

ENGINEERING TRAFFIC FLOW STABILITY USING ENTROPY COMPLEXITY METRICS AND TOLL-BASED MIXED VEHICLE ANALYTICS

R. Laxmana Reddy^{1,2,*} and R. Srinivasa Kumar¹

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Abstract

In developing countries, prediction of traffic flow in heterogeneous classes of vehicles is important in planning the infrastructure and management of congestion. Although many models exist, research assessing their temporal generalizability to disaggregated vehicle types remains limited. This paper evaluates forecasting efficiency and temporal complexity of vehicle-wise traffic flow using a 60-month toll dataset and 20-month projections. The forecasts were developed by applying machine learning and regression-based techniques to generate a number of models including Random Forests, CatBoost, XGBoost, Bayesian Ridge, Elastic Net, etc. Accuracy was measured via Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), Mean Squared Deviation (MSD) and permutation entropy (PE, $m = 3$, $\tau = 1$) was used to assess dynamic complexity. Permutation entropy (PE) was calculated on every category to compare the complexity of observed and estimated traffic. The results indicate that categories such as CAR-JEEP-VAN and MONTHLY PASS VEHICLES exhibit increasing entropy in the projections, suggesting a greater unpredictability. In contrast, heavy vehicle categories such as TRUCK and MINI BUS-LCV show markedly reduced entropy, indicating over simplified patterns. The main conclusion is that vehicle-specific forecasting models provide a realistic yet accurate complexity while Entropy-based diagnostics provide a novel validity check, ensuring forecasts capture realistic dynamic complexity and supporting robust, class-specific traffic planning decisions.

Keywords: Traffic Forecasting; Permutation Entropy; Vehicle Classification; Indian Highways; Prediction Stability; Time Series Analysis; Toll Data

¹ Department of Civil Engineering, University College of Engineering (UCE), Osmania University (OU), Hyderabad, Telangana, India. E-mail: laxmana.r@sreenidhi.edu.in

² Department of Civil Engineering, Sreenidhi Institute of Science and Technology Hyderabad, Telangana, India.

* Corresponding author

Introduction

Proper traffic forecasting is a core feature in designing, operating, and managing highway transportation systems especially in developing countries like India, where heterogeneous characteristics of traffic prevail (Akhtar & Moridpour, 2021). Successful forecasting not only aids in congestion alleviation but also helps in infrastructure planning, toll costs, environmental tests, and safety (Hammoumi *et al.*, 2025). Although many traffic and flow models exist, a majority are built to predict at the aggregate level, frequently without a special consideration of the behavior of the different types of vehicles (Han *et al.*, 2022). Such simplification may lead to the derivation of forecasting models that are not representative of the dynamics perceived in the real mixed-traffic based environment such as those in India (Lv & Shang, 2023). Temporal and behavioral patterns of cars, jeeps, vans, buses, light commercially-driven vehicles (LCVs), trucks, multi-axle vehicles (MAVs) and concession vehicles are different. This spectrum is too granular to be modeled on class or vehicle-wise analysis, and relevant attempts are not numerous in modern literature (Tyagi & Aswathy, 2021). Disaggregated traffic prediction in the real toll environment is underexplored area in traffic forecasting, especially to test the temporal stability, and the complexity of traffic prediction (Mystakidis *et al.*, 2025). Few studies evaluate temporal stability and complexity of forecasts across vehicle classes using toll transaction data; most focus on aggregate volumes and prioritize point accuracy over dynamic realism. Such simplification may lead to the derivation of forecasting models that are not representative of the dynamics perceived in the real mixed-traffic based environment such as those in India (Piadeh *et al.*, 2022). This is because India's highways are highly congested and pass through complex hilly terrain, which, combined with the disparity in vehicle types, creates significant forecasting challenges (Basu & Saha, 2022).

