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Review of driving-behaviour simulation: VISSIM and artificial intelligence approach

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ABSTRACT

Examining driving behaviour is crucial for traffic operations because of its influence on driver safety and the potential for increased risk of accidents, injuries, and fatalities. Approximately 95% of severe traffic collisions can be attributed to human error. With the progress in artificial intelligence in recent decades, notable advancements have been achieved in computer capabilities, communication systems and data collection technology. This increase has significantly influenced our capacity to replicate driver behaviour and comprehend underlying driving mechanisms in diverse situations. Traffic microsimulation facilitates an understanding of traffic performance inside a given road network. Among the microsimulation software packages, Verkehr In Städten – SIMulationsmodell (VISSIM) has garnered significant attention owing to its notable ability to accurately replicate traffic circumstances with high dependability in real-world scenarios. Given the diverse applicability of VISSIM-based schemes, this review systematically examines the applications of the VISSIM-based driving-behaviour models within different research contexts, revealing their utility. This review is designed to provide guidance for researchers in selecting the most suitable methodological approach tailored to their specific research objectives and constraints when utilising VISSIM. Five important aspects, including calibration, driving behaviour, incident, and heterogeneous traffic simulation, as well as utilisation of artificial intelligence with VISSIM, are assessed, which could yield substantial advantages in advancing more precise and authentic driving-behaviour modelling in VISSIM.

1. Introduction

The software known as “Verkehr In Städten – SIMulationsmodell” (VISSIM), which translates to “Traffic in cities - simulation model,” the software developed at the University of Karlsruhe in Karlsruhe, Germany, during the early 1970s. Since its release in 1993, VISSIM has been sold and maintained by PTV Transport Verkehr AG [1]. VISSIM is a simulation model based on behaviour, operating on a time-step basis, and consisting of three essential components: traffic control, traffic flow, and data analysis. VISSIM can analyse several aspects of infrastructure geometrics, including highway operations, dynamic traffic assignments, intermodal transportation

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interactions, signal prioritisation and optimisation, traffic management strategies, and pedestrian mobility [2]. With PTV VISSIM, traffic simulation, planning, construction, and running transportation networks are possible.

Traffic simulations are valuable for examining and evaluating different traffic models. Furthermore, computer simulation software is cost effective because no system is required for testing [3]. The conduct of drivers is a crucial element in every microscopic simulation model. Each driver-behaviour model consists of parameters with pre-set values, enabling individuals to insert values across a defined range by the prevailing traffic state in their locality. Nevertheless, due to the significant variation in driver behaviour relying on geographical location and driving conditions, the default values for such parameters often do not accurately capture the local traffic features and circumstances of a certain area [4]. Therefore, it is necessary to adjust the default values of these variables to replicate the local driving characteristics accurately.

VISSIM functions with eight vehicle-behaviour models: following, car-following, lane-change, lateral, signal control, autonomous, driver error, and mesoscopic. The car following behaviour in VISSIM is contingent on Wiedemann's psychophysical and discrete models [5], which assume that a driver can be in any of four driving regimes: following, free driving, closing in, or braking. These regimes are defined by thresholds (or action points) representing the points at which a driver changes driving behaviour. The lane-changing model in VISSIM is based on the Sparmann model, which was initially developed by Willmann and Sparmann in 1978. According to Ref. [6], the Sparmann model is a rule-based model in which lane-changing behaviour is classified as lane changing to a faster or slower lane.

Artificial intelligence (AI) has come into view as a crucial facilitator for Intelligent Transportation Systems (ITSs) in tackling tasks of unparalleled complexity. The increasing prevalence of deep learning models is noticeable in various ITS applications, including scene comprehension, integration of multimodal data, federated learning, and reinforcement learning. These use cases range from vehicle perception and driver-behaviour characteristics to traffic forecasting and vehicle self-diagnostics. Metaheuristic optimisation and clustering algorithms are two examples of AI-based algorithms widely used in other learning paradigms including the optimisation of vehicular telecommunication and the segmentation of multidimensional data. Today, virtually every ITS-related research field is fuelled by AI, which is unleashed whenever a machine learns how to solve a complex task on its own [7]. An artificial neural network (ANN) is a computational model that emulates inspiration from the organisation and operations of the human brain. These models exhibit fast training capabilities and can effectively address diverse nonlinear problems by employing appropriate learning algorithms [8]. There are several uses for ANNs with microsimulation software, such as data generation, learning, and testing environments [9].

This review is closely related to many studies conducted on microscopic simulations; however, it presents a distinct perspective and approach. A review by Ref. [10] conducted a study on two-dimensional (2D) microscopic traffic-flow models and concisely expounded on the utilisation of VISSIM in simulating heterogeneous traffic flow [11]. analysed applications of microsimulation modelling for traffic safety evaluation using different simulation tools in a heterogeneous traffic environment [12]. carried out a study on car-following models and their adjustments to simulate two-dimensional traffic, integrating both lateral and longitudinal behaviours to account for mixed traffic conditions [13]. recognised car-following models and modelling tools for both human and autonomous driving behaviour. They underscored the importance of VISSIM microsimulation, specifically its psychophysical car-following models (namely, Wiedemann 74 and Wiedemann 99), and its application in simulating autonomous vehicles (AVs) and connected and autonomous vehicles (CAVs) through the adaptation of Wiedemann model parameters and other driving behaviours. This study primarily concentrates on comprehending the evaluation of traffic microsimulation and critically assessing the various commercial and open-source simulation platforms, along with their significance in traffic microsimulation research. Subsequently, an analysis of contemporary methodologies employed in the microsimulation of AVs is provided [14]. [15] offers an in-depth and evaluative overview of surrogate safety measures, exploring their diverse uses in safety studies related to Connected and Autonomous Vehicles (CAVs). Each of these review articles has a distinct methodological perspective. This study comprehensively examines kinematic surrogates and explores their potential for contextualisation across different road geometries. Moreover, this study investigates video-processed and observer-based surrogate indicators for analytical purposes. The potential benefits and drawbacks of surrogacy are discussed in relation to its prospective applications [16].

VISSIM is one of the microsimulation software considered in earlier studies. In each of these studies, the researchers examined the software from a particular perspective corresponding to the subject matter of their study. This study examines the existing literature on VISSIM driver-behaviour models with AI and their utilisation in different approaches to understand how VISSIM functions and develops guidelines to facilitate the identification and classification of these approaches. Therefore, the review's fundamental concerns are as follows:

I. What are the different calibration methods employed in driving-behaviour research, focusing on the most utilised approach and driving-behaviour parameters that have been most extensively calibrated?
II. What is the use of car-following and lane-change models in modelling driving behaviour?
III. What can be learned from the predominant techniques employed in simulating incidents using VISSIM by examining the frequently utilised variables in measures of effectiveness (MOE) and incident-related variables?
IV. Can VISSIM simulate heterogeneous traffic, and what is the prevailing method for using VISSIM in heterogeneous environments?
V. What is the main function of ANN when employed in conjunction with VISSIM through the component object model (COM) interface feature?

This study considers a theory model review that attempts to clarify driving-behaviour modelling using the PTV VISSIM microsimulation software and highlights the utilisation of AI and ANN in each main section of the review. Furthermore, the limited geographic scope of the review and the process of literature search and curation face limitations due to the dynamic and multidisciplinary nature of the subjects. The review primarily focuses on simulating driving behaviour at the micro level, with a particular emphasis on lane change, car-following, and lateral driving behaviour models; it does not study driving-behaviour simulation at the macro level and does not investigate the utilisation of other VISSIM modules such as driver error and signal control models.

1.1. Research strategy

This review included academic papers identified in different repositories (Web of Science, Scopus, Science Direct, Taylor & Francis, Google Scholar, and Mendeley). The search began with a relevant title referring to the category sought and focused on applying VISSIM. The principal keywords used for the online searches included VISSIM calibration, incident simulation using VISSIM, VISSIM driving-behaviour models, simulation of heterogeneous traffic using VISSIM, and employment of ANN using VISSIM. Fig. 1 displays the keyword co-occurrence network, and Table 1 displays the principal keywords and number of retrieved articles. The search yielded 250 relevant documents. The process of analysing the executive summaries or abstracts of the aforementioned documents resulted in a more focused selection of records, which were then subjected to a comprehensive evaluation of their entire text.

A retrospective analysis was conducted to uncover supplementary pertinent documents by tracing the full text of the review in reverse chronological order. The curation procedure yielded approximately 125 articles, which progressed to the review stage. This review is organised into six main sections. The introduction is presented in the first section; the second reviews and summarises the literature based on the title and approach employed. The third section assess and evaluate the previous section illustrating the assessment with simple charts to emphasise the main points of the reviewed approaches. The fourth section is a discussion. The fifth section addresses the gaps research and future research directions. The final partition presents the conclusion.

2. VISSIM application literature review

This section introduces the key aspects of the review and a list of the reviewed literature with essential approaches to each section.

2.1. VISSIM calibration

Traffic microsimulation models have become popular in transportation research and are extensively utilised in industry and research. Numerous earlier methods were unable to capture the stochastic nature of transportation regulation's dynamic characteristics, an area in which traffic microsimulation models have succeeded. Nonetheless, software calibration is a primary concern for microsimulation users. Improper calibration could lead to inaccurate conclusions and choices, resulting in irreversible expense or

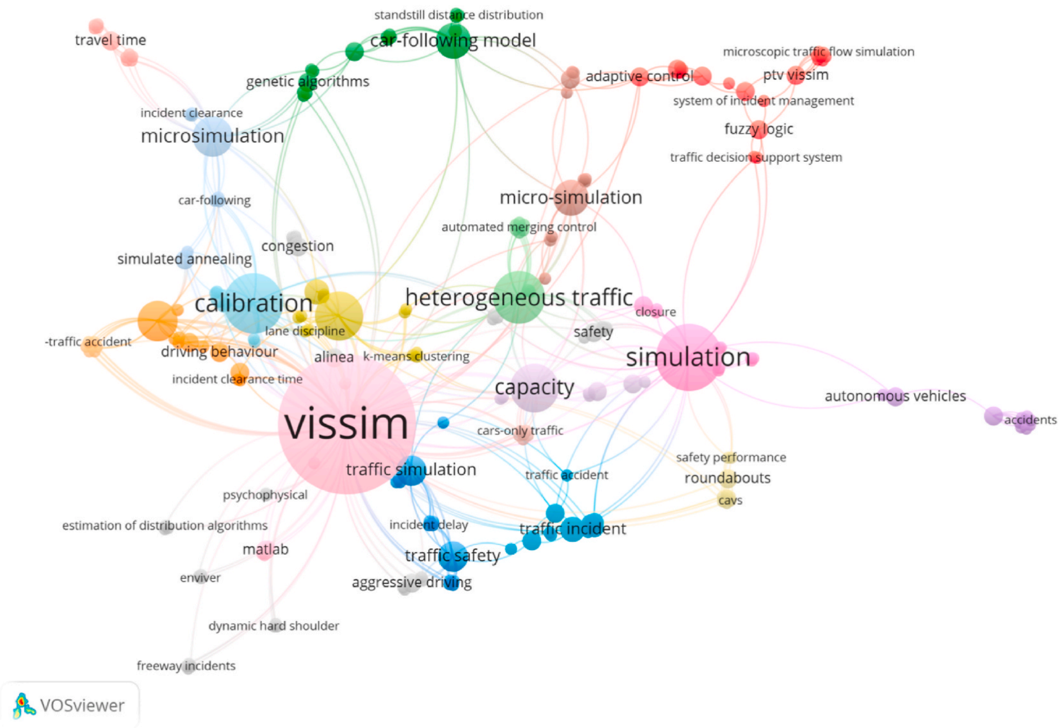

Fig. 1. Display the keywords co-occurrence network..

