A General Conceptual Framework for Applying Artificial Neural Networks in Predicting Mixed Traffic Parameters

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Abstract:

Predicting traffic behaviour under mixed traffic conditions poses a significant challenge due to the simultaneous operation of various vehicle types, including two-wheelers, cars, auto-rickshaws, buses, and non-motorized vehicles, on the same roadway. The absence of strict lane discipline and variations in driver behaviour further complicate traffic flow dynamics. Conventional analytical and simulation-based models, which assume homogeneous, lane-based traffic, often fail to capture the nonlinear and stochastic interactions that occur in real-world, heterogeneous environments. The present study discusses the potential of Artificial Neural Networks (ANNs) for accurately modelling and predicting traffic parameters, such as speed, flow, and density. ANNs, being data-driven and adaptive, can effectively learn from empirical data and capture intricate, nonlinear relationships among these variables without the need for predefined equations. By applying ANN models to mixed traffic data, this research aims to develop a more reliable and flexible prediction framework that assists in traffic management and capacity analysis. The study proposes a generalized ANN-based framework that can guide future empirical modelling of mixed traffic systems

Keywords: Artificial Neural Networks, mixed-traffic, traffic prediction, traffic modelling

1. Introduction:

Mixed traffic conditions, prevalent on metropolitan highways in developing nations like India, involve the concurrent movement of many vehicle types, including two-wheelers, automobiles, buses, lorries, autorickshaws, and non-motorised vehicles. The lack of lane discipline and the diversity in vehicle sizes, acceleration rates, and manoeuvring behaviours result in extremely varied and intricate traffic interactions. Conventional macroscopic traffic flow models, such as Greenshields, Greenberg, and Underwood, assume homogeneity and steady-state flow, rendering them insufficient for accurately capturing traffic dynamics. Microscopic simulation models such as VISSIM, AIMSUN, and SUMO require multiple calibrated parameters, which are challenging to estimate reliably under these conditions. Artificial Neural Networks (ANNs) offer a powerful approach to simulating mixed traffic behaviour, owing to their ability to learn nonlinear and intricate correlations directly from data. Modelled after the architecture and operation of the human brain, artificial neural networks (ANNs) comprise interconnected processing units (neurons) that adaptively adjust their weights during training to reduce prediction errors. This enables the identification of complex patterns in essential traffic metrics such as speed, flow, and density without requiring explicit definitions of physical interactions.

In traffic engineering, artificial neural networks (ANNs) have been effectively employed for tasks such as traffic flow prediction, congestion assessment, trip time calculation, and Level of Service (LOS) categorisation. Their data-driven nature enables them to handle noisy, incomplete, or unclear field data, which is commonly encountered in urban settings. Furthermore, artificial neural networks may extrapolate acquired correlations to novel traffic scenarios, providing adaptability and precision beyond traditional models.

The use of Artificial Neural Networks offers a robust and flexible framework for understanding, modelling, and controlling mixed traffic flow, making them an essential tool for contemporary transportation analysis and planning.

2. Literature Review:

Several studies have demonstrated the potential of ANNs in traffic flow modelling:

Chien et.al. (2002) developed an ANN model for bus arrival times. They assessed the microscopic simulation model CORSIM, which has been calibrated and validated using real-world data collected from Route 39 of the New Jersey Transit Corporation. Chandra and Kumar (2003) highlighted the inadequacy of conventional lane-based models under mixed traffic and called for data-driven approaches. The study by Vanajakshi and Rilett (2010) focused on developing a real-time bus arrival time prediction system suited to heterogeneous and mixed Indian traffic conditions. Kumar et al. (2013) applied an Artificial Neural Network for short-term prediction of traffic volume using past traffic data. Besides traffic volume, speed and density, the model incorporated time and the day of the week as input variables. Johar et al. (2015) predicted bus travel time using an Artificial Neural Network. They indicated that the developed model was slightly proficient in achieving the predicted travel time with sufficient accuracy. Sahraei and Puan (2018) conducted a study on the modelling of control delays at unsignalized intersections using Artificial Neural Networks. The statistical analysis revealed good agreement between formulas obtained from the ANN model and those from the field studies.

Despite notable progress in traffic flow modelling, limited research has focused exclusively on mixed traffic environments. Recognizing this gap, several researchers have emphasized the need for Artificial Neural Network (ANN)–based approaches to capture the complex, nonlinear relationships among traffic variables. ANNs offer strong learning capabilities and adaptability, making them suitable for heterogeneous traffic conditions where conventional models fail. Their use can enhance prediction accuracy for speed, flow, and density, providing a robust alternative to traditional analytical methods. Such efforts underscore the increasing importance of ANN applications in effectively understanding and managing mixed traffic dynamics. Most existing studies focus on isolated traffic parameters or specific applications, with limited emphasis on a unified modelling framework suitable for mixed traffic environments

3. General Framework for Using ANN in Mixed Traffic Prediction:

Artificial Neural Networks (ANNs) offer a data-driven modelling framework that can capture the nonlinear and complex relationships inherent in mixed traffic conditions. The systematic steps involved in developing, training, and validating an ANN model for predicting key traffic parameters such as speed, flow, density, and congestion indices under heterogeneous environments are outlined in the following subsections. Figure 1 shows general methodology steps of ANN.