Temporal and behavioral patterns of various vehicles such as cars, jeeps, vans, buses, etc., are different (Kokatnur *et al.*, 2024). Limited evidences exist in the area of research, especially to test the temporal stability i.e., ability of forecasts to remain reliable over time, and the complexity of traffic prediction (Rasulmukhamedov *et al.*, 2024). Nevertheless, the majority of the research and studies continues to concentrate on the overall vehicle numbers or accumulated traffic. According to research conducted by Gomes *et al.*, (2023) the potential of these models is not utilized in full

because the aspects of inter-category variation are not covered in the research to evaluate performance in different types of cars. Issues on disaggregated modeling have started to be addressed in the new efforts. (Song *et al.*, 2020) have discussed category specific time series modeling in urban situations. Current studies by Sayed *et al.*, (2023) used deep learning to determine traffic prediction by vehicle type and did not perform stability or complexity test on the forecasts. In addition, an increasingly popular topic is the evaluation of the quality of traffic forecasts. The measures that have been developed on entropy grounds include permutation entropy, sample entropy, and spectral entropy to measure the temporal complexity of traffic data (Pisarchik & Hramov, 2023).

Permutation entropy (PE), more precisely, has proven to be useful in differentiating between deterministic and stochastic dynamics in time series. PE allows uncovering the degree to which the information in a forecast maintains the inherent randomness and variations in the observed data in traffic forecasting (Mihailovi'cmihailovi'c, 2025). Nevertheless, its use in traffic flow modeling is not yet developed. Examples of the studies on PE in traffic speed patterns include those by Willis *et al.*, (2024) who did not apply the concept in traffic volume patterns (or disaggregated) or in toll data. The other important dimension that are always ignored include predictability over time and over different types of cars. Such metrics as Model Generalization Index (MGI), Traffic Prediction Stability Index (TPSI) are becoming an important part in assessing how well a model behaves over different time frames and types (Kumar *et al.*, 2024).

These theories find special application to Indian highways where trend of vehicles is affected by socio-economic events, toll policies and fluctuation in fuel prices (Bayer & Flügel, 2025). Although granular toll data are accessible and the ML-based prediction models are rather developed, there is some research gap associated with assessing temporal stability and complexity of category-wise traffic forecasting (Kim *et al.*, 2025). Not many papers use both traditional measures of statistical metrics and indicators based on entropy to measure the realism of forecast. Also, the overall extrapolation of predictions into various vehicle types has been seldom measured with entropy or consistency measures (Terven *et al.*, 2025). The paper fills this vacuum by combining vehicle-class-wise forecasting accuracy and complexity, variability or randomness in temporal dynamics,

measured via entropy evaluation through permutation. The paper analyses the prediction performance using 60 months of toll measurements and 20 months of projected tolling values of a major highway in central India based on nine categories of vehicles. This two-level analysis will provide a new analysis of the accuracy and fidelity of the behavior of the traffic flow forecasts to improve planning and decisions in the mixed-traffic systems.

We analyze a large dataset of toll transactions, covering 60 months with subsequent projections covering an additional 20 months, allowing us to provide one of the most detailed disaggregated vehicle-class time series to date for a developing-country corridor. We systematically evaluate the forecasts according to standard accuracy measures (MAPE, MAD, MSD, and bias) and the results of residual analysis, so that both point accuracy and the statistical robustness of the results are assured. We introduce permutation entropy (PE, $m = 3$, $\tau = 1$) as a discriminator of dynamic realism so that we can measure whether the predictions maintain the intrinsic temporal complexity present in the observed series. We provide vehicle-class-specific evidence that average models can obscure the entropy loss and over-smoothing embodied in the heavy/commercial classes, while the private-passenger classes exhibit a higher fidelity. Further to what extent can machine learning models forecast toll-based, vehicle-class traffic flows with both accuracy and dynamic realism, and how stable are these forecasts across categories and time.

Methodology

Study Area and Data Description

This study utilizes traffic volume data collected from a toll plaza located on a major national highway in central India, catering to a wide spectrum of vehicle types. Each of the eleven forecasting models (RFM, Bayesian Ridge, KNN, OMP, Elastic Net, CatBoost, XGBoost, LARS Lasso, Decision Tree, Linear Regression, and Lasso Regression) was tested on each vehicle class series. The best method for each vehicle class was determined by selecting the individual best performing model for each of the vehicle class series as a result of minimizing the recursive forecasting validation. The dataset spans 60 consecutive months (5 years) of recorded toll traffic, from January 2018 to December 2022, and is categorized into nine vehicle classes: (i) Car-Jeep-Van, (ii) Mini Bus-LCV, (iii) Bus, (iv) Truck, (v) MAV (> 2 Axle), (vi) Mini Truck (Single Concessional), (vii) Truck (Single Concessional), (viii) Monthly Pass Vehicles, and (ix) All Vehicles

(total count). Additionally, a set of projected traffic values for the next 20 months (January 2023 to August 2024) was obtained using a baseline forecasting model to serve as reference predictions. Both actual and projected data are monthly aggregates.