Table 1
Principal keywords and number of retrieved articles.

Principal Keyword	Number Of Retrieved Articles
VISSIM Calibration	101
VISSIM Driving Behaviour Simulation	32
Incident Simulation Using VISSIM	69
Heterogenous Traffic Simulation With VISSIM	49
Employment Of ANN With VISSIM	37

issues [1]. According to Ref. [17], the process of adjusting multiple parameters of the simulation model until it accurately replicates the field conditions is referred to as calibration. Throughout the calibration process, the network behaviour settings in VISSIM are updated so that the model reflects the actual site conditions. Adjustable calibration parameters can be classified based on their function.

The multiple parameters in VISSIM can be tweaked to recreate a specific traffic scenario. However, not all traffic conditions have an identical influence on all parameters [18]. Consequently, the essential characteristics for a specific traffic scenario under consideration must be defined and collected by performing a sensitivity analysis.

2.1.1. Sensitivity test

A sensitivity test systematically analyses the impact of driving behaviour models' parameters in VISSIM on selected outputs to Identify the initial critical parameters and establish their dependable ranges and effective increments. Numerous tests were noted during the review, and the most frequently used tests are mentioned. Elementary Effects (EE) is a probabilistic and qualitative analysis technique used to evaluate important and intricate parameters in a model [19]. EE is employed primarily in computationally expensive mathematical models or models with multiple inputs when other sensitivity measures are prohibitively expensive. The EE concept employs the notion of the one-at-a-time technique, wherein each phase of the analysis involves modifying only one input parameter of the model by a specified value while holding the importance of the other parameters constant. The subsequent examination entails the utilisation of Latin hypercube sampling, a technique that partitions the dimensions of each variable into nonoverlapping intervals of equal probability. This method randomly selects samples from each interval, facilitating the exploration of a broad spectrum of parameter values while mitigating parameter correlation. Random samples are paired in a randomised manner for each variable. The combination with the least significant correlation among the variables is selected from all available options [20]. Analysis of Variance ANOVA, the last test, is the most effective parametric method for assessing experimental data. The original design was to evaluate variations among the diverse treatment groups, therefore bypassing the need to do numerous comparisons between groups using t-tests [21].

2.1.2. Calibration methods

The calibration procedure entails iteratively adjusting the microsimulation's parameters to achieve a high degree of precision when replicating real-world field circumstances. Several commonly used calibration models and their corresponding definitions are as follows. Genetic algorithm (GA) is an optimisation methodology that utilises heuristics to emulate the processes of evolution and genetics for the purpose of optimising a given dataset (population) over multiple generations. This objective is accomplished by systematically eliminating individuals that are not well-suited and combining the most fit individuals to produce improved offspring (new values). Consequently, the fitness function value could be viewed as the quotient obtained by dividing the predefined target acceptable gap value of the field by the 85th percentile acceptable gap value derived from the simulation result. A smaller number of errors indicates a more optimal match. Several iterations of the VISSIM simulations are conducted to obtain the optimal results, and genetic algorithm is used to reduce the error until it becomes progressively negligible. The input model parameters corresponding to the best-fit are then returned with their ideal values [22].

Manual calibration involves a trial-and-error approach, whereby discrete values for each parameter are intuitively selected and different combinations of several parameters are tested until the required outcomes are attained. Nevertheless, one can easily find themselves trapped in an endless cycle of resolving one issue and generating another while inadvertently using this approach. The manual calibration process can be time-intensive and is only recommended when the number of parameters is limited [23]. The population-based stochastic optimisation method known as Particle Swarm Optimisation (PSO) was first suggested in 1995 by Eberhart and Kennedy; the inspiration for this study was derived from observing the social behaviour exhibited by fish in schooling formations and birds in flocking formations [24]. The PSO algorithm is an iterative technique involving the movement of a population of particles throughout a search space. This movement is determined by considering the value of the provided goals and velocity of the particles (which represent the direction and intensity of their movement), location, and knowledge of the best position found thus far within their immediate neighbourhood.

The Whale Optimisation Algorithm (WOA) is a metaheuristic algorithm that draws inspiration from the foraging behaviour of humpback whales and is rooted in principles derived from nature. Such an algorithm identifies the target prey, leading to the identification of the best solution. Once the process is initiated, the candidate solution obtained by the most efficient search agent is in close proximity to the optimal solution. Subsequently, other search agents adjust their positions relative to the optimal search agent. The location is iteratively updated using a spiral pattern mimicking the bubble-net attack tactics used by humpback whales. This approach facilitates an iterative optimisation process, allowing for the identification of the most optimal solution [25]. AI optimisation strategies have been demonstrated to enhance the efficiency and cost-effectiveness of procedures for identifying an optimal solution from a range

Table 2
Driving-behaviour's calibration and validation previous studies review.

Author	VISSIM Model	Sensitivity Model	Calibration Model	Validation	Calibrated Parameters
[3]	Lane-change (Ln. Chg.)	Based on reviewed literature	The variables and their values were chosen based on the literature.	–	Minimum Headway (MinHdwy), Lateral minimum distance, Number of observed vehicles.
[18]	W 99	Latin hypercube design (LHD), ANOVA	(GA)	The calibration model was subjected to testing using new field data collected throughout the day.	Standstill distance (CC0), Gap time distribution (CC1), Threshold for entering (CC3), Oscillation acceleration (CC7).
[22]	W 74 & Ln. Chg.	(EE method)	(GA)	Data sets other than the one used for calibration were used to validate the model.	Average standstill Distance (W74ax), Additive part of safety distance (W74bxAdd), MinHdwy, look ahead distance minimum, Look back distance minimum, Maximum deacceleration (own), Maximum deacceleration (trail).
[23]	W 74 & Ln. Chg.	Based on VISSIM manual recommendation	(GA), Simulated annealing (SA) and Tabu Search (TS).	Measures of effectiveness (MOEs) include traffic volumes and travel times.	(W74ax), (W74bxAdd), Multiplicative part of safety distance (W74bxMult), Maximum deceleration (own).
[28]	W 99 & Ln. Chg.	Based on previous studies.	The modification of input data (needed speeds) is carried out to reduce deviation from the real data.	The travel times optimised were compared to new travel data obtained separately.	CC1, Following distance oscillation (CC2), Maximum trailing vehicle deceleration Factor for reducing safety distance. Maximum rate of deceleration for cooperative braking.
[30]	W 99	Based on previous literature.	The model was optimised by utilising volume and speed as measures of effectiveness.	Using the queue length obtained from shockwave theory for validation.	CC0, CC1, CC2.
[31]	W 99 & Ln. Chg.	ANOVA	Orthogonal Experimental Design.	Validation is based on real bottleneck data from the field and that gained from simulation.	CC0, CC1, CC2, Negative speed difference (CC4) & Positive speed difference (CC5), Minimum deceleration, Safety distance reduction factor (S-Fact), Maximum deceleration for cooperative braking (MaxCD), Maximum speed difference for cooperative (MaxSD), Distance of merging area (LC-Dist).
[32]	W 99	Parameters selection based on previous studies.	(GA) & (TS)	Comparison between the observed and simulation.	CC0, CC1, CC2, CC3, CC4, CC5, CC7
[33]	W 99	Statistical Tests	Solver Function	Utilising distinct sections of a multi-lane highway.	CC0 CC1 CC2
[34]	W 99	ANOVA	(GA) & Simultaneous Perturbation Stochastic Approximation (SPSA)	The tool's functionality is assessed through a dataset acquired from the expressway.	CC0, CC1 CC2 CC5 CC6
[35]	W 74	Statistical Analysis	Queue Length	Contrasting the observed queue length with the simulation.	(W74ax), (W74bxAdd), (W74bxMult).
[36]	W 74	ANOVA	(GA)	Use the calibrated parameters on another Intersection for validation	(W74ax), (W74bxAdd), (W74bxMult).
[37]	W 99	(LHS)	(GA)	Compared the speed between the simulation and the field.	CC0, CC1, CC2, CC4 CC7
[38]	W 74 & Ln. Chg.	Based on previous studies.	Evolutionary Algorithms (EA) & Parallel Computing Techniques (PCTs)	Compared the simulation data and real traffic data after the calibration process.	–
[39]	W 99 & Ln. Chg.	Findings from the literature.	Time Headway Distribution	Replicating interval-based average velocities and mean queue discharge rates derived from their field-measured values.	CC0, CC1, CC2, Saturation Flow Rate (SRF), Cooperative Braking Maximum, Deceleration for Cooperative Braking.
[40]	W 99 & Ln. Chg.	ANOVA	(GA)	Using the SSAM tool to compare field-measured conflicts to VISSIM-simulated data.	Desired speed Observed vehicles ahead,

(continued on next page)

Table 2 (*continued*)

Author	VISSIM Model	Sensitivity Model	Calibration Model	Validation	Calibrated Parameters
[41]	W 74 & Ln. Chg.	–	(GA) & Particle Swarm Optimisation (PSO)	Compared the simulation data and real traffic data after the calibration process.	CC0, CC1, CC2, CC3, CC6, CC7, Acceleration from standstill (CC8). W74ax, W74bxAdd, W74bxMult, Max. look back distance, Max. look ahead distance, Standstill distance, No. of observed preceding vehicles, Reduction rate for leading (own) vehicle, Accepted deceleration for leading (own) vehicle, MinHdwy, Safety distance reduction factor.
[42]	W 74 & Ln. Chg.	The parameters are selected based on the vehicle performance and sensitivity of road network capacity.	Genetic Algorithm (GA) & Fusion Genetic Algorithm	Simulation and field delays were compared.	MinHdwy (front/rear), (MaxDC), (AvgSD), Additive Part of Safety Distance (AddSD), Multiple Part of Safety Distance (MulSD).
[43]	W 74 & Ln. Chg.	Based on reviewed literature.	(GA) & (PSO) & Whale Optimisation Algorithm (WOA)	Discrepancy between the simulated number of conflicts and the field.	Average standstill distance (ASSD), Additive factor for safety distance (AFSD), Dimensionless multiplicative factor for safety distance (MFSD), Safety distance reduction factor (SRF), MinHdwy.
[44]	W 99	Based On Former Studies	Trial and Error	Kolmogorov–Smirnov test (K–S test)	CC0, CC1
[45]	W 74	ANOVA	(GA).	Applying the proposed methodology to another intersection.	(W74ax), (W74bxAdd), (W74bxMult).
[46]	W 99 & Ln. Chg.	Based on Previous Studies.	Extreme Value Theory (EVT) & (GA).	A comparison between the calibrated VISSIM parameters and a previous study.	CC0, CC1, CC4 & CC5, Desired Deceleration (RF), (SRF).
[47]	W 99	Microscopic trajectory data	Derive Average Values	Indicator Average Queue Dissipation Time	CC1, CC2, CC4 CC5
[48]	W 74	Based on PTV VISSIM manual	The Difference of Means Statistical Test.	The Difference of Means Statistical Test.	(W74ax), (W74bxAdd), (W74bxMult).
[49]	W 99 & Ln. Chg.	(EE)	One-At-a-Time (Trial & Error)	The output of the VISSIM model was validated utilising field data obtained one day in advance.	CC0, CC1, CC2 Diamond Shape queuing. Look ahead distance, Look back distance.

of repeatedly compared replies. The application of classical methodologies results in a system of simultaneous nonlinear equations that can present challenges in terms of solvability [26].

