A machine learning meta-model for efficient quantification of intersection performance in large-scale urban road networks

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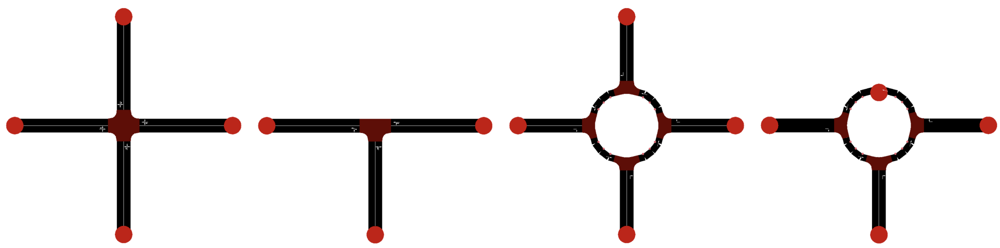
1 INTRODUCTION

Recent advancements in Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, enhanced by autonomous vehicle technologies, have significantly solidified the foundation for intersection management, drawing increased attention to the topic (Namazi *et al.*, 2019). Studies such as Autonomous Intersection Management (AIM, Dresner & Stone (2008)) and Cooperative Vehicle Intersection Control (CVIC, Lee & Park (2012)) illustrate that modern algorithms outperform traditional traffic signals by minimizing delays and emissions at intersections. Yet, their scalability to large-scale urban road networks remains unproven, due to the challenges of field-testing and the extensive computational demands of city-wide microscopic traffic simulations.

Emerging techniques in machine learning (ML) for predicting vehicle emissions and traffic movements show promise for addressing these challenges, potentially reducing the resources needed for large-scale algorithm validation. Rivera-Campoverde *et al.* (2021) developed a model for predicting emissions based on driving conditions, Wang *et al.* (2020) used Long Short-Term Memory (LSTM) models to estimate emissions from traffic flow, and Mahmoud *et al.* (2021) demonstrated LSTM's ability to predict short-term traffic movements at signalized intersections. However, these models depend on detailed vehicle trajectories, typically obtained from field tests or microscopic simulations, which are impractical for large-scale evaluations.

To address these limitations, we propose an ML-based meta-model framework to estimate key performance indicators (KPIs) for intersections using sequential vehicle traffic data and intersection features. Our analysis illustrates that our proposed approach achieves accuracy comparable to microscopic simulations while significantly reducing computational time, thus providing a more efficient method for evaluating intersection performance across extensive urban networks. With this framework, exhaustive field tests or microscopic simulations are only necessary for a select subset of intersections to generate training data, enabling the proposed model to efficiently extrapolate performance metrics for the remaining intersections in the network.



(a) Four-way cross-junction (b) Three-way cross-junction (c) Four-way roundabout (d) Three-way roundabout

Figure 1 – *Different intersection structures used in the simulations*

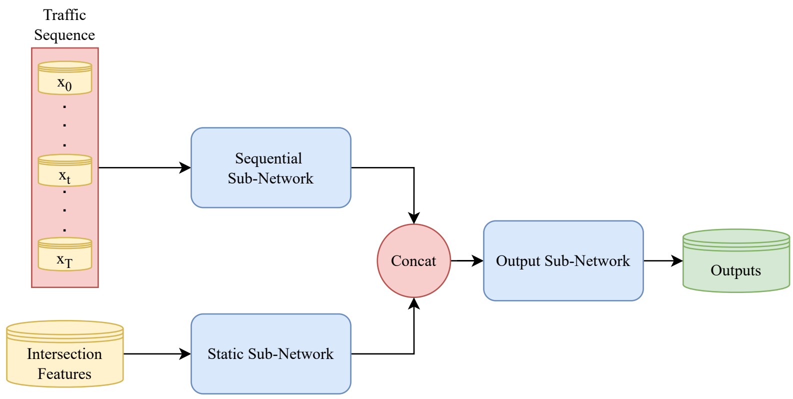


Figure 2 – *Model architecture, comprising of three modules: sequential, static and integration. Inputs to the model include a sequential component (traffic) and a static component (intersection features), while the outputs are purely static.*