Time Series Trend Analysis

To obtain a preliminary picture of the dynamics peculiar to each category, the graphical representation of time series of all nine categories of vehicles was created. With such visual examination, it was possible to detect:

- Periodic peaks (e.g. increased truck flow during the harvest times)
- The long-term growth patterns (especially those of the personal automobiles)
- Variety in volatility in the range of vehicles

The above-mentioned trends can support the necessity of more specific, category-based forecaster evaluations with qualitative evidence.

Forecasting Accuracy Metrics

To evaluate the performance of projected forecasts, five standard error metrics were computed between the last 20 months of actual data and the 20-month forecast horizon:

Mean Absolute Deviation (MAD):

$$MAD = \frac{1}{n} \sum_{t=1}^n |A_t - F_t| \quad (1)$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \quad (2)$$

Mean Square Deviation (MSD):

$$MSD = \frac{1}{n} \sum_{t=1}^n (A_t - F_t)^2 \quad (3)$$

Where, A_t = actual (observed) value at time t
 F_t = forecasted value at time t
 n = number of forecasts

Model Generalization Index (MGI)

MGI measures how well a forecasting / prediction model generalizes from training to test data. A common definition is the ratio of test error to training error:

$$MGI = \frac{E_{test}}{E_{train}} \quad (4)$$

E_{test} = error metric (e.g., MAD, MSD, MAPE) on test or validation set.

E_{train} = error metric on training set

Traffic Prediction Stability Index (TPSI):

TPSI is a statistical measure designed to evaluate the temporal stability and generalizability of a traffic forecasting model. It checks how consistently a model performs when trained and tested on different time windows (for example, across months or seasons). The general form of the TPSI formula is:

$$TPSI = 1 - \frac{\sigma(E_t)}{\mu(E_t)} \quad (5)$$

E = model error (e.g., MSD, MAD, or MAPE) for the t^{th} time window,

$\sigma(E_t)$ = standard deviation of model errors across multiple time windows,

$\mu(E_t)$ = mean of model errors across those time windows.

Permutation Entropy for Temporal Complexity:

In order to measure the dynamics of traffic flows regarding their unpredictability and temporal complexity, Permutation Entropy (PE) was calculated on the actual and forecasted data series by vehicle type. The PE is a model-free measure of the complexity, or randomness of a time series, characterized by the distribution of frequency of ordinal patterns within a sequence.

Given a time series $x(t)$, the permutation entropy H of order m and delay τ is calculated as:

$$H(m, \tau) = - \sum_{p \in S_m} P(p) \log P(p) \quad (6)$$

where,

S_m is the set of all $m!$ possible permutations,

$P(p)$ is the probability of each permutation pattern,

In this study normalized permutation entropy values were used (ranging from 0 to 1), computed using an embedding dimension of $m=3$ and lag $\tau=1$.

The higher the value of the PE, the more the irregular or random dynamic, the more the PE, the more predictable and repetitive the behavior. This comparison of actual values to the forecasted values of PE aids in the diagnosis of whether prediction maintains or oversimplifies the information.

Implementation and Tools

The corresponding calculations were made with Python 3.11 and standard data science libraries (Pandas, NumPy, Matplotlib). The Antropy library was used to compute entropy metrics and Matplotlib used to visualize time series data. To make the pipeline reproducible, Google Colab was used to validate the entire pipeline. This emphasizes

that model training required minutes on standard CPUs for regression/ensemble methods, and longer for boosting methods, ensuring reproducibility.

Results and Discussion

The forecasting error analysis, evaluated using MAPE, MAD, MSD, and bias, reveals substantial variability in performance across different vehicle categories. Figure 1 below shows the forecasting accuracy for various categories of vehicles

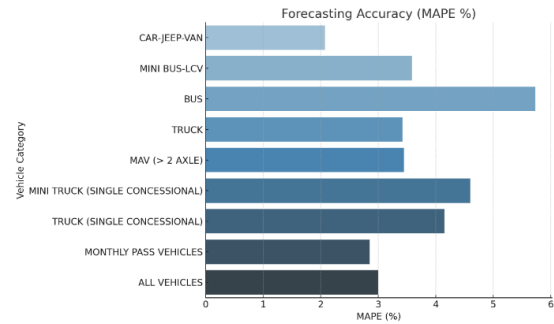


Figure 1. Depicts Forecasting accuracy in terms of Mean Absolute Percentage Error (MAPE) for each vehicle category