One limitation associated with the use of AI in sensitivity and calibration approaches is that the obtained outcomes only reflect the characteristics of the samples under investigation without providing insights into the variables that have the most significant influence. The presence of extraneous variables can introduce interference in the data, thereby leading to poor outcomes due to the quality of the work. In the context of model calibration, it is imperative to perform sensitivity assessments so as to define the effect of various factors on the obtained findings [27].

2.1.3. Validation

Prior to conducting the simulation, the final step involves ensuring that the calibration step accurately reproduces the field conditions, which is known as the validation process. The validation process verifies that the model generates accurate data, thereby ensuring its suitability for various purposes [28]. Model validation tests aim to verify model's accuracy by comparing anticipated traffic-flow data with real field data. The validation process is contingent upon the calibration approach, as the calibration technique is crucial to guarantee the faithful replication of actual traffic patterns [29]. The most commonly employed methods for validation include comparing the simulation outcomes with field data and measuring the MOEs by comparing the main parameter values between the field and simulation data (Table 2).

2.2. Driving-behaviour simulation in VISSIM

Under psychophysical models, a driver's conduct exhibits variability contingent on the prevailing traffic circumstances, encompassing factors such as the driver's engagement in unrestricted movement, proximity to the preceding vehicle, adherence to the vehicle ahead, or the act of deceleration. The amalgamation of the relative velocity and distance to the preceding vehicle often characterises the boundary conditions of various states [50]. The behaviour of vehicle drivers on a specific road segment is crucial for determining the transportation network's performance. It is essential for fine-tuning the output of traffic simulation models to simulate road

Table 3
Review on driver behaviour modelling in VISSIM software for related studies.

Author	VISSIM Model	Geometry	Approach	Significant Finding
[51]	W 99 & Ln. Chg.	Intersection	Investigating the impact of AV on potential conflicts.	Autonomous vehicles will result in major safety benefits. A reduction in collision rate was noted. Increasing the AVs will enhance the safety of the network.
[54]	W 99 & Ln. Chg.	Freeway	Analysing the influence of important traffic parameters on lane change regarding traffic safety.	The rate of lane changes goes up as the average desired speed increases within a predetermined speed range. A higher frequency of lane changes occurs when the speed dispersion is set to a large value, while a lower frequency of lane changes occurs when the speed distribution is set to a small value.
[57]	W 99	Expressway	Analysing the (HOV) Lane to determine their suitability as sustainable highway operations.	The bus travel speed increased markedly with the High Occupancy Vehicle Lane (HOV) lane enforcement. The movable median lane enforcement improves car efficiency due to the increased travel speed of the total vehicles.
[58]	W 99	Freeway	Analysing the operational efficiency of two managed lanes.	There is a difference in capacity between the one-lane, two-lane and queue discharge flow. There was a drop in capacity, but the flow didn't show substantial change.
[59]	W 74	Intersection	Connected vehicle Signal control (CVSC)	The proposed CVSC method was performed admirably to minimise travel time delays and the average number of stops per vehicle.
[60]	W 99	Intersection	Investigating Connected Vehicle (CV) technology in the context of traffic control.	A decrease in average fuel consumption and a reduction in average vehicle delays and queue length were observed. When traffic congestion increases, the traffic light control system outperforms the First-Come-First Serve (FCFS) based non-signalised control.
[61]	W 74	Arterial	Estimating travel time and routing for Emergency Vehicle (EV).	Travel time estimation was inaccurate after the calibration and validation the error decreased significantly. The reduced manoeuvrability of EV (Emergency Vehicle) led to an increased dynamic PCU for high flow rates.
[62]	W 99	Intersection & Roundabout	The safety impacts of AVs are examined through simulation.	With higher penetration rates, AVs significantly improve safety. There is a clear decrease in conflicts when the AV penetration rate reaches 100%.
[63]	W 74 & W 99	Arterial	Use the traffic calming features to reduce the negative effects of vehicles use.	The capacity decreased in both directions when the traffic clam strategy was applied the same thing was noticed in speed, travel time and delay.
[64]	W 99	Expressway	Modelling Car-Following on urban Expressway	Intelligent Driver model (IDM) has a better transferability to model traffic conditions compared to the Wiedemann 99 for a Chinese expressway.
[65]	Ln. Chg.	Expressway	The identification of the proper spacing for lane changes in off-ramp situations.	There will be less congestion at the off-ramp area (or even none) as the larger the lane-changing spacing interval. When lane-changing intervals are long enough, vehicles can quickly pass through the off-ramp area. By creating diverging flows in off-ramp areas, congestion was less likely to occur.
[66]	W 99 & Ln. Chg.	Freeway	Examining the use of Ramp-Metering (RM) on a motorway.	Overall, the RM operation performed better than the others. The signal on the ramp with the shortest red time performed best regarding average queue length reduction. The highway traffic condition directly affects the metering rate; this technique performed best in average speed improvement.
[67]	W 74	Intersection	Estimating the speed-based vehicle exhaust emission using Car-Following model.	Modifying the signal green interval time in accordance with the current volume of traffic can drastically reduce emissions. After a change in vehicle composition, it was noticed that the amount of NOx increases dramatically as a result of the increased number of diesel-powered buses offered to the network.
[68]	W 99	Freeway	Understanding the consequences of aggressive driving.	Aggressive driving, such as closely following, rapid lane changes, and fast deceleration, would jeopardise steady interactions with neighbouring vehicles. Unstable vehicle engagements are strongly linked to the possibility of a crash.
[69]	W 99	Expressway	Dynamic Climbing Land Control	Using the dynamic climbing control resulted in faster travel, shorter travel time, and reduced delay. The use of dynamic climbing control considerably reduced rear-end and lane-changing conflicts.
[70]	W 99	Expressway	Assessment of highway capacity taking into account the impact of driver behaviour.	As a result of the simulation, the capacity obtained is very close to the capacity suggested by the highway capacity manual.

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Table 3 (*continued*)

Author	VISSIM Model	Geometry	Approach	Significant Finding
[71]	W 99 & Ln. Chg.	Intersection	Establishing different CAV penetration rates.	The benefits of increasing CAV penetration rates in traffic flow are more considerable. Higher penetration rates of CAVs improve safety significantly.
[72]	W 99 & Ln. Chg.	Highway	Analysing the lane-change with homogenous traffic.	The number of lane changes appears to level off once the traffic volume reaches capacity. Lane changes initially increase with volume but then decrease as volume continues to rise.
[73]	W 74	Highway	Examined the parking manoeuvres on the roadside on traffic flow.	There is a 7% reduction in the capacity per 100 parking manoeuvres. For the same parking rate if there is an increase in the flow rate there was a speed reduction.
[74]	W 99 & W 74	Rodway	Simulation vehicle following behaviour in mixed traffic environments.	Based on the trajectories, it is obvious that even under mixed traffic conditions, the hysteresis phenomenon (representing the following behaviour) is observed among the vehicles (even though the vehicles tend to move in groups). The study strongly disapproves of the principle of modelling urban roads using W 74 high-speed roads using the W 99 model. The study findings suggest that both models are quite consistent.
[75]	W 99 & Ln. Chg.	Expressway	Analysing driving behaviour model on congested highway.	The merging/diverging traffic flow ratio at the merging area, link length and distance between on-ramp and off-ramp, and the percentage of heavy vehicles significantly affect driver characteristics. Additional parameters for on-ramp and off-ramp connectors have significant effects such as emergency stop and lane-change parameters, and activation of 'observe adjacent lane(s)' for lateral parameters.
[76]	Lane-Change	Expressway	Using intelligent connected vehicles in weaving areas to manage active lanes.	Fine lane management measures make road traffic safer and considerably minimise delays in weaving regions. Lane-changing isolation in weaving zones helps reduce mishaps by ensuring the speed inside straight-driving vehicles.
[77]	W 99 & W 74 & Ln. Chg.	Freeway	Examined the influence of car-following and lane-change parameters on traffic flow distribution within a lane.	The parameters CC3 and CC1 in Wiedemann's model are crucial as they determine the headway at which a vehicle expresses a desire to change lanes. CC1 has a significant influence in the W 99 context, while the bxadd and bxmult parameters do not affect the lane flow distribution when utilising W 74.
[78]	W 99	Freeway	Analysing the distribution of standstill distance and time headway can provide valuable insights into estimating journey time reliability.	A specific pattern characterises the distribution of standstill distances and time headways. By integrating stochastic factors associated with standstill distance and time headway into car-following models, it becomes feasible to enhance the precision and effectiveness of evaluating travel-time reliability measures.
[79]	W 74	Roundabout	Evaluate the movements of vehicles through three types of roundabouts.	Traffic conflicts and pollutant emissions, the roundabout design is found to influence traffic performance. Single-Lane roundabout represents a significant difference regarding the safety concerns and emissions compared to the others.

sections meritoriously. Similarly, lateral and lane-changing behaviours play a key role in defining driving behaviour [51]. The precision of the traffic simulation model is directly relevant to the precision with which the vehicle movements within the network are estimated. In the microsimulation, the behaviour type of each connection is linked to the driving behaviour. VISSIM's traffic flow model is a time-step-based, microscopic, discrete, and stochastic representation, depicting vehicle units as individual substances. The suggested approach incorporates a psychophysical car-following model to simulate the longitudinal movement of vehicles, as well as a rule-based system for controlling lateral motions. The model was founded upon a continuous investigation conducted by Ref. [52] on car-following and lane-change actions.

