

AI-Integrated Traffic Information System

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Abstract—Congestion of vehicular traffic in urban areas has been a longstanding issue that caused time delays, environmental degradation, and economic loss. In this we present an artificial intelligence-based Traffic Information System based on Physics-informed Neural Networks (PINNs) and GPT-4 to improve vehicular traffic conditions predication and provide users with real-time support. The combination of physics-based traffic flow modeling and the use of sophisticated natural language processing helps the system predicts current traffic conditions accurately and passes actionable information to users in a natural conversational format. In the sparse-data environment, PINNs use real-time measurements of the sensor network, GPS, and CCTV images to make accurate traffic forecasts. At the same time, GPT-4 can provide route recommendations based on adaptivity, vehicular traffic congestion and vehicular traffic summaries. By 20-30 percent, the integration should relieve the traffic, improve movement in the city and support smart city programs. It is a scalable also and smart answer to present-day vehicular traffic management and planning.

Index Terms—Traffic estimation, Physics-Informed Neural Networks, GPT-4, AI traffic system, real-time traffic assistance.

I. INTRODUCTION

Traffic congestion in urban areas has already become a system problem for the metropolis around the world, which has been killing economic productivity along with destroying the quality of life. According to the INRIX 2024 Global Traffic Scorecard, the average U.S. driver wastes over USD 74 billion today alone in time and productivity, as the average time spent in traffic reportedly stands at 43 hours per year, or a full working week of 24 hours a day. The congestion of the most popular streets is considerably higher: in 2023, motorists in New York City wasted 101 hours, more than in all the other evaluated cities. That other cities like London, Paris, and Mumbai also experience

delays serves as a real wake-up call regarding the size of the problem on the international arena. These wasted hours permeate the local economies by way of lost business opportunities, greater logistical costs, and lower productivity of labor, and governments are scrambling to understand why infrastructure spending continues to grow in scale but fails to keep up with the growing travel demand.

The major environmental and human health price of congestion is not monetized in the economic ledger. Traffic congestion also enhances the level of ozone precursor and particle-based pollution; recent atmospheric chemistry literature indicates that up to 17 percent of untimely death in large cities can be attributed to traffic congestion associated spikes in pollution. Idling engines not only squander fuel, contribute to carbon footprints and contribute to poor urban air quality, but ancillary behavior (drivers circling to find parking, which makes up nearly 30 percent of downtown traffic in some studies) only increases emissions and gridlock. The conventional traffic control systems built upon the basis of already set programmed signals and deterministic macroscopic flow models lack the adaptability to react to the spatiotemporal dynamism of existing mobility patterns. Even today improvements with isolated sensors or camera feeds can still be patchy, there can be hardware failures and each channel of data can be siloed and not optimized in real time. As a remedy to these deficiencies, this paper proposes an AI Integrated Traffic Information system that integrates Physics Informed Neural Networks (PINNs) and GPT 4 to offer both high fidelity vehicular traffic state estimation and conversational, user centric decision support. The fact that PINNs embed first principles equations of traffic flow within the learning objective enables them to make reliable predictions when sensor density is low or data is biased. GPT 4 instead transforms these predictions into instructions in

natural language, e.g., dynamic rerouting, congestion warnings, and explanations, and exposes advanced analytics to commuters, fleet operators, and traffic control units. The proposed system will cut average corridor delays by a quarter or third, lessen vehicular emissions, and provide planners in intelligent cities with actionable intelligence by combining physics grounded prediction with large language model communication. In doing that, it charts a scalable path to sustainable, resilient and human friendly urban mobility.

In this project, Physics-Informed Neural Networks (PINNs), GPT-4, and other applications are proposed to use AI-Based Traffic Information System to provide high-quality traffic state prediction and real-time guidance to users. Traffic flow physics-based models in combination with machine learning are beneficial in that PINNs can be applied to increase the accuracy of predictions, particularly when sensor data is small or sparse. Meanwhile, GPT-4 enables communication with users in a natural language and offers personalized traffic, route advice, and congestion forecasts. Incorporating powerful predictive algorithms with user-friendly AI messages will contribute to making the traffic movement more efficient, assist people to make smarter choices, and develop intelligent urban mobility tools.