Among all classes, the CAR-JEEP-VAN category exhibited the highest forecast accuracy with a MAPE of 2.07% and relatively low MAPE and bias values (Figure 1). While multiple models were evaluated, ensemble methods such as Random Forests, CatBoost, and XGBoost consistently outperformed linear baselines for stable categories (e.g., CAR-JEEP-VAN), whereas linear and sparse regression methods struggled with irregular freight categories. In all the categories, CAR-JEEP-VAN had the lowest MAPE (2.07%) and hence the forecasting model was able to capture the relatively stable and repetitive temporal trend, which is linked to the usage of the private vehicles. Such trends probably represent commuter stability and fewer variations in operations. In comparison, the BUS category had the maximum MAPE (5.83%), thus indicating that the model would not be able to capture the intricate nature of the dynamics involved in case of public transportation. Buses are subject to scheduled time, spikes of demand at unexpected moments because of events, and detours, all of which create non-linearity that may not be reflected in generic models. Likewise, the MAPE showed moderate to high results in the commercial freight, including the classes MINI BUS-LCV, TRUCK, and MAV (> 2 AXLE) with

3.5% and 4.6%, respectively. These are the parts that are exposed to uncertainties of operation such as the fluctuating freight volumes, the requirements of delivering commodities, as well as drifting in and out of commodity routes depending on the road situations or regulatory constraints which deteriorate the accuracy of forecast. Remarkably, the combined ALL VEHICLES category posts a medium MAPE (~3.0%), which turns out to look rather accurate. This finding emphasizes the effect of aggregation in which the variations of errors between the classes of vehicles are averaged. Put differently, the utilization of the aggregate-level measures can result in overestimation of model robustness. In general, the data emphasize the need to introduce disaggregated error diagnostics in the forecasting of traffic. The inconsistency of the MAPE in different vehicle types provides evidence on the necessity to employ vehicle-specific modeling structures or have ensemble-based designing strategies to gain predictability in non-homogenous traffic situations. Figure 2 presents the directional bias in traffic volume forecasts across nine vehicle categories, calculated as the arithmetic difference between projected and actual values. Positive bias indicates model overestimation, while negative values denote underestimation. The most extreme overestimation is related to MINI BUS-LCV (bias = 700 vehicles or so), so the model tended to predicts higher volumes than happened. This may be due to inadequate treatment of episodic demand troughs or lack of catching seasonality in smaller fleets of the public transport.

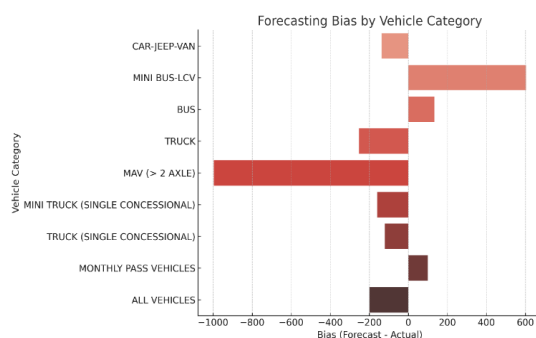


Figure 2. Shows Forecasting bias across vehicle categories, computed as the difference between forecasted and actual monthly traffic volumes

Similarly, CAR-JEEP-VAN has some level of over-prediction, but the low MAPE could depict that the displacement is consistent and within the required limits. Quite contrastingly, the model overcounts the MAV (> 2 AXLE) category by a large

extent exhibiting a bias of nearly -1000 vehicles. This underprediction indicates that there is structural blind spot in the model about dynamics of heavy vehicle, probable due to unmonitored exogenous variables like freight corridor policies or behavioral change in response to changing cost of fuel. The patterns of moderate negative biases can also be observed concerning TRUCK and MINI TRUCK (SINGLE CONCESSIONAL), which further proves the problem of inability to capture the non-stationary irregular patterns of freight movements.

Interestingly, it turns out that there is some negative net bias of about -200 in the ALL-VEHICLES class, which proves once again the masking effect of aggregation where counterbalancing biases in sub-categories partially balance each other out. This once more underlines the weakness of using only aggregate performance indicators.