2.2.1. Driving-behaviour models

VISSIM employs the Wiedemann psychophysical car-following model. In fact, a car-following behaviour defines how a vehicle interacts with the movements of vehicles in front of it. This behaviour is based on the premise that a vehicle's on-road behaviour is primarily influenced with the behaviours of either one or more preceding automobiles. Car-following models are crucial for preserving the accuracy of simulation models when analysing the impacts of congestion, especially considering that a substantial number of automobiles operate in this manner during crowdedness conditions. These models can assess traffic-flow characteristics, safety, and capacity [53]. VISSIM offers two car-following models, namely Wiedemann 99 and Wiedemann 74. The former is recommended for urban arterial roads, whilst the latter is more suitable for highways. Lane changing in traffic flow represents a complex and important behaviour for road traffic safety.

Frequent lane changes can give rise to significant traffic safety issues, especially in sections of two-lane motorways. Within the VISSIM simulation software, two distinct models for lane changes are utilised: an obligatory lane-change model and a free lane-change model. The process of executing a necessary lane shift involves strategically adjusting the position of the driver within a lane in order to effectively transition to the subsequent connection along a given route. A lane change executed by a vehicle to gain speed advantages or additional space is sometimes referred to as a free lane change. The successful execution of a lane-change manoeuvre is contingent upon achieving the required safety distance in the target lane. The determination of the safety gap is dependent on the velocities of both the trailing vehicles and the lane-changing vehicle in the target lane [54].

2.2.2. Automated modelling

The notion of autonomous vehicles (AVs) as a pivotal component of intelligent urban traffic systems has garnered considerable attention in recent years. It is anticipated that, in the future, human-driven vehicles (HVs) and autonomous vehicles will coexist within traffic systems. AVs are generally understood to possess varying degrees of connectivity, encompassing basic navigation capabilities as well as sophisticated functionalities for cooperative driving. The term "automated vehicle" refers to a vehicle with the capability for autonomous operation at any level of automation, often referred to as self-driving cars or robotic cars, thereby classifying them as a type of mobile robot [55].

The synthetic system comprises different components: environmental observations, behavioural decision-making, motion planning, and intelligent control. AVs are associated with diverse socioeconomic advantages. First, it is anticipated that there will be a substantial decrease in the occurrence of accidents, as research has indicated that more than 90% of accidents can be attributed to human error. AVs can reduce travel expenses. Moreover, when implemented in public transportation, AVs can reduce labour expenses [56]. Microscopic traffic simulations, also known as traffic simulation, such as VISSIM, offer a proactive methodology for evaluating the consequences of automated traffic on different aspects, including transportation efficiency, safety, equity, and the environment [26,55] (Table 3).

2.3. Incident simulation with VISSIM

Highway traffic incidents including stalled vehicles, split cargo, traffic incidents, road maintenance, and climatic problems occur irregularly and reduce highway capacity. However, highway traffic incidents are dangerous and frequent [80]. An unexpected traffic event can lead to traffic congestion on upstream routes, resulting in fatalities, delays in traffic flow, and increased travel time, significantly influencing the road network [81].

Traditionally, road safety analyses have been carried out with historical collision data. The reactive approach employed in this context exhibits different deficiencies, namely, the constrained accessibility and substandard nature of collision data and the challenge of discerning factors. This contributes to the occurrence of collisions, which is an ethical quandary arising from the necessity of observing a sufficient number of collisions over an extended duration to conduct a statistically reliable safety analysis [82–84]. Hence, the employment of surrogate measures, such as the surrogate safety assessment method (SSAM) in conjunction with resources of The Swedish Traffic Conflict Technique, as a proactive and supplementary strategy for examining road safety from a more comprehensive standpoint rather than solely relying on collision-based analysis [85–87] has been recommended. The SSAM tool extensively extracts instances of traffic clashes from road drivers' trajectories obtained from microscopic simulation models like VISSIM [88].

VISSIM is a modelling tool for micro-driving behaviour that models and analyses traffic operations in diverse traffic situations. The assessment of traffic engineering design and road planning can be facilitated by utilising beneficial instruments. VISSIM predominantly functions as a microscopic traffic-simulation system that focuses on modelling time and behaviour. This system parameterisation of relevant highways is helpful for motorway simulation and the modelling of emergency traffic diversions.

2.3.1. Time dependant

In the context of VISSIM microsimulations, time-dependent factors encompass a range of elements that exhibit temporal variability and influence the simulation. This pertains to the measurement and analysis of traffic volume and flow rate. Fluctuations in the number of cars and their corresponding velocities can introduce variability into simulations. The speed-time curves of vehicles depict the variation in vehicle speed as a function of time, encompassing the simulation process. Temporal variations in vehicles' increasing and decreasing speed can influence the simulation. The braking rate of vehicles could exhibit temporal variations, which can influence the model. The dynamic nature of driver behaviour and lane-changing actions can significantly influence the simulation outcomes. The driver route-choice in user equilibrium refers to the selection of routes by drivers, which is influenced by the observed journey times inside the network. The temporal parameters of traffic signals have the potential to vary, thereby influencing the simulations. The variability in vehicle queue lengths can influence the simulation. The elements mentioned above play a critical role in ensuring the models' reliability when accurately representing local conditions. The validation and calibration of microsimulation models often prioritise the examination of temporal variables [89–94].

2.3.2. Incident simulation method

The VISSIM software package lacks an incident simulation feature, and its user manual does not address incident modelling. To overcome this dilemma, researchers use one of these approaches to simulate incident occurrence: First Parking Lot. The software package proposes a parking event as an extraordinary modelling example. Two simulation entities are used in the proposed approach: parking space and route determination. Before starting the model, the parking lot operative just during the incident. To facilitate the use of the open lane(s) by other vehicles, the route decision involves implementing a partial route during the incident, directing all traffic through a newly established connector. The duration of the partial route is set to match the duration of the incident [95].

Another approach is based on the fact that signal light installation is time-dependent. Speed-reduction regions and signal heads can be used to simulate incidents in VISSIM. The traffic signal head specifies its location and simulates the occurrence of an incident. The signal head number correlates with the number of closed lanes at the location of the incident. The "red" time of the signal head utilised for event modelling is defined as the duration of the incident. In the final approach, the duration and location of the bus stop are set to the same parameters as the duration of the incident [96]. In the last approach, the bus stop location and duration are set to the same parameters as the duration of the incident.

Table 4
Review of incident simulation in VISSIM software for related studies.

Author	Incident Simulation	Incident Duration	Measures of Effectiveness (MOE)	Incident Variables
[80]	Parking-Lot	500 Second	Traffic Flow Speed	Incident Detection
[81]	Signal Light	(15, 18, 23, 33 and 37) Minutes	Crowded Dissipation Time Residual Capacity Vehicle Collision	Incident Delay Time Incident Type
[95]	Parking-Lot	(15,20,25,30 and 50) Minutes	Delay Travel Time Capacity No. of Stops	Incident Duration
[96]	Signal Light	60 Minutes	Delay	Incident Duration Incident Location
[97]	Bus Stop	(30–120) Minutes (15 Minutes Interval)	Traffic Volume Roadway Clearance Time	Incident Duration Blocked Lane Incident Clearance Time
[98]	Add-vehicle function	(10,20,30) Minutes	Travel Time.	Incident Duration. Number of Blocked lanes
[102]	Signal Light	30 Minutes	Delay Queue Length Traffic Volume Travel Time	Blocked Lanes Incident Duration Upstream Traffic Volume
[103]	Bus Stop	(90,120) Minutes	Travel Time Total Delay Diversion Rate	Incident Duration Number of Blocked Lanes Capacity Reduction
[104]	Signal Light	60 Minutes	Travel Time Queue Length	Incident duration
[105]	Signal Light	(5−60) Minutes (5 Minutes Interval)	Traffic Flow Density Delay	Incident Duration Shockwave Dissipation Time
[106]	Signal Light	1 Hour	Travel Time Traffic Volume	Number of Blocked Lanes
[107]	Parking-Lot	100 Seconds	Traffic Rate Traffic Volume	Incident Type Incident Location
[108]	Signal Light	(25,60,75) Minutes	Traffic Volume	Incident Duration Incident Location
[109]	Bus Stop	(15,35,45) Minutes	Capacity Traffic Flow	Incident Location Incident Duration
[110]	Signal Light	(1,2) Hour	Travel Time Aggregate Delay	Incident Duration Incident Location
[111]	Parking-Lot	30 Minutes	Travel Time	Incident Location
[112]	Parking-Lot	20 Minutes	Delay Time Warning Distance	Time to Collision
[113]	Bus Stop	(30,45) Minutes	CV Penetration Rate Travel Time	Incident Location Number of Blocked Lanes Incident Duration
[114]	Signal Light	(15,35,45) Minutes	Delay Capacity	Incident Duration Number of Blocked Lanes
[115]	Parking-Lot	(30,45,60) Minutes	Delay Travel Time. Queue Length	Incident Duration Demand Level V/C Ratios Diversion Rates
[116]	Parking-Lot	40 Minutes	Speed Vehicle Dissipation Time	Incident Duration
[117]	Parking-Lot	(15,20,25,30 and 50) Minutes	Travel Time Delay	Incident Duration
[118]	Parking-Lot	15 Minutes	Average Stop Delay Travel Time Vehicle Stops	Incident Duration Number of Blocked Lanes
[119]	Parking-Lot	(15,20,25,30 and 50) Minutes	Travel Time Delay Number of Stops	Incident Duration Incident Location No. of Blocked Lanes
[120]	Bus Stop	(30,60) Minutes	Traffic Flow Delay	Incident Duration Penetration Rate

Table 5
Review of heterogeneous traffic simulation in VISSIM Software for related studies.

