaussian Process	0.29	0.19
Multi-class physics-informed LSTM	0.19	0.16

Table 5. Training time

	Time [sec]
Multi-class physics-regularized Gaussian Process	18.200
Multi-class physics-informed LSTM	2109

The plots, prediction error tables, and the training time table clearly indicate that our study evaluates two key aspects: (i) the impact of transitioning from a mono-class to a multi-class modelling approach, and (ii) the trade-offs between the two model types—multi-class physics-informed LSTM and multi-class physics-regularized Gaussian Process.

First, the advantages of incorporating traffic heterogeneity are evident when contrasting mono-class and multi-class scenarios. Prediction errors are consistently higher in the mono-class setting, where vehicle types are not differentiated. For instance, the multi-class version of the physics-regularized Gaussian Process model reduces the MAPE to 0.21 for flow and 0.16 for speed, compared to 0.23 and 0.17, respectively, in the mono-class version. A similar pattern is observed with the physics-informed LSTM model: the mono-class version yields MAPE values of 0.18 (flow) and 0.15 (speed), while the multi-class version improves performance to 0.17 and 0.11, respectively. Although these reductions may seem modest in absolute terms, they are consistent and meaningful—especially in real-time traffic control scenarios where predictive precision is critical. The multi-class models enhance the network's ability to capture traffic patterns by enabling the modelling of each vehicle class (e.g., cars and trucks) with distinct dynamics.

Second, the trade-off between training time and prediction accuracy has significant implications for model architecture and overall performance. The multi-class physics-informed LSTM model achieves the best predictive performance, particularly in the multi-class case, with error levels of 0.17 for flow and 0.11 for speed. This improvement stems from the LSTM's inherent ability to effectively capture temporal dynamics and long-term dependencies in traffic data.

In addition to its superior predictive accuracy for both flow and speed, the multi-class physics-informed LSTM model is also computationally efficient, requiring only 2,109 seconds for training. In contrast, the multi-class physics-regularized Gaussian Process (PRGP) model demands significantly more computational resources, with a training time of 18,200 seconds.

This substantial difference in training time stems from the fundamental nature of the two models. The physics-informed LSTM (PI-LSTM) relies on iterative, gradient-based optimization over multiple epochs, whereas the PRGP model depends on matrix-based computations. When physical knowledge is incorporated into the PRGP framework, the regularization scheme and the covariance structure must be adapted accordingly, increasing computational complexity. PRGP's kernel-based architecture becomes more cumbersome when integrating physical constraints. In contrast, PI-LSTM enables a more modular and flexible integration of physical knowledge through modifications to the loss function, enhancing its scalability and adaptability to diverse traffic dynamics.

5. CONCLUSIONS

In this study, we implemented and evaluated two models for traffic state prediction: the physics-informed Long Short-Term Memory (PI-LSTM) model and the physics-regularized Gaussian Process (PRGP) model, applied to both mono-class and multi-class traffic data. The models were tested using a real-world highway dataset for predicting vehicle flow and speed.

The results indicate that multi-class models consistently outperform their mono-class counterparts by achieving higher prediction accuracy through the incorporation of vehicle-specific dynamics.

Among the evaluated approaches, the multi-class PI-LSTM model demonstrated superior predictive performance while also significantly reducing training time. Its architecture is comparatively simpler to implement, requiring only modest adjustments to the loss function to incorporate physical constraints. In contrast, although the PRGP model also benefits from physics-based regularization, its implementation is more complex due to the need for modifying kernel structures and managing computationally intensive matrix operations. This leads to higher computational costs, making it less suitable for real-time applications.

Overall, the findings suggest that the multi-class physics-informed LSTM model offers the best trade-off between predictive accuracy, computational efficiency, and implementation complexity. It stands out as a practical and effective solution for real-time traffic prediction in heterogeneous traffic environments.

DECLARATIONS

Data Accessibility

All data used in this study are publicly available and have been previously published or referenced in scientific sources.

Author Contributions:

Kleona Binjaku had full access to all the data and assumes responsibility for the accuracy and integrity of the data and results. The study concept, methodological design, and model development were primarily led by Binjaku, with substantial input from Kajo Meçe and Sacone. Data acquisition, preprocessing, and model training were performed by Binjaku, under the supervision of Pasquale and Sacone. All authors contributed to the interpretation of results and formulation of the comparative framework. The initial manuscript draft was written by Binjaku. Kajo Meçe, Pasquale, and Sacone provided critical revisions and intellectual guidance throughout the writing process.

Author Approval

All authors reviewed and approved the final version of the manuscript.

Declaration of AI use:

No generative AI has been employed in writing this article.

Conflict of Interest Declaration

The authors declare no conflict of interest.

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