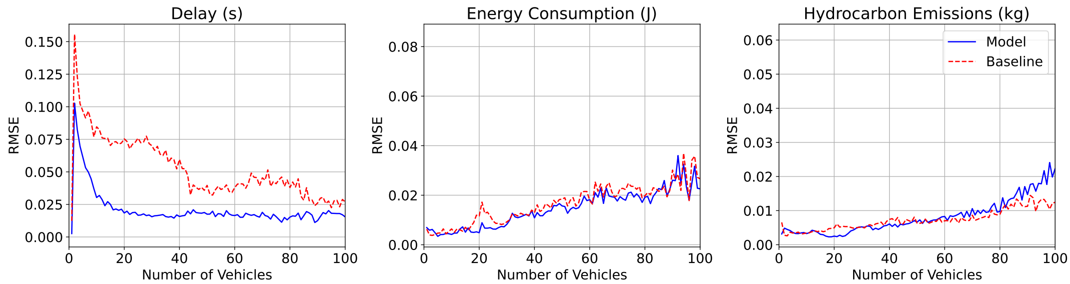
2 METHODOLOGY

2.1 Data Preparation

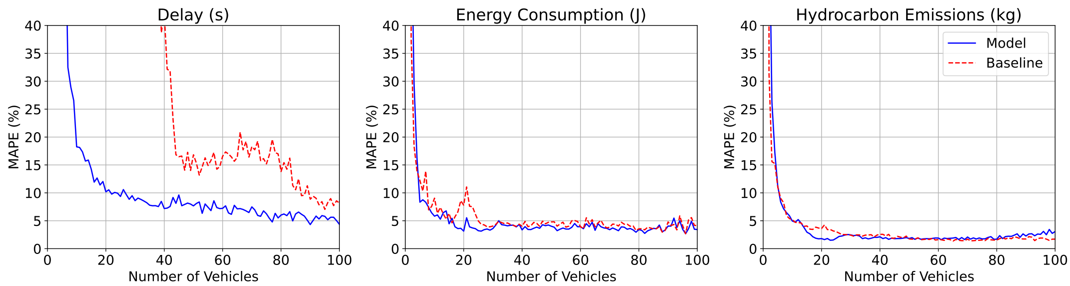
Our model employs sequential traffic data and static intersection features, with intersection KPIs generated through microscopic simulations as labels. We synthesized traffic sequences by randomly determining vehicle arrival rates, entry directions, and maneuvers. The elements of each sequence are characterized by arrival time, entry direction, and destination. These sequences were integrated into detailed road network models that includes lane configurations and traffic signals, facilitating the simulation of unique vehicle trajectories over 300-second intervals. These trajectories enabled the computation of the intersection's key performance indicators (KPIs). Utilizing SUMO (Lopez *et al.*, 2018), we constructed four different types of intersections, shown in Figure 1, each with varying numbers of lanes. We describe the intersections using three features: type of intersection (cross junction or roundabout), number of directions and number of lanes. The modular nature of our framework allows for seamless incorporation more complex features to better capture intersection dynamics.

2.2 Model Framework

Our proposed model architecture, depicted in Figure 2, consists of three specialized neural network modules: a sequential module, a static module, and an integration module. The sequential module employs a sequence-to-one approach, encoding temporal dependencies within the traffic data. Concurrently, the static module processes intersection-specific features, generating an en-



(a) Root mean square error (RMSE)



(b) Mean absolute percentage error (MAPE)

Figure 3 – *Test set metrics of our proposed model compared against the baseline model for each KPI, including a) root mean square error and b) mean absolute percentage error, shown against the number of vehicles in each of the scenarios tested.*

coded representation. These outputs are then concatenated and directed into the output module, which amalgamates traffic and intersection data to predict the intersection's KPIs. We implemented an LSTM architecture (Hochreiter & Schmidhuber, 1997) for the sequential sub-network and utilized multilayer perceptrons (MLP) for both the static and output sub-networks.

3 RESULTS

For the purposes of this study we chose a small set Key Performance Indicators (KPIs), namely mean delay, vehicle energy consumption, and total hydrocarbon emissions for all vehicles at the intersection over a 300-second episode. These KPIs were chosen to represent traffic throughput, energy efficiency and environmental impact of the vehicles using the intersection. The delay for each vehicle was calculated based on the difference between the actual travel time through the intersection and the travel time when driving at the speed limit (freeflow conditions). Energy consumption was determined based on the Vehicle Specific Power (VSP) model (Jimenez *et al.*, 1999). Total hydrocarbon emissions were estimated using a hybrid regression model (Ahn *et al.*, 2002).

We evaluate the performance of our model, shown in Figure 3, using root mean square error (RMSE) and mean absolute percentage error (MAPE). We compare our model to a baseline model that does not utilise intersection features and directly predicts KPIs from sequential traffic data. Figure 3 clearly illustrates that out model significantly outperforms the baseline for delay prediction, indicating the importance of the structure of the intersection in predicting traffic flow. Although our model performs similarly to the baseline model in predicting energy consumption and hydrocarbon emissions, the MAPE of our model remains under 5% for both metrics, indicating consistent accuracy across different vehicle counts. Additionally, Figure 4 illustrates that our ML model, utilizing GPU acceleration on a NVIDIA GeForce RTX 3090, achieved inference times up to two orders of magnitude faster than simulations on an AMD

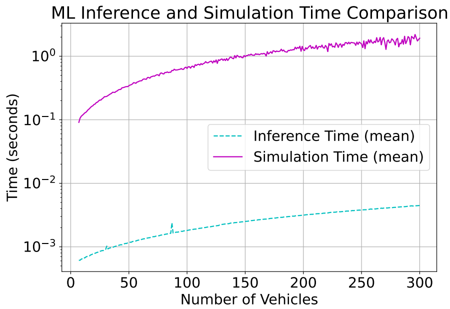


Figure 4 – *Mean time taken for the proposed model to estimate intersection KPIs compared to mean time taken to simulate the intersections for different scenario complexities, as indicated by number of vehicles in the scenario.*

Ryzen ThreadRipper 3990x 64 core CPU, highlighting our method's efficiency.

Our model's computational efficiency suggests great potential for real-time monitoring of large-scale road networks. This efficiency could lessen dependence on intensive microscopic simulations. Integrating our model into traffic systems allows for extensive monitoring with fewer resources, promoting sustainable urban planning and enhancing system responsiveness to changes. Thus, our model is pivotal in developing efficient urban traffic solutions and better technology integration in public infrastructure management.

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