Author	VISSIM Use	Approach	Significant Finding
[123]	Analyse and investigate the traffic patterns of diverse transportation facilities under varying traffic situations.	Examining showcasing the modelling aspects when employing VISSIM to simulate heterogeneous traffic flow.	VISSIM can detect different intersection control levels, spanning from unsignalized intersections to signal control with VAP. At minor intersections within the network, the proportion of missing turnings is assumed to balance out the recorded traffic count at these locations.
[128]	VISSIM simulates a heterogeneous environment with poor lane discipline, enabling an analysis of the suggested layout.	Improve traffic operations underneath the flyover.	The proposed layout improved the average delay, queue length, number of stops per vehicle, and average stopping. The level of service was improved, and the available intersection space could be segregated effectively to efficiently and safely manage the heterogeneous traffic.
[129]	Using the capacity obtained from simulation to compare it with other methods.	Using different methods to estimate roundabout capacity under heterogeneous traffic operations.	The capacity derived from VISSIM closely aligns with the field value. Thus, VISSIM emerges as a more suitable option for estimating capacity values in heterogeneous traffic conditions.
[130]	Using the simulation environment to generate the traffic data.	Estimate link travel time of heterogeneous traffic flow.	Traffic composition has a significant role in travel time estimation. In heterogeneous flows, slow vehicles have a major impact on trip times.
[131]	Speed, Flow, and roadway capacity were estimated using VISSIM	Modelling heterogeneous traffic flow and estimating the capacity.	The VISSIM simulation model can precisely recreate the heterogeneous traffic flow on the expressway. The speed-flow relationship is a suitable method for describing the effect of changes in traffic composition on the characteristics of traffic flow in heterogeneous traffic.
[132]	The heterogeneous traffic simulation and the validation of the proposed model are conducted using VISSIM.	Dynamic traffic signal control for heterogeneous traffic	With moderate traffic volumes, the model can provide a realistic depiction of flow dynamics. The model proves beneficial in reducing delays in systems with medium and high traffic flow.
[133]	To represent the heterogeneous conditions appropriately and simulate different signal timing.	Displaced Left-turn Crossovers (DLTs) under the presence of heterogeneous traffic.	The cycle length of the intersections was reduced compared to the existing cycle length. All performance indicators exhibited clear improvements, including the total travel time, overall delay, average number of stops, average speeds, queue lengths, and intersection capacity.
[134]	Simulating the Heterogenous traffic under varying traffic conditions	Incorporating urban mobility dynamics of the Heterogeneous traffic through Microsimulation.	Microsimulation clearly demonstrates that the heterogeneous urban traffic flow of Peshawar can be modelled with high accuracy under varying traffic conditions. Incorporating parameters related to vehicle characteristics and driving behaviour improves the quality of the model.
[135]	A microsimulation environment was used to simulate the heterogeneous traffic to analyse and estimate the investigated intersections' level of service (LOS).	An intersection's impact and operational performance under heterogeneous traffic situations are investigated.	No-Lane-based traffic system, aggressive driving behaviour and dynamic properties were the most influential parameters affecting the intersection's performance and the LOS. Due to their diverse dynamics, there could be an impact on the queue discharging rates of the existing traffic compositions.
[136]	The aim is to replicate the diverse traffic patterns found on expressways in order to extract valuable flow characteristics.	The aim is to analyse how the composition of traffic and the use of paved emergency lanes affect the capacity of the road.	Increasing the percentage of truck composition from 0 to 100% decreases the capacity and critical speed. Vehicles using the emergency shoulder lane do not experience a significant change in critical speed. The speed-flow curve drops more as the percentage of heavy vehicles increases.
[137]	By utilising the dynamic assignment model, the most optimal alternative path for contraflow can be determined.	The VISSIM software is employed to predict the operation of contraflow under conditions of heterogeneous traffic.	The model adaptation algorithm has been shown to effectively reduce CO emissions of road users with standard engine types by a significant 80%, while also achieving a best travel time of 526 s with an average delay of 46 s.
[138]	VISSIM was used to validate model results.	Restriction of the movement of heavy trucks in a heterogeneous traffic network.	After applying the truck restriction methodology, the total delay was reduced.

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Table 5 (*continued*)

Author	VISSIM Use	Approach	Significant Finding
			Utilisation of the network capacity improved as a result of the restriction.
[139]	Simulation of the traffic network and collecting the data.	Signal pre-emption for an emergency vehicle in heterogeneous traffic conditions.	Emergency Vehicle Approaching Scenarios (EVSP) is an efficient system and helps to save time for Emergency Vehicles. The detection distance for emergency vehicles is between (213–418) m, and the extended red time is between (14–30) seconds.
[140]	Modelling a heterogeneous traffic flow.	Using LPV controls heterogeneous traffic flows, including autonomous and human-driven vehicles.	The proposed robust LPV control can guarantee the system's performance specifications. The control strategy's role is to ensure maximum outflow while minimising the impact of disturbances.
[141]	The VISSIM output result (speed, flow, and density) assesses the service level.	Estimating capacity and proposing a new methodology for determining level of service (LOS) thresholds.	The proposed methodology successfully estimated the (LOS), from speed-flow and density-flow curves. To a satisfactory extent, the simulation model is able to replicate the heterogeneous traffic flow on expressways. The base simulation model can be easily recalibrated for a location to replicate site-specific traffic and geometric characteristics.
[142]	An assessment is conducted to determine the benefits and potential significance of such designs.	Under heterogeneous traffic flow, investigate Unconventional Alternative Intersection Designs (UAIDs).	Unconventional Alternative Intersection Designs (UAIDs) offer shorter travel times compared to conventional intersections. Notably, the Displaced Left-Turn (DLT) design consistently outperforms existing conventional intersections.
[143]	Examine the effectiveness of driver speed limit acquiescence in a heterogeneous environment.	Investigating the effect of increased driver compliance on traffic capacity.	Estimated roadway capacity rises as the percentage of vehicles that comply with posted speed limits rises. With increasing driving acquiescence levels with speed limits, vehicles may make the entire traffic flow much smoother.
[144]	Using VISSIM efficiently to investigate such differences in traffic factors and further quantify these effects in terms of PET.	Using proximal safety indicators to assess un-signalised intersections.	Speed bumps reduced conflicts in the field from 1099 to 965 following their construction. According to GEV analysis, the construction of speed bumps reduces annual crash frequency by 35%. Simulations reveal that the number of conflicts decreases with a decrease in speeds and volume, and vice versa.
[145]	VISSIM's environment demonstrates the efficacy of the propositioned algorithm.	Signal control for Heterogeneous traffic under Vehicle-to-infrastructure (V2I) communication.	Under low, medium, and high-demand traffic situations, evaluate the performance of the suggested algorithms with VA control and AQ-BP control. Because of its ability to reflect non-lane-based heterogeneous traffic circumstances, TAO-BP was proven superior in lowering queue lengths and delays.
[146]	Modelling a roundabout in heterogeneous conditions and analysing the resulting methods using a microscopic simulation technique.	Analysing the influence of changes in two-wheeler composition on roundabout capacity in heterogeneous traffic.	By varying the proportion of two-wheelers between 35% and 55%, there is no significant difference in PCU value. PCU values remain steady regardless of the composition of two-wheelers in the traffic stream. Similar variation in the two-wheeler proportion does not significantly affect the entry capacity.
[147]	Microscopic traffic simulation is employed to study the effects of dedicated lanes for motorised two-wheelers (MTW).	Examine the effects of establishing distinct lanes for (MTW) in heterogeneous traffic.	Prohibiting the use of MTW dedicated lanes and vehicle movement in the curb lane results in increased capacity values for the road section. The aggressive behaviour of smaller vehicles causes a chaotic traffic flow.
[148]	The proposed approach's effectiveness is assessed through the use of microscopic traffic and vehicle simulation models utilising the VISSIM software.	The influence of various market penetration rates of (CAVs) on fuel consumption is evaluated within a heterogeneous traffic environment.	In congested scenarios, optimal coordination control provides maximum fuel efficiency and emissions reduction benefits when the CAV's MPR exceeds 40%. Depending on the CAVs MPR, the fuel reduction under moderate congestion ranges from 8% to 24%.

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Table 5 (*continued*)

Author	VISSIM Use	Approach	Significant Finding
[149]	Validate the proposed dynamic behaviour model via simulation.	Heterogeneous traffic light control with an optimisation model.	After applying the optimisation model, the network delay time was reduced. Using the proposed model, the bottleneck in a network could be identified. Traffic signals reduce traffic congestion during times of high and medium traffic demand.
[150]	Exploring the queue-jumping phenomenon using Car-Following and Lateral behaviours to recreate heterogeneous traffic conditions.	Investigating Queue-jumping in heterogeneous traffic flow.	The analysis of green time flow dynamics shows that traffic flow is not uniform within the green time. The traffic flows at a different rate during the green time, especially in heterogeneous traffic with weak lane discipline.
[151]	VISSIM is generated and calibrated the present field condition based on traffic data.	Optimising traffic operations by using different traffic management measures.	The inclusion of a free left movement is crucial in improving vehicle flow and reducing delays. This improvement is reflected in the increase of the Level of Service (LOS) from F to C, alongside a widened road approach and free left movement from all approaches.

The initial step in coding a traffic incident in VISSIM involves the definition of the "public transport line" courses on the motorways. Subsequently, the installation of "public transport stops" is carried out along the "public transport lines" at the projected location of an incident. The impact of a bus coming to a halt at a bus station on the traffic lanes is analogous to that of a traffic incident. In accordance with the criteria established for the clearance time of the incident, the duration of the bus dwell should be equivalent to the incident clearance time. Finally, different "bus dwell periods" are inputted to replicate the sample incident clearance time and produce multiple scenarios [97].

Finally, the AddVehicle function uses the COM interface features. This tool enables users to build and remove automobiles at specific times and locations. Using this capability, a vehicle with no speed is designed to replicate an incident. The automobile is positioned in the model at the incident location and time. This is eliminated once the incident is resolved. The "incident active" period is characterised by the presence of a vehicle with zero speed. Multiple vehicles can be moved to adjacent lanes at precise moments of insertion and withdrawal to simulate an occurrence involving two or more blocked lanes. The lane length blocked by an incident can be altered by adjusting the vehicle size.

In addition, variations in the number of closed lanes during an incident can be predicted [98]. The most significant source of capacity and travel losses is non-recurring congestion induced by traffic incidents. The duration of the incident is an important issue that must be addressed efficiently and accurately to reduce its influence on traffic operations; thus, researchers focus on examining different incident durations and their effects on traffic operations [99]. Multiple MOEs are employed to appraise the simulation model performance of the simulation model and how it could deliver outcomes that are close to reality concerning safety, mobility, and the environment. Incident variables, which are sometimes referred to as traffic-incident characteristic variables, serve as indicators of traffic-flow variations caused by traffic incidents. The variability of event variables differs across traffic incidents. There is a notable difference when comparing the usual condition with a superior range of conflict. These MOEs include vehicle movement, travel duration, delays, and stops [100]. The most significant incident factors are the duration, number of obstructed lanes, and incident location [101] (Table 4).

2.4. Heterogeneous traffic simulation with VISSIM

Competitive traffic streams of varying characteristics resulting from varied vehicle dynamics and driver preferences govern traffic-flow dynamics. For example, cars, transit fleets, and lorries share rights-of-way in a multimodal system. The different vehicle characteristics require varying safety distances, desirable speeds, and travel lanes. Drivers can also demonstrate varied driving behaviours, such as maintaining gaps when following a leading car, applying brakes frequently, and changing lanes continually, complicating the overall traffic dynamics. Similarly, heterogeneity is a common feature of real-world traffic flow [121]. The distinctions between homogeneous and heterogeneous traffic systems, frequently referred to as mixed traffic systems, are primarily attributable to the diverse operational and performance characteristics of vehicles. Mixed-flow traffic can be divided into powered and non-powered automobiles moving at various speeds.