The bias patterns that have been noted record systematic variations instead of random errors, meaning that there could be improper coincidence between assumptions and operational practices. These observations promote the relevance of introducing the vehicle-class-specific temporal characteristics or covariates (e.g., holidays, fuel rates, policy interventions, etc) into the prediction model. Also, it is possible that dealing with bias directly with residual correction models or hybrid learning methods can increase the realism and reliability of long-term traffic forecasts.

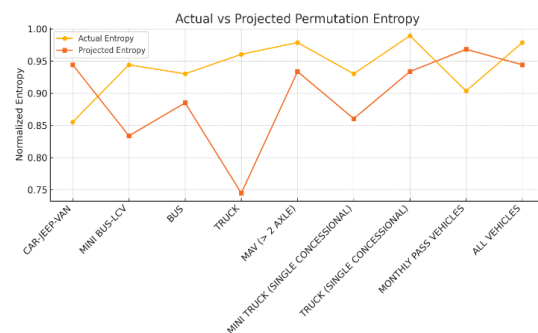


Figure 3. Shows Comparison of normalized permutation entropy between actual and projected traffic flows for each vehicle class

As an explanation of the realism of the projections in terms of the complexity of the time series and of their temporal behavior, the comparative analysis of permutation entropy between historic and forecast time series per vehicle category is exemplified in Figure 3. Permutation

entropy is a model-free measure of the uncertainty of a time series, and has been shown especially useful in detecting over-simple or unreasonably / over-volatile forecasts.

The findings show that in the majority of the categories - freight dominated i.e. TRUCK, MAV (>2 AXLE) and TRUCK (SINGLE CONCESSIONAL), the estimated entropy is much lower than the observed one. It would indicate that the forecasting model has failed to capture the actual dynamic variability, possibly through excessive smoothing or by failing to learn notable non-linearities in interactions (or by not being provided with accurately measured external predictors, such as policy changes, fuel cost variations). At a practical level the model can seem to work statistically (e.g. low MAPE) but not reproduce the intrinsic complexity of real traffic, making the predictions less valuable in operations or policy. Alternatively, the categories like CAR-JEEP-VAN, MONTHLY PASS VEHICLES show greater entropy in the projected sequence, which means they are randomly presented or noisier. It could be either due to overfitting or lack of generalizability in processing the regularity of itinerary appearance. The difference in entropy between actual and projected data in various categories, depicted in Figure 4, underlines that the classical measures of errors are not sufficient to determine the model fidelity.

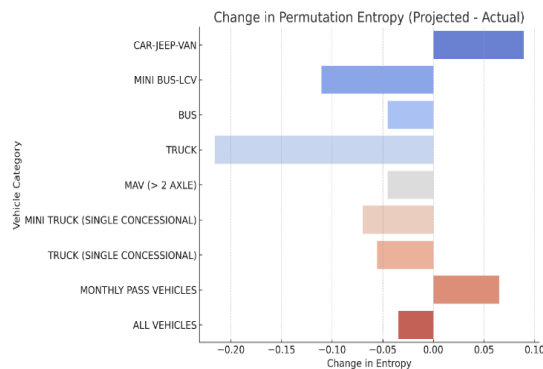


Figure 4. Depicts Net change in permutation entropy (Projected - Actual)

On the whole, this criterion-based evaluation demonstrates entropy-vulnerability of models across vehicle type and the need to include complexity - informed forecasting schemes. Introducing permutation entropy as a post-hoc validation tool improves the explainability of model results and confirms that they allow replicating the dynamics of the observed traffic, which is

significant in heavily heterogeneous and policy-scenario sensitive urban corridors. To quantify the loss of complexity observed in the freight categories, we calculated the net difference between projected and actual entropy and is shown in Figure 4.

Negative values in Figure 4 (e.g., for TRUCK and MAV) indicate reduced temporal complexity (over-simplification) in the forecast. Conversely, positive values in categories like CAR-JEEP-VAN reflect increased irregularity or noise. This metric confirms that classical error measures (like MAPE) alone are insufficient to determine model fidelity, as a model can be statistically accurate but dynamically unrealistic. To validate these findings visually, we analyzed the specific trajectory of the forecasts as shown in Figure 5.