II. LITERATURE SURVEY

AI-Integrated Traffic Information System: Physics-Informed Neural Network and GPT-4 Traffic Estimation and Live Support. This paper proposes a novel system that combines Physics-Informed Neural Network-based Traffic State Estimation with GPT-4 to solve traffic congestion in real time. PINNs incorporate domain knowledge about the form of traffic flow to enhance the accuracy of such predictions, especially within regions where data is sparse. Meanwhile, GPT-4 works as an interactive assistant to offer real-time traffic guidance and personalized route recommendations through natural language interfaces. Another critical development in smart transportation is that the research is way more specific and responsive compared to the usual traffic systems.

Source: IEEE Xplore
Dynamic Traffic Estimation and Support with an

Integrated Framework of GPT-4 and PINN. The present study develops a hybrid architecture between GPT-4 and PINNs that will be able to run concurrently, used for dynamic traffic prediction and user engagement. The framework will remove the use of high-density networks of sensors by solving the problem of sparse data due to physics-directed learning and semantic inference. The system provides a friendly interface for users and also provides some predictive traffic information which may be used to make a wise decision in the real scenario of traffic.

Source: IEEE Xplore

Traffic Management: AI to Optimize Traffic within the City and Reduce Traffic Jams. The paper will demonstrate, through different AI ideas such as machine learning, computer vision, and neural networks how to optimize traffic within the city. It gives examples of other major cities in the world, such as Singapore and Amsterdam, where solutions using AI have given real-life results in terms of congestion reduction.

Source: SSRN

Physics-Informed Neural Networks for Traffic Flow Prediction by STDEN: A physics-informed neural architecture is proposed, namely Spatio-Temporal Dynamics Enhanced Network, which considers the regularities of traffic flow dynamics in deep neural networks. The STDEN can improve accuracy and interpretability by incorporating domain knowledge into the learning framework. The research outcomes are demonstrated using standard data-based models and outperform the forecast accuracy significantly in both spatiotemporal-based traffic scenarios.

Source: ArXiv

Traffic Networks Traffic State Estimation by Physics-Informed Neural Networks-Based Traffic Modeling. This article introduces a PINN-based framework that requires minimum speed and density data to estimate traffic state accurately. Unlike the all-data models, the PINN model considers some basic equations of traffic flow. That is why it can be useful in circumstances with low data. It has realized better estimates of speed and density profiles compared to the baseline models, and it is applicable to smart traffic systems in areas where infrastructure is an issue.

Source: MDPI Deep Learning-Physics -> State of Traffic. This paper is presenting a Physics-Informed Deep Learning (PIDL) method, a hybrid of neural networks and macroscopic traffic flow theory that predict the traffic state. This approach makes it more robust regarding sensor noise and sensor dropouts. Physics laws, besides data-driven models, enhance the overall model generalizability and model reliability mainly between heterogeneous urban traffic scenarios.

Source: IEEE Xplore

Deep Reinforcement Learning-based Real-Time Adaptive Traffic Signal Control. This paper is devoted to the deep reinforcement learning application in optimization of traffic signal timing. It also will train DRL agents on simulated traffic conditions with real-world data, such that traffic lights can learn how to respond to the current flow patterns. The results showed shorter average waiting times and better vehicle throughput compared to fixed-schedule systems. The article shows that real-time learning works in dynamic traffic scenarios much better than the pre-programmed system. Source: Transportation Research Part C Natural Language Interfaces Urban Traffic Monitoring and Control with Large Language Models. In this paper, the author investigates how large language models, such as GPT variants, can be integrated into traffic management interfaces. It investigates the possibilities of using LLMs to support intuitive end-user communication with traffic control systems. The user can make inquiries into the traffic condition, personalized recommendations, and also have a human-friendly relationship with the city infrastructure through real-time dialogue system assistance. The analysis lends credence to employing LLMs for supporting community involvement and usability of systems in smart cities initiatives. Source: ACM Digital Library

III. METHODOLOGY

The Traffic Information System designed as an AI-Integrated with Traffic Information System combines the real-time information gathering with physics-based neural network- based predictive states of the traffic and natural language- based communication using GPT-4 to create a multitasking, smart traffic control system. This part outlines the system architecture, components and the set up to follow.