2.4.1. Heterogeneous and homogenous traffic

Non-motorised vehicles encompass bicycles, manually powered rickshaws, cycles, and animal-drawn carts. On the other hand, motorised vehicles consist of cars, mopeds, buses, motorcycles, trucks, scooters and auto-rickshaws. Such vehicles differ in their dimensions, manoeuvrability, control mechanisms, and stationary and moving characteristics. Mixed-flow traffic typically does not adhere to lane markers. Traffic flow is not linear; rather, it has significant lateral movement [122]. The examination of heterogeneous traffic through vehicle-to-vehicle interactions and the development of solutions are imperative for comprehending congestion and the formation of bottlenecks within such a flow. Car-following models emulate the behaviour of drivers who trail other vehicles. Such models are extensively employed the evolution of traffic-simulation models, as well as in capacity and safety analyses [53]. VISSIM's capability to accurately replicate heterogeneous traffic lacking lane discipline by incorporating lane-changing, car-following, and lateral behaviours places it at the forefront of traffic-flow simulation options [123].

2.4.2. VISSIM performance under live data

The performance of VISSIM can vary when it operates with live data, depending on the application scenario and simulation complexity. To illustrate this, we consider examples of how VISSIM performed in circumstances involving real-time data. This study focused on real-time traffic management in densely populated urban areas [124]. The goal was to model and optimise traffic signal timing using the flow data obtained over time. The crucial objective of this study was to assess the incident management effectiveness by simulating the real-time influence of traffic incidents and assessing alternative detour routes for their viability [125]. This study also examined how AVs interact with cars on a designated road using real-time data collected from vehicle sensors [126]. Lastly, the objective of [127] was to implement transit signal priority (TSP) systems that prioritise buses based on their location and schedule.

VISSIM can be utilised to rapidly evaluate the impact of incidents and test mitigation strategies. The performance can depend on the complexity of the incident scale and detour plans. This software can simulate mixed traffic scenarios with AVs and provide insight into how they interact with traditional vehicles. Performance can vary based on the number of AVs and their sensor data requirements. VISSIM could be utilised MOF of a TSP on traffic and transit reliability. The performance can be influenced by the frequency of live data updates and the complication of TSP algorithms (Table 5).

2.5. AI with VISSIM software

A network of corresponding input-output links, each with its weight, is an ANN. The neural network is composed of multiple intermediate layers, an input layer, and an output layer. The process of neural network learning is facilitated by adjusting the weights of the connections. The network performance can be improved by iteratively adjusting the weights. Their connectivity allows ANNs to be divided into feedforward and recurrent networks. The connections between feedforward units in a neural network do not form a cycle, whereas those in a recurrent neural network do [152]. Learning rules, architecture, and transfer functions influence the behaviour of neural networks. The weighted sum of the inputs activates the neural network. The transfer function sends an activation signal that yields a single neural output. The activation signal produced by the transfer function results in a single neural output. This transfer function introduces nonlinearity to the network. During training, the connectivity weight is adjusted until the desired level of accuracy is achieved. Several advantages can be gained, such as parallelism, less influence from noise, and high learning ability [153].

VISSIM is a powerful microsimulation tool. Given the user-friendliness of the software interface, it is easily useable by beginners. However, simulation software is an independent and relatively closed system. To optimise the signal control parameters and validate the research model, external control algorithms often require traffic-flow data to be implanted into the simulation system. However, functions of VISSIM frequently do not satisfy this requirement. VISSIM supports the execution of COM interface script files [5].

2.5.1. COM interface

The COM interface is a component technology proposed by Microsoft in 1993. Secondary development technology based on the COM interface belongs to the advanced application category of VISSIM. Certain tasks can be automatically performed in VISSIM using external programming to control road network objects. The external application initiates VISSIM through the COM interface, uses the AttValue method to read all characteristic attributes of the road network, and processes them individually. In addition, the control program can be written based on the project requirements, and instructions can be sent to VISSIM through the COM interface. Manipulating the traffic lights and regulating the traffic flow on each road is permissible [154,155].

The COM interface module add-on serves the purpose of data preparation and postprocessing. It effectively manages the scenario analysis sequence, including the creation of the control algorithm and the ability to retrieve every network attribute. Using the COM interface, incorporating control algorithms, and gaining entry into all network object features, VISSIM objects can be accessed and launched from other applications or scripts. They can use a variety of programming environments such as Visual Basic for Applications in Microsoft ExcelTM, Visual C++ or Visual J++, and basic script languages such as VB Script or Python [156,157].

2.5.2. Limitations of AI and ANN

The incorporation of AI into microsimulation applications, particularly those involving diverse datasets, presents distinct challenges in attaining precise outcomes. The assessment of AI performance, specifically deep-learning ensemble-based models, is significantly influenced by uncertainty quantification (UQ). Nevertheless, the utilisation of UQ through existing AI techniques is constrained not only by computer resource limitations but also by modifications to topology and optimisation procedures, in addition to the requirement for multiple evaluations to monitor model instabilities [158]. ANN is designed as a computational model for predicting and classifying different situations. Nevertheless, during the training phase of ANNs, selecting optimal values for network weights is exceedingly challenging. Conventional weight-update techniques frequently encounter challenges in escaping local optima and exhibit slow convergence towards optimal solutions. The term "slow convergence" pertains to circumstances in which the learning process is prolonged to attain a state of minimal loss or mistake. This implies that the training loss function gradually decreases as the iterations progress [159]. The term "local minima" pertains to a scenario in which the optimisation process aimed at minimising a cost function is confined to a local minimum instead of discovering the global minimum. This phenomenon occurs because of the utilisation of optimisation methods such as gradient descent within ANNs. These algorithms facilitate the adjustment of the network weights by iteratively updating them to minimise the error most efficiently, as indicated by the negative gradient. Suppose the algorithm reaches a

Table 6
Review of employment AI with VISSIM software for related studies.

Author	VISSIM Use	ANN Model	Approach	Finding
[154]	Creating the traffic network and the coordination control system for the traffic signals.	Adaptive Genetic Algorithm (GA)	Coordinate traffic signal control based on a genetic algorithm.	The proposed methodology resulted in reductions in the average parking delay time, average parking stops and average delay.
[170]	Test the model performance	Reinforcement Learning Corridor (TRASCR-c)	Traffic adaptive signal control	The advantage of this approach is that it does not rely on a forecasting model like other cutting-edge models, thus making the information used for decision-making more reliable. The concept makes explicit use of intersection use. It is more efficient in field implementation because it simply requires stopping line detector information.
[171]	To assess the viability and efficacy of the lane-changing probability forecast approach.	Self-Organization Map (SOM) & Back Propagation (BP)	Establishing Lane-Changing Probability Model Using Neural Network.	This technique can avoid highway incidents by letting the back car's driver know the intention of the front car lane changing.
[172]	Test the proposed approach using simulations focusing on mainstream speed and travel time.	Q-Learning algorithm	Q-learning for control ramp metering.	An improvement in the mainstream travel time was obtained from applying Ramp-Metering control. The mainstream speed was improved after applying Ramp-Metering control.
[173]	All the necessary data was gathered from the simulation environment to begin the optimisation process.	Genetic Algorithms	Finding near-optimal signal timing using Artificial Neural Network	The D-SPORT signal control system can substantially decrease travel times, depending on congestion levels and the selected control type. The suggested control model does not adversely affect traffic on intersecting streets. D-SPORT dynamically allocates green times to achieve a balance between the requirements of transit traffic and general traffic.
[174]	Evaluation of the proposed methodology.	Algorithm of ALINEA	Metering a local ramp based on ALINEA strategy.	ALINEA effectively maintains favorable traffic conditions upstream and downstream of the ramp. ALINEA is essential in relieving congestion before it reaches the merging point upstream.
[175]	Testing the proposed detection algorithm.	Back of Queue (BOQ) algorithm	The impact of queue warning in the connected vehicle (CV) environment	Despite its low market penetration, the BOQ algorithm exhibited a high level of accuracy and reliability in estimating the length of queues. Detecting the bottleneck and queue formation more quickly with CV data was possible. Additionally, the implementation of the Queue Warning System (QWS) contributed to an improvement in safety conditions by minimising the occurrence of rear-end conflicts (QWS).
[176]	To test the model under real-world conditions.	Meta Heuristic Algorithms	Internal-External Traffic Metering Strategy (IETMS)	The objective of the mentioned model was to optimise not just the upstream flow parameters like offset and queue length, but also to maximize the outflow towards the downstream network to avoid congestion in the protected sub-network. This strategy can improve the averages of the speed and delay in the total condition of the network. (IETMS) may manage the queue for arterials entering sub-networks.
[177]	The volume and the speed distribution profile of vehicles were extracted from the simulation environment.	Neuro-Fuzzy Inference System (ANFIS)	Prediction of Passenger Car Units (PCUs) of different vehicle types.	Traffic mix and volume-to-capacity ratio were both found to be significant variables when estimating PCUs. Compared to ANN and MLR, ANFIS provided the best estimation results,

(*continued on next page*)

Table 6 (*continued*)