3.1 Problem Definition

The initial step in ANN-based modelling is to define the problem and clearly state the modelling objectives. Mixed traffic, typical of urban roads in developing countries, involves the simultaneous movement of diverse vehicle types—two-wheelers, cars, auto-rickshaws, buses, and heavy vehicles—without strict lane discipline. This heterogeneity results in complex and nonlinear interactions among speed, flow, and density, which traditional lane-based models cannot adequately represent.
Accordingly, the problem is defined as developing a predictive framework that can capture these nonlinearities using an ANN. The modelling objectives may include predicting average speed, flow rate, density, or derived performance indices such as the Traffic Congestion Index or Level of Service (LOS). The defined problem should specify the purpose of prediction, the scope of applicability, and the expected outcomes. A well-defined problem ensures that data collection, variable selection, and model design are appropriately aligned with the study's goals.

3.2 Data Collection

Reliable and representative data form the foundation of ANN modelling. In mixed traffic conditions, data should reflect variability in vehicle composition, driver behaviour, and roadway geometry. Empirical data can be obtained from videographic surveys, GPS tracking, or automatic traffic counters installed at selected road sections. The core parameters generally include vehicle speed, flow rate, density, and classified vehicle counts for different categories. Supplementary variables such as road width, gradient, traffic control type, and weather conditions enhance the robustness of the dataset.
To ensure comprehensive coverage, data must represent various traffic states, including peak, off-peak, and intermediate periods. Adequate sampling across these conditions ensures that the ANN model generalizes effectively. All collected data are carefully reviewed for accuracy and completeness before being used for further processing. Traffic data are typically aggregated over short time intervals such as 5-minute or 15-minute periods to capture temporal variations while maintaining statistical reliability. Since mixed traffic does not strictly follow lane discipline, lane-based measurements are either aggregated across the carriageway or transformed into stream-based traffic variables.

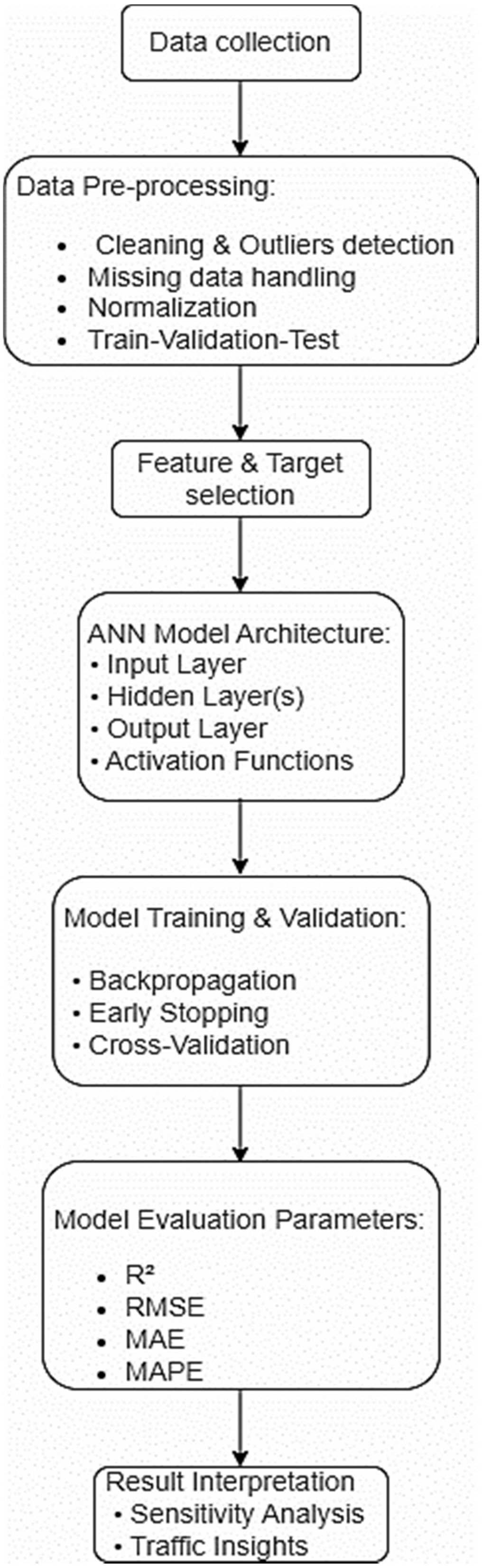

Figure 1 General methodological framework for applying Artificial Neural Networks (ANN) in mixed traffic prediction

3.3 Data Pre-processing

Data pre-processing is a crucial step in improving quality and reliability, as raw field data often contains inconsistencies, missing values, and outliers that arise from observational or recording errors. The procedure involves data cleaning, error checking, imputation of missing values, and outlier detection using statistical or machine learning techniques. Normalization or standardization is then applied to bring all variables to a comparable scale typically within the range of 0 to 1 to prevent scale bias during training. Generally the processed dataset is randomly divided into three subsets: training, validation, and testing, commonly in a 70:15:15 ratio. This systematic pre-processing enhances convergence, improves computational efficiency, and ensures that the ANN learns genuine traffic patterns rather than noise or anomalies. Outlier detection may be performed using statistical techniques such as z-score and interquartile range (IQR), or machine-learning-based methods. Missing values can be handled using interpolation or ANN-based imputation techniques. These steps enhance data reliability and prevent biased learning during model training.