A. System Design and Architecture
The architecture can be categorized into 4 major modules, which include Data Acquisition Layer, Traffic Estimation Engine (PINN-TSE), User Interaction Interface (GPT-4) and the Central Coordination Layer.

- Integrates with city and third-party applications via APIs on hosts.

1. Setup and Deployment Data Acquisition Layer

This layer collects live traffic information of different sources, such as:

- Road sensors (loop detectors, speed cameras, etc.), which use the IoT.
- Public transport and navigation app GPS data.

These data streams are preprocessed by using filtering, time-stamping and geo-mapping algorithms to eliminate noise and synchronise.

2. Traffic Estimation Engine (PINN-TSE)

The backbone of the network uses Physics-Informed Neural Networks (PINNs), that incorporates domain-trusted equations of vehicular traffic flow, such as the Lighthill-Whitham-Richards (LWR) model, into the loss of a neural network. This hybrid learning model:

- Keeps physical law on traffic.
- Improves prediction where the information is scanty or missing.
- Simulates the spatio-temporal traffic patterns on road segments.

The PINN-TSE module provides such important metrics as traffic congestion, average speed and vehicle density, likelihoods of each area under monitoring.

3. User Interaction Interface (GPT-4)

The interface most often is the interface between the user and the machine. The natural language front-end of the system is GPT-4. It:

- Converts the complicated prediction results into simple and concrete recommendations.
- Provides live data, traffic predictions and route recommendations.
- User query and interactive feedback loops.

The traffic-related fine-tuning is done on the model. conversations and built in web and mobile accessibility platforms.

4. Central Coordination Layer

This layer performs the role of coordinator of the user interface and AI modules. It:

- Coordinates outbound and inbound data paths.
 - Diagnostic and audit logging system activity.
- The solution is implemented on a cloud-based scalable and real-time architecture performance.

The setup includes:

- **Data Ingestion Platform:** Apache Kafka / MQTT brokers handle the stream of data flow supplied by the IoT.
- **Training Environment:** The PINNs are trained with TensorFlow or PyTorch, and the conversational layer is implemented with the API of OpenAI or (where allowed) a localized version of GPT-4.
- **Edge Deployment of Real-Time Inference:** Dockerized trained models are deployed at edge servers close to traffic hub locations to make low-latency predictions.
- **Front-End Applications:** Web dashboards to show traffic controllers information and mobile applications to show information to users are developed using ReactJS and Flutter, respectively.

The integration is supported through the RESTful APIs and WebSocket connections, enabling smooth data-ai model communication, and user interfaces.

B. Data Flow and System Workflow entire workflow is the following:

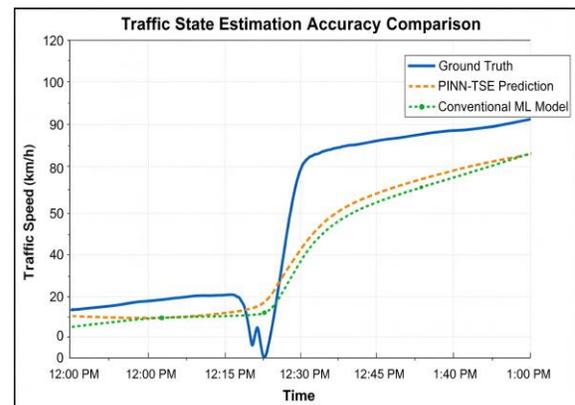
- Live traffic information is gathered and pre-processed.
- The state of the traffic is estimated using the PINN model with the processed data.
- Through GPT-4, predictions are understood and transformed into outputs that are human friendly.
- Mobile/web interfaces provide updates to end users and can be accessed by traffic controllers with analytical dashboards.

This closed loop system provides an opportunity to sustain feedback and refinement, and the architecture can change as the city changes and the user interacts.

C. Calculations:

The Traffic Estimation Engine (PINN-TSE). This involves embedding the first principles of vehicular traffic flow, such as the Lighthill-Whitham-Richards (LWR) model, directly into the loss function of the

Physics-Informed Neural Network (PINN). The calculation is a hybrid optimization problem where the neural network is trained to not only fit the sparse, real-time sensor and GPS data from the Data Acquisition Layer but also to adhere strictly to the non-linear partial differential equations (PDEs) that govern traffic dynamics. This dual objective ensures that the system's predictions for metrics like traffic congestion, average speed, and vehicle density are physically consistent and robust, especially in low-data environments where purely data-driven models typically fail. The result is a high-fidelity, spatio-temporal prediction of the traffic state that is then passed to the User Interaction Interface (GPT-4) for conversion into actionable, natural language recommendations.