Author	VISSIM Use	ANN Model	Approach	Finding
				namely, the lowest RMSE and MAPE values. ANFIS model estimates were more closely matched to the associated simulated PCU values than MLR and ANN models.
[178]	Using the simulation environment lets the agent learn before testing it in the real world.	Deep Q-Learning Algorithm	Signal control of isolated intersection using deep reinforcement learning.	The performance of the intersection has significantly improved, according to model results. The model reduces the total system delay by 20%.
[179]	Queue lengths, Delays and Queue Stops were extracted from the simulation.	Artificial Immune Systems (AIS)	Intelligent Traffic Signal Control System (TSCS) to manage traffic disturbances at intersections.	Regarding traffic disturbances, the proposed TSCS outperforms the LQF-MWM Algorithm and Fixed Time Control Strategy. The proposed TSCS adds another element of learning to CBR by allowing documentation of every control decision made by the immune memory. The proposed TSCS can be enhanced to classify disturbances using data mining and clustering techniques.
[180]	Verifying the adaptive traffic signal control system is valid and correct.	Adaptive Fuzzy Neural Network (AFNN) algorithm.	Enhancing traffic efficiency by adjusting signal cycles and green splits.	Traffic efficiency is enhanced, and fuel consumption is reduced with adaptive signal control. Following the implementation of the (AFNN) algorithm, the average number of stops, average delay time, and average queue length dropped while the average fuel economy increased.
[181]	Evaluate the effectiveness and robustness of the model.	Perceptron NN	Estimating queue length using connected vehicle (CV) data.	The queue estimating methodology suggested in this work, which is particularly precise in saturated traffic conditions, is an appropriate approach to provide information for adaptive traffic signal controllers. The suggested model can estimate the queue length significantly, regardless of the arrival pattern or intersection layout.
[182]	Acquire the data collection, including vehicle to vehicle (V2V) data (including the target and preceding vehicle speed).	Back Propagation Neural Network (BP-NN)	Using historical speed data to predict the velocity of intelligent connected vehicles.	The suggested technique effectively predicts the vehicle's speed using data from the Internet of Vehicles. Results reveal that v2v information influences the precision of vehicle speed forecasts.
[183]	Planning the traffic network, configuring the simulation environment, and producing the results.	Estimation of Distribution Algorithms (EDAs)	Optimise the traffic signal with (EDAs).	Under various traffic situations, mEDAve and mEDA-VWH successfully decreased all cars' mean delay time. Both the mEDAve and mEDA-VWH are capable of handling varying traffic volumes. Both EDAs successfully reduced the mean delay time and identified appropriate solutions.
[184]	Evaluation of intersection performance both before and after optimisation.	Adaptive Neuro-Fuzzy Inference System (ANFIS)	Developing an Artificial Intelligence model to estimate the extent of traffic emission and optimise the cycle time.	A hybrid methodology will promote the modelling process and improve the output quality to predict air pollution levels. There is a reduction in NO2 emissions in both study areas due to increased traffic congestion. Delays at the intersection will be significantly minimised by facilitating traffic flow.
[185]	VISSIM was used for simulation and evaluation.	Predictive Artificial Neural Networks Algorithm based Longest Queue First (PANNAL	Traffic control and emergency vehicle guidance.	The integrated control framework ensures minimal delay for all vehicles, including emergency vehicles, while effectively addressing congestion issues

(*continued on next page*)

Table 6 (*continued*)

Author	VISSIM Use	ANN Model	Approach	Finding
				and emergencies. This framework exhibits efficient guidance capabilities for emergency vehicles, even under varied and disrupted traffic scenarios, while simultaneously maintaining smooth traffic flow.
[186]	Develop a simulation model for testing and validating the signal control.	Max-Pressure Algorithm	For network-wide signal regulation, a Fixed Time (FT) Control System, Max-Pressure Cycle-Based (MPC), and Slotted-Based Max-Pressure Control (MPS) were utilised.	To prevent congestion by spreading vehicles to other road segments, (MPC) is more effective than the current technique. MPC algorithms provide better performance control results than Fixed Time (FT) control systems. When MPS and MPC controls were used, vehicles' queue length or travel time on non-disturbed roads remained normal.
[187]	Generate traffic data.	Artificial Neural Network/ MATLAB	Estimating traffic delay using (ANN)	Using the delay estimator, a reasonable delay can be predicted accurately. Heavy goods vehicles, such as freight trucks, have different dynamics than ordinary vehicles in estimating the delay.
[188]	Evaluate the proposed algorithm through simulation using the com-interface feature.	Signal control algorithms based on graph theory.	Optimising delays at intersections in under-connected vehicle environments using graph theory.	The cycle time of the intersection and the green time of every phase were optimised using the proposed algorithm. The green splits of each phase were optimised based on area occupancy over time. The average delay and average queue length decreased when the algorithm was modified.
[189]	Visualisations of real-time trajectory optimisation for each vehicle.	Multiagent Reinforcement Learning Algorithm (MARL).	In a CAV setting, variable headway control in a highway work zone area.	Solving the problem of merging behaviour in the merging region provides more opportunities to find time gaps for advanced lane changing. The proposed approach helps to alleviate traffic congestion, resulting in smoother trajectories. The overall vehicle operating state was improved after using the proposed approach.
[190]	Evaluating the effectiveness of the suggested approach.	Adaptive neuro-fuzzy inference system (ANFIS)	Adaptive traffic signal control method for an isolated intersection under mixed traffic conditions	Vehicle delay, average travel time and maximum queue length are reduced after using the ANFIS model. The ANFIS model regularly investigated the traffic conditions to decide on a length of green time.
[191]	Microsimulation was utilised to validate the practicability and efficacy of the proposed technique.	MFAC-PC Algorithm	Optimising signal control based on Model-Free Adaptive Control (MFAC).	Implementing an MFAC-PC strategy avoided the problems of model mismatch and complex computation associated with model-based control methods. The proposed MFAC-PC strategy performs better than the FT, the DC-MFAC, the PC-FT and the PC-CC strategies by selecting appropriate MFAC parameters.
[192]	Testing the performance through simulation.	Reversible Lane Control Algorithm	Reversible Lane Control	After adopting the variable lane control system, the average queue length, the maximum delay time, and the average carbon emission, the average queue length decreased.
[193]	Generating a large data sample through Simulation.	Convolutional Neural Network (CNN)	Using the automatic vehicle identification and probe vehicle trajectory data to estimate Dynamic Path Flow	The dynamic path flows estimated by the trained model can be applied to travel information provision, proactive route guidance, and signal control with high real-time requirements. The CNN model's suggested data fusion technique improves the accuracy of estimation and training time.

state in which all possible paths increase the error, specifically, a local minimum. In this case, it becomes immobilised as it solely perceives the gradient within its immediate surroundings [160,161]. The phenomenon of overtraining in ANN domains pertains to a situation in which the network undergoes excessive training, potentially leading to a subsequent decline in its predictive capacity. This phenomenon is observed due to the capability of an NN hidden layer equipped with neurons sufficiently numb to replicate any given training set accurately. The model can acquire knowledge regarding the dependencies under investigation and any extraneous information that could exist in the dataset. The presence of this noise can diminish the predictive capacity of the network. Two factors influenced this issue: the magnitude of the ANN and the length of time dedicated to training the ANN. Overfitting pertains to a situation in which the size of an ANN surpasses its ideal capacity, whereas overtraining refers to the period of training an ANN that could ultimately lead to a decrease in the network's predictive capability [162,163]. Overfitting is a phenomenon that arises when a model acquires an excessive amount of intricate information, including noise from the training dataset. Consequently, the model exhibits high performance on the training data yet evinces below-average-level performance when applied to unseen or test datasets. In essence, the model exhibits an overfitting of the training data. Overfitting can be identified by comparing the metrics obtained from the training and validation data throughout the training process. If the performance metrics on the validation dataset are significantly poorer than those on the training dataset, it can be inferred that the model is experiencing overfitting. Overfitting can be detected when the model demonstrates favorable metrics during the training phase yet fails to identify the data in the test set appropriately [164,165].

Recently, numerous sophisticated machine learning models have been proposed by scholars as viable alternatives for traffic forecasting. For example [166], developed long short-term memory (LSTM) and stacked autocoder (SAE) for road-traffic prediction. The authors validated their proposed models by utilising real and simulated data from VISSIM. Additionally, the authors of this research put forth a model called Temporal information enhancing Long Short-Term Memory neural networks (T-LSTM), which incorporates temporal aspects and recognises the significance of temporal information in traffic-flow prediction. The model under consideration demonstrates superior accuracy compared with alternative standalone models [167]. Researchers investigated convolution and LSTM, known as Convo-LSTM, to extract the spatiotemporal aspects of traffic [168]. The convolutional model effectively mitigated overfitting. Incorporating additive moment estimation as an optimiser for the LSTM expedited the convergence process. To address the constraints associated with the individual models, a hybrid model was presented in Ref. [169]. They discovered that the hybrid model proposed in their study had a notable level of accuracy in making predictions (Table 6).

3. VISSIM application assessment and evaluation

This section presents an assessment and evaluation of the literature reviewed in the second section. The main methods used in each review section are illustrated in the figures for understanding.

3.1. VISSIM calibration

Calibration is crucial for obtaining realistic results. The selection of the simulation model depends on the geometric data and the approach of the desired study. Based on the calibration literature review section presented in Table 1, the Wiedemann 99 model had the highest number of selections among the other models, as indicated in Fig. 2.

Reviewing the literature reveals that numerous calibration methods are available; those that use the AI approach and others based on statistical methods. Fig. 3 displays the different calibration methods and number of times they were used.

The Wiedemann 99 model has ten adjustable parameters. The selection of these parameters relies on sensitivity analysis, which depends on the study area and approach. During the literature review, the calibrated parameters were recorded; Fig. 4 displays the W 99 coefficients and number of times each parameter was calibrated. The car-following model has two driving-behaviour models, W 74 and W 99. Given that the Wiedemann 74 has only three parameters, the researcher chose to not conduct a sensitivity analysis for the Wiedemann 74 parameters and used all the parameters at once. Only one study conducted a sensitivity test for the Wiedemann 74 parameters, which was [21], and the sensitivity analysis determined that two of the three parameters were sensitive: W74ax and W74bxAdd.

The lane-change model has more than ten parameters, which are difficult to use simultaneously; thus, a sensitivity analysis was necessary. As previously mentioned, the selection of parameters relies on the approach of the study. Fig. 5 displays the lane-change parameters mentioned twice or more during the review and the number of times each parameter was calibrated. The Safety

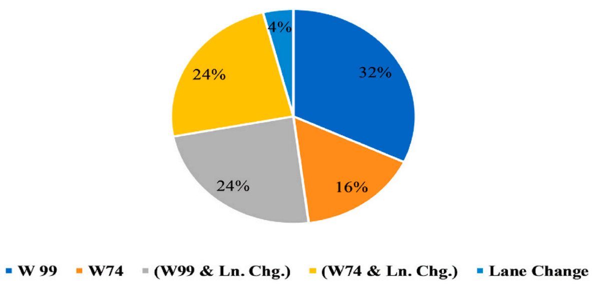

Fig. 2. Display the utilisation of driving behaviour models in the calibration section of VISSIM software..

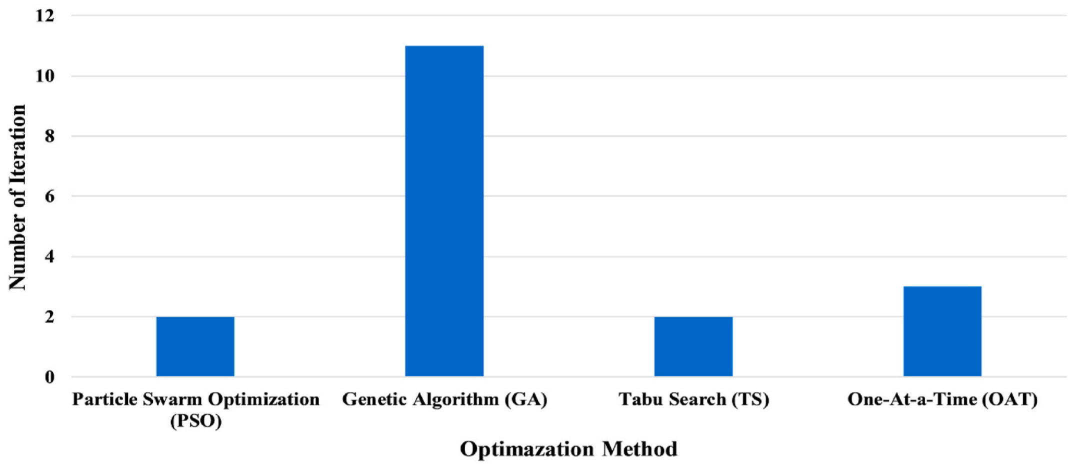

Fig. 3. Display the iterations for VISSIM calibration methods..