3.4 Selection of Input and Output Variables

Selecting the appropriate input and output variables is crucial for making accurate predictions. Input variables typically include measurable traffic and road parameters, such as traffic flow, density, vehicle mix, headway, and lane width, while output variables may be average speed, congestion index, or density. Variable selection should rely on both theoretical relationships (such as the speed–flow–density model) and empirical correlation analysis to ensure that the variables are relevant.
Over-selection of weakly correlated parameters can lead to overfitting and increased computational costs, while excluding important variables can reduce model sensitivity. Therefore, a balanced and well-justified input–output setup is crucial for the ANN to effectively capture the nonlinear relationships that define mixed traffic behavior. Feature selection techniques such as correlation analysis, Principal Component Analysis (PCA), or mutual information analysis may be employed to identify the most influential variables. This helps reduce dimensionality, improve learning efficiency, and minimize the risk of overfitting.

3.5 Model Architecture Design

The architecture of an ANN influences its learning ability and prediction accuracy. A typical setup includes an input layer, one or more hidden layers, and an output layer. The number of neurons in the input and output layers matches the chosen parameters, while the number of hidden neurons is fine-tuned through experimentation or cross-validation.
Nonlinear activation functions, such as ReLU, sigmoid, or tanh, are used to enhance learning efficiency. Training algorithms, such as Levenberg–Marquardt, Adam, or standard backpropagation, are employed to minimize prediction errors. Important hyperparameters—such as learning rate, batch size, and epochs—are adjusted to find a balance between model accuracy and computational resources. The architecture needs to be complex enough to model nonlinear relationships but constrained enough to avoid overfitting.

3.6 Model Training and Validation

Model training involves providing input–output pairs to the ANN and iteratively adjusting the connection weights to minimize prediction error, typically measured by Mean Squared Error (MSE). The training dataset is used for learning, while the validation dataset helps fine-tune parameters and monitor performance. The process continues until the model reaches an optimal error level or validation results stabilize. Techniques such as early stopping, dropout, and k-fold cross-validation are used to prevent overfitting and enhance generalization. After training is complete, the model is tested on an independent dataset to assess its predictive ability under unseen conditions. Effective training and validation ensure that the model accurately captures the complex dynamics of mixed traffic flow.

3.7 Model Evaluation

Model evaluation measures the predictive performance and generalization ability of the trained ANN. Standard statistical indices—such as the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)—are used to quantify accuracy. Higher R^2 values and lower error metrics indicate better performance.
In addition to statistical measures, visual validation through graphical comparisons between observed and predicted values, residual plots, and error histograms is important. Assessing the model across various traffic

conditions ensures it maintains consistent performance across different flow levels and vehicle mixes. A thoroughly evaluated model builds confidence in its real-world applicability for mixed traffic prediction.

3.8 Result Interpretation

Result interpretation translates the numerical performance of the ANN into meaningful traffic insights. Analysis focuses on understanding how variations in input parameters affect predicted outcomes. Techniques such as sensitivity analysis or partial dependency plots can be used to identify the relative influence of different inputs. The trends observed from the ANN predictions can be compared with traditional traffic relationships, such as speed–flow and flow–density curves, to verify their consistency with real-world behaviour. Interpretation should also acknowledge the model's limitations, including its reliance on data quality and its inherent black-box nature. Despite these limitations, ANN results offer valuable insights into congestion dynamics, interaction effects, and performance levels across different traffic conditions.

4. Conclusion and Future Scope:

This study presents a comprehensive methodological framework for utilizing Artificial Neural Networks (ANNs) to predict mixed traffic parameters. The framework methodically combines stages such as problem definition, data preparation, variable selection, model design, training, validation, and evaluation, ensuring a thorough understanding of the modelling process. It highlights ANN's ability to capture nonlinear and interactive effects among different vehicle types, making it a strong tool for urban traffic analysis. Although this work is conceptual, it lays the groundwork for future empirical research that focuses on calibrating and validating ANN models using real-world data. Future studies may expand this framework by incorporating hybrid models that combine ANNs with evolutionary algorithms or fuzzy logic systems, as well as integrating real-time sensor and IoT-based traffic data. Such developments will enhance ANN's role as an intelligent and adaptive approach for analyzing and managing mixed traffic systems in developing urban areas.

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