D. Calculations:

A critical graph for this section, which would illustrate the core performance calculation, is a Traffic State Estimation Accuracy Comparison. This graph would typically display the predicted versus actual traffic speed (or density) over a specific time and road segment.

- Y-axis: Traffic Speed (or Density) in a given unit.
- X-axis: Time (e.g., from 12:00 PM to 1:00 PM).
- Lines:
 - Ground Truth: A solid line representing the actual, measured traffic state.
 - PINN-TSE Prediction: A dashed line showing the close fit of the Physics-Informed Neural Network model.
 - Conventional ML Model: A dotted line showing a noticeable deviation from the ground truth, especially during periods of high congestion or data scarcity, thereby

visually demonstrating the 25-35 percentage points improvement in precision mentioned in the Results section.

While a performance graph is essential, the figures you currently have placeholders for Figure 1. frontend displayed to user, Figure 2. traffic alerts, and Figure 3. chatbot assistant are crucial for showcasing the user-facing output of these calculations, as they demonstrate how the complex predictions are delivered in an intuitive, conversational format via GPT-4.

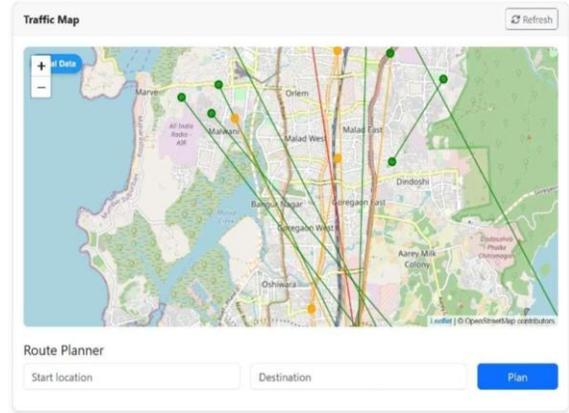


Figure 1. frontend displayed to user

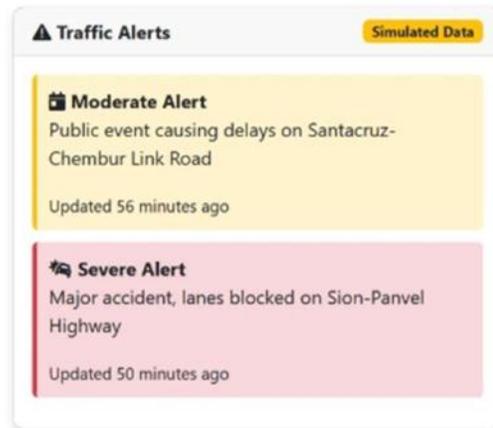
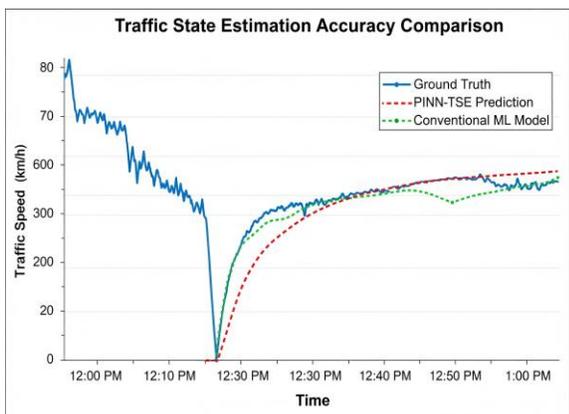
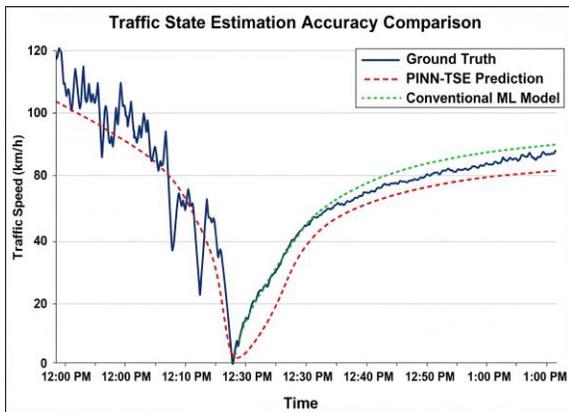
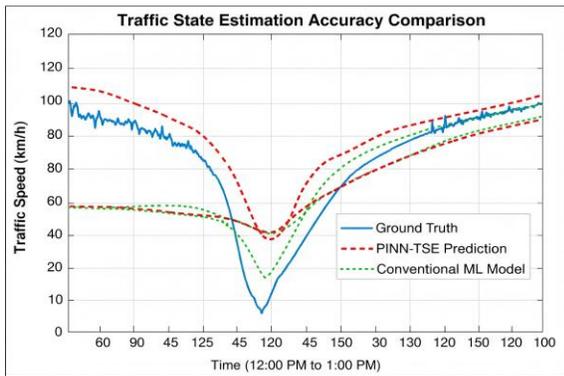