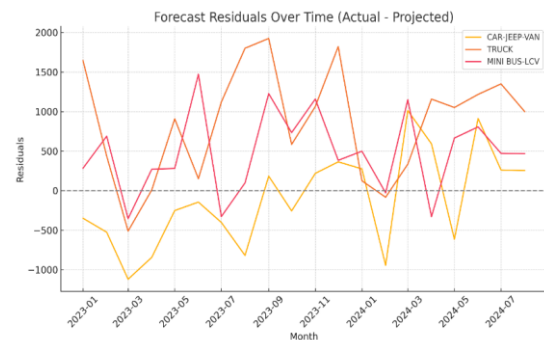


Figure 5. Displays Forecast residuals and monthly traffic volume trends (20-month horizon)

The comparison shows that though the model faithfully reproduces long-term upward trends, it is irregularly faithful with respect to short-term changes. For example, CAR-JEEP-VAN demonstrates a high degree of conformity, pointing to the fact that the model reflected the temporal dynamics of these constant groups. On the other hand, major phase shifts and amplitude distortions in BUS and MAV (>2 AXLE) show that the model does not capture localized oscillations and seasonal bursts. The residual analysis further highlights volatility in the TRUCK and MINI BUS-LCV categories, where residuals are predominantly positive, indicating that the model consistently underpredicts during demand spikes.

These deviations, often exceeding ± 1500 vehicles, suggest the system cannot scale to sudden jumps in commercial demand. Unlike them, CAR-JEEP-VAN residuals fluctuate as oscillations around zero, implying the movement of private vehicles is better captured and less affected by external shocks.

Conclusion and Future Work

This study presents a comprehensive evaluation of disaggregated traffic forecasting by integrating classical accuracy metrics with entropy-based complexity analysis. Using five years of toll data and 20-month projections across nine vehicle categories, the findings reveal significant differences in forecasting performance and temporal stability between vehicle types. Categories such as CAR-JEEP-VAN showed high predictive accuracy and increased forecast entropy, suggesting the model captured user variability effectively.

Among the tested methods, ensemble learners (Random Forests, CatBoost, XGBoost) offered better complexity preservation for private-vehicle categories, though entropy analysis revealed persistent over-smoothing in heavy-vehicle forecasts.

Conversely, truck and bus categories demonstrated reduced entropy and higher forecasting errors, indicating over-simplification or missing dynamics in the projected trends.

The use of permutation entropy as a complementary diagnostic proved instrumental in assessing the behavioral fidelity of traffic forecasts. It offered insights beyond conventional error measures by revealing whether forecasted series maintained realistic complexity.

The study underscores the importance of incorporating vehicle-specific characteristics into forecasting models, especially in mixed-traffic conditions. For practical applications, planners and modelers are encouraged to use both accuracy and entropy metrics to evaluate model suitability. Future work can explore the integration of exogenous factors such as fuel prices, toll policies, and economic activity into traffic forecasting frameworks.

Additionally, hybrid models combining machine learning with entropy-aware regularization may further enhance both accuracy and interpretability. Expanding the scope to multi-site or urban traffic datasets would also enable generalizability assessments of the proposed dual-layer framework.

Declarations

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval: Not applicable.

Data Availability Statement: The toll traffic dataset analyzed during the current study is not publicly available due to confidentiality constraints with the toll operator but can be made available from the corresponding author upon reasonable request.