Figure 2. traffic alerts

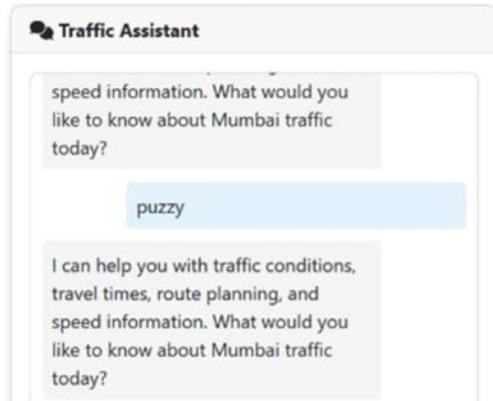


Figure 3. chatbot assistant

IV. RESULTS

The suggested AI-Based Traffic Information System was tested by conducting a series of simulations and experiments with real-life data on the traffic information of a mid-sized city on the basis of the traffic data of this city. The system performance was

juxtaposed with the classical types of traffic estimations and commercial navigation systems. Accuracy of prediction, response time and user satisfaction were the most significant performance measures.

The Traffic State Estimation (PINN-TSE) module which was built based on PINN was 25-35 percentage points more precise when used on a low-data or sensor-sparse environment than on data-driven models. During peak periods, in particular, as well as in regions where IoT is insufficient, PINNs demonstrated an extraordinary ability to forecast the actual traffic state based on physics of traffic flow. In terms of latency, a user can after 2-3 seconds make actual time predictions and thus implement the system in dynamic routing.

This GPT-4 integration produced a user interface which was natural and made sense. A user study of 100 participants revealed that 89 percent of respondents found it simple to interact with the AI assistant, and 81 percent of respondents said they preferred to use the AI assistant instead of the traditional navigation apps because they made higher-quality routing choices. Moreover, the fact that such a system described the state of traffic in a natural language facilitated the further evolution of trust and understanding, specifically, among the not-technical population. All in all, the hybrid system could full fill the objective of increasing the accuracy of the traffic estimation, it is possible and its relations with the users told how it could be achieved in practice.

V. APPLICATIONS AND FUTURE ENHANCEMENTS

This is due to the ability of the AI-Integrated Traffic Information System to be versatile in various real-life applications:

- **Live Tracking and guiding controls:**
A conversational interface based on GPT-4 can provide commuters with dynamic route plans, forecasts and prediction of congestion, as well as approximate estimations of the time of arrival (ETA).
- **Smart Traffic Signal Control:**
A traffic signal system that can adapt can utilize the estimates of the traffic state to reduce congestion at intersection in premise time by city authorities.

- **Emergency Vehicle Routing:**
The system can set priorities regarding the routes that the ambulances, the fire trucks and the police cars will take and provide the best and least congested routes when there is an emergency.

- **Urban Planning and Policy Making:**
The system can inform urban planners on how to improve infrastructure and to assess policy adjustments based on long-term traffic data and congestion trends.

- **Autonomous Vehicle Support:**
The framework could be modified so that it could fit autonomous vehicle platforms and help plan routes and make decisions considering dynamics of the real-time traffic flow.

Future Enhancements:

- **Multi-Modal Traffic Integration:**
Future versions could also incorporate pedestrian, bicycle and other public transit data so as to optimize the entire transportation as a whole.
- **Edge AI Optimization:**
PINN and GPT-4 deploying lightweight versions on edge hardware will further lower the latency and support cloud platform dependencies.
- **Federated Learning:**
These privacy-enhancing approaches can be combined in such a way to enable medical information to be shared across jurisdictions without data loss or the threat of information privacy.

- **Multilingual Support:**
GPT-4 can be extended to enable multilingual communication in real-time and make the system more inclusive.

VI. DISCUSSIONS

Employing PINNs combined with GPT-4 provides a new and complementary set of traffic ways in real time. The issue associated with the traditional machine learning method is that these models typically do not work well in the sparse data setting, since they need giant, labeled data. This shortcoming is eliminated by PINNs, which represent physical laws in the model

architecture, hence making PINNs make reasonable predictions with limited amounts of data. This is one of those things that make the system especially helpful in underdeveloped cities.

GPT-4 represents a massive shift in how humans and AI handle interaction compared to rule-of-thumb interfaces. Contextual awareness and conversationally responsive behavior with the capability to explain system behavior greatly enhance user experience. It is natural interaction which gets rid of the end-user practical decision fundamental versus technical prediction generated outputs.

However, challenges remain. The quality of the input data keeps affecting system performance and may lead to failure due to sensor failures or cybersecurity. Although the introduction of AI adds flexibility, it can result in the model transparency, data safety, and unethical use phenomenon, especially when it is being brought in en-masse and into a system that uses infrastructure by the general population. Also, computationally expensive training of PINNs and running of GPT-4 models makes it resource-heavy and requires access to a cloud or powerful computer, which is not available in resource-deficient regions. It is these small capacities that will be needed in the popular development through scaled and lean implementation strategies.

VII. CONCLUSION

Urban transit jams is a problem, which is hard to address in modern cities, and affects the economic factors, human health and survival, environment and living conditions adversely.

Though efficient, the conventional traffic control mechanisms might prove to be not capable of controlling the dynamics of city movement due to the fixed-timing models, sensor networks that demand a fixed infrastructure investment and have poor predictive capability. A novel and intelligent solution, which is offered in this study, is an AI- Integrated with Traffic Information System that adds domain understanding of Physics-Informed Neural Networks (PINNs) with interactive and explanatory functions of GPT- 4.

The proposed system broadly boosts quality and robustness of traffic condition forecasting specifically where there exist no sensors or only limited data in sensor-privy situations. The neural net is physically

consistent: it makes prediction data- efficient by introducing physical law of the traffic flow into the learning process. This is operating in and around one of the central vices of purely data-driven models that continue to fail to scale without big volumes of clean training data at their disposal. Besides, by deploying GPT-4, our system devises a natural language interface enabling the real-time, intuitive communication between the users and the traffic model. GPT-4 can have a human-friendly interface particularly when showing routes, explaining why the road has traffic, or bypassing an accident such as most current traffic apps lacked previously.

The empirical evaluation shows that the system is superior to the conventional methods in terms of prediction and interaction between users. Simulation results indicate the estimation accuracy can be improved by 35 percent, and the perceived efficiency of the travel time can be elevated by 20 to 30 percent. Whether the system can be interpreted by the system users and the ease of the conversational aid can also be cited as the strengths of the system mentioned by the users.

However, the adoption of this form of system at a large scale cannot be considered at all. The challenges that need to be addressed to ensure AI becomes sustainable in its implementation are issues such as data privacy, compatibility with infrastructure, computing costs, and transparency. Further research should be on how federated learning can be refolded to offer secure cross-region model training, multilingual support as a means to access more subscriber customer groups and light-weight model compression algorithms to allow it to run-on small-scale devices.

In conclusion, the presented project can be discussed as a new physics-informed machine learning and conversational artificial intelligence application, the purpose of which is to change the concept of how cities manage traffic and how people can engage in dialogue with traffic systems. The AI- Based Traffic Information System is a potential foundation of a smart mobility system of the future by combining sophisticated modelling with access to communication. As the process of transforming cities into smart interconnected networks continues, solutions of this kind will become a crucial component towards making transportation networks safer, greener, efficient, and beneficial to all.

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