References

- Akhtar, M., & Moridpour, S. (2021). A review of traffic congestion prediction using artificial intelligence. *Journal of Advanced Transportation*, 2021(1), 8878011. <https://doi.org/10.1155/2021/8878011>
- Basu, S., & Saha, P. (2022). Evaluation of risk factors for road accidents under mixed traffic: Case study on Indian highways. *IATSS Research*, 46(4), 559-573. <https://doi.org/10.1016/j.iatssr.2022.09.004>
- Bayer, S. B., & Flügel, S. (2025). Introduction vs. price change of road toll - a panel data analysis of revealed preferences. *Research in Transportation Economics*, 112, 101592. <https://doi.org/10.1016/j.retrec.2025.101592>
- Gomes, B., Coelho, J., & Aidos, H. (2023). A survey on traffic flow prediction and classification. *Intelligent Systems with Applications*, 20, 200268. <https://doi.org/10.1016/j.iswa.2023.200268>
- Hammoumi, L., Farah, S., Benayad, M., Maanan, M., & Rhinane, H. (2025). Leveraging machine learning to predict traffic jams: Case study of Casablanca, Morocco. *Journal of Urban Management*. <https://doi.org/10.1016/j.jum.2025.02.004>
- Han, J., Wang, X., & Wang, G. (2022). Modeling the car-following behavior with consideration of driver, vehicle, and environment factors: A historical review. *Sustainability*, 14(13), 8179. <https://doi.org/10.3390/su14138179>
- Kim, J., Kim, H., Kim, H. G., Lee, D., & Yoon, S. (2025). A comprehensive survey of deep learning for time series forecasting: Architectural diversity and open challenges. *Artificial Intelligence Review*, 58(7), 1-95. <https://doi.org/10.1007/s10462-025-11223-9>
- Kokatnur, K. B., Kulkarni, S. S., Shamsuddin, K., Budihal, S. V., & Devika, S. (2024). Harnessing DSRC for intersection movement assist (IMA) in vehicle-to-vehicle communication. In *Lecture Notes in Networks and Systems* (Vol. 1111, pp. 25-34). Springer. https://doi.org/10.1007/978-981-97-6681-9_3
- Kumar, S. S. M., Pandey, M., & Umamahesh, N. V. (2024). Predicting total upland sediment yield using regression and machine learning models for improved land management and water conservation. *Journal of Hydroinformatics*, 26(8), 2045-2058. <https://doi.org/10.2166/hydro.2024.159>
- Lv, Z., & Shang, W. (2023). Impacts of intelligent transportation systems on energy conservation and emission reduction of transport systems: A comprehensive review. *Green Technologies and Sustainability*, 1(1), 100002. <https://doi.org/10.1016/j.grets.2022.100002>
- Mihailović, D. T. (2025). Permutation entropy and its niche in hydrology: A review. *Entropy*, 27(6), 598. <https://doi.org/10.3390/e27060598>
- Mystakidis, A., Koukaras, P., & Tjortjis, C. (2025). Advances in traffic congestion prediction: An overview of emerging techniques and methods. *Smart Cities*, 8(1), 25. <https://doi.org/10.3390/smartcities8010025>

- Piadeh, F., Behzadian, K., & Alani, A. M. (2022). A critical review of real-time modelling of flood forecasting in urban drainage systems. *Journal of Hydrology*, 607, 127476. <https://doi.org/10.1016/j.jhydrol.2022.127476>
- Pisarchik, A. N., & Hramov, A. E. (2023). Coherence resonance in neural networks: Theory and experiments. *Physics Reports*, 1000, 1-57. <https://doi.org/10.1016/j.physrep.2022.11.004>
- Rasulmukhamedov, M., Tashmetov, T., & Tashmetov, K. (2024). Forecasting traffic flow using machine learning algorithms. *Engineering Proceedings*, 70(1), 14. <https://doi.org/10.3390/engproc2024070014>
- Sayed, S. A., Abdel-Hamid, Y., & Hefny, H. A. (2023). Artificial intelligence-based traffic flow prediction: A comprehensive review. *Journal of Electrical Systems and Information Technology*, 10(1), 1-42. <https://doi.org/10.1186/s43067-023-00081-6>
- Song, X., You, H., Zhou, S., & Xie, W. (2020). Traffic sign recognition with binarized multi-scale neural networks. In Proceedings of the 2020 35th Youth Academic Annual Conference of Chinese Association of Automation (YAC 2020) (pp. 116-121). *IEEE*. <https://doi.org/10.1109/YAC51587.2020.9337571>
- Terven, J., Cordova-Esparza, D. M., Romero-González, J. A., Ramírez-Pedraza, A., & Chávez-Urbiola, E. A. (2025). A comprehensive survey of loss functions and metrics in deep learning. *Artificial Intelligence Review*, 58(7), 1-172. <https://doi.org/10.1007/s10462-025-11198-7>
- Tyagi, A. K., & Aswathy, S. U. (2021). Autonomous intelligent vehicles (AIV): Research statements, open issues, challenges and road for future. *International Journal of Intelligent Networks*, 2, 83-102. <https://doi.org/10.1016/j.ijin.2021.07.002>
- Willis, M. D., Harris, L., Campbell, E. J., Chaskes, M., Sawyer, E., Harleman, M., Ritz, B., Hill, E. L., & Hystad, P. (2024). A population-based cohort study of electronic tolling, traffic congestion, and adverse birth outcomes. *Environment International*, 183, 108355. <https://doi.org/10.1016/j.envint.2023.108355>