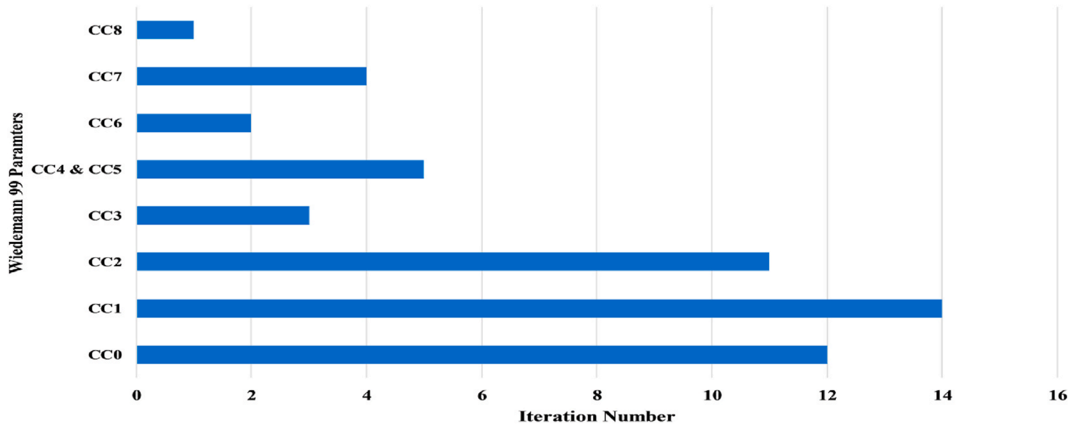

Fig. 4. Displays the number of calibrations of Wiedemann 99 for each parameter..

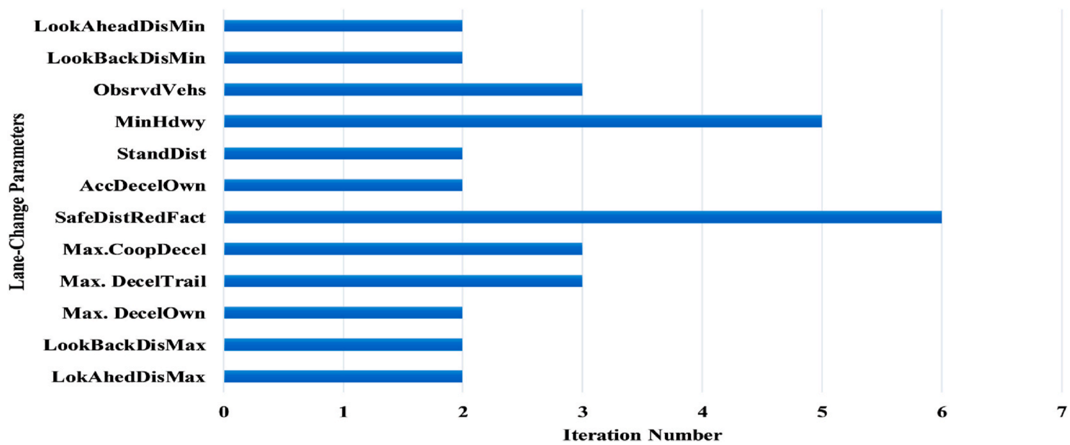

Fig. 5. Displays the number of calibrations of Lane-change for each parameter..

Distance Reduction Factor (SafeDistRedFact) had the highest number of calibrations and was second only to the minimum headway (MinHdwy).

3.2. Driving-behaviour simulation in VISSIM

Table 3 displays the significant relationship between the geometric data and choice of simulation model based on VISSIM manual. The models W 74 and W 99 have limitations in their use. W 74 is suitable for intersections, roundabouts, and arterials with speed limits less than 80 km/h; for highways and speed limits of 80 km/h and greater, the priority was for W 99. Lane changes can be used with both, depending on the study approach. Fig. 6 displays the geometric data pertaining to driving behaviour, revealing that the majority of the literature, specifically 60%, focuses on investigating driving behaviour on highways using different approaches.

The use of driving behaviour is different depending on the study approach. Fig. 7 illustrates the car-following and lane-change models and their use percentage. W 99 has the highest number of uses at 36%, followed by W 99 and lane-change at 24% and W 74 20%.

W 74 is suitable for studying driving behaviour in intersections, roundabouts, and arterials with speed limits less than 80 km/h. It was used in 20% of the literature review. The remaining 80% used lane-change parameters and a combination of W 74 and W 99 parameters. The W 99 model is used differently, obtaining the highest percentage of the approaches [57]. used the Wiedemann 99 parameters to analyse high occupancy vehicles and movable lanes to define their suitability as sustainable highway operations [58]. used the same model to analyse the operation of two high-occupancy toll lanes [64]. studied naturalistic driving behaviour by modelling the car-following driving behaviour. Understanding the effects of aggressive driving on highway safety [68], modified the driving-behaviour parameters to effectively represent a driver's aggressiveness. Using the psychophysical parameters of the Wiedemann model [69], developed a dynamic control of climbing-lane operation regarding flow and safety [70]. evaluated the capacity of a multilane motorway by considering the effect of driving-behaviour characteristics.

As demonstrated in Ref. [78], trip duration can be estimated by examining the standstill distances and time headway distributions and integrating these into car-following characteristics. From the PTV VISSIM manual and previous studies, Wiedemann 99 has been used for highway studies but not for [60,62], which used W 99 parameters to investigate connected vehicles (CVs) in the context of traffic control and examined the safety of AVs at an intersection.

The combines Wiedemann 99 and lane-change model parameters and their approaches [66]. analysed the applicability of ramp metering to a motorway utilising car-following and lane-change parameters. Using driving behaviour values [54], investigated the consequences of critical traffic characteristics for traffic safety on lane-change incidence. Establishing different CAV penetration rates [71] involves studying the traffic influence and design elements of intersections based on the driving behaviour of CAVs [72]. used a car-following model to simulate traffic flow and analysed lane changes under a non-lane discipline [75]. modelled driving behaviour on a congested motorway using a microsimulation approach [51]. investigated the influence of AVs on potential conflicts at non-signalised intersections by employing the Wiedemann and lane-change parameters.

Using a second car following the model Wiedemann 74 [59], presented a real-time traffic light control system for use in a CV environment [54]. successfully estimated the journey time and route for emergency vehicles (EVs) using Wiedemann 74 parameters. A car-following model was employed by Ref. [67] to rate speed-based vehicle exhaust emissions for an urban signalised intersection. Micro-driving behaviour in various roundabout layouts was studied by Ref. [79] to determine the influence of driving fluctuation on traffic clashes and pollutant emissions. According to the literature [73], is the only study that uses the Wiedemann 74 model to examine the leverage of roadside parking manoeuvres on highway traffic flow. In the lane-change approach [65], used the lane-change model to determine a suitable lane-changing space for urban motorway off-ramp areas. For the weaving areas [76], employed the lane-change parameters under intelligent CVs to control the active lanes of urban motorways. A combination of W 99 and W 74 was used to mitigate the detrimental effects of the vehicles [63]. employed car-following models and traffic-calming measures, and [74] used trajectory data to assess the effectiveness of several following models in the presence of mixed traffic. Car-following and

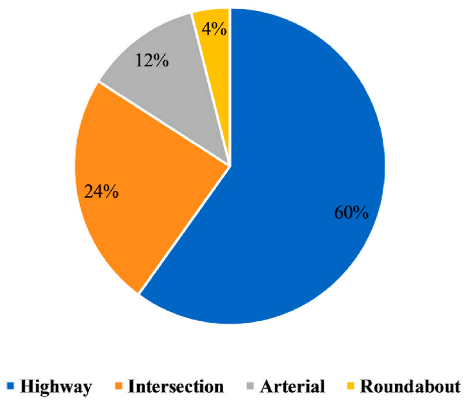

Fig. 6. Showing the types of geometric data in driving-behaviour simulation.

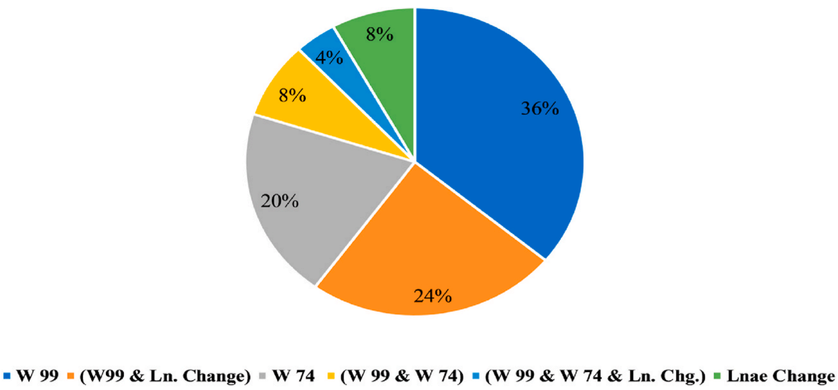

Fig. 7. Display the driving-behaviour models utilisation of VISSIM software in literature..

lane-change models (W 99, W 74, and lane change) were used by Ref. [77] to analyse their influence on the distribution of lane flow.

3.3. Incident simulation with VISSIM

The PTV VISSIM lacks an incident simulation package. Different methods were used to replicate incident occurrences within VISSIM. Table 4 lists four options for incident simulation: creating a parking lot in the incident area, installing a signal head, adding a bus stop, and adding a vehicle function. Fig. 8 displays the simulation methodologies and number of uses. The parking lot method was used the most (ten times), the signal light was used nine times, the bus stop was used five times, and the add vehicle function was used only once. The parking lot was used most frequently because the use and control of the number of blocked lanes was made easier by adding more parking lots.

Incident duration is one of the significant factors for incident simulation and represents how long the incident can last. It relies on the incident severity, capabilities of the traffic-incident management department, and how they address incidents. Developed countries such as the USA have a special department with numerous agencies including medical, police, and law enforcement; these agencies work together to ensure the incident duration is reduced. Fig. 9 (A) displays the studied incident duration; the duration selection depends on the field incident data collection, previous studies, and/or self-observation. Thus, the researcher set different incident durations and studied their influence on traffic operations. MOE is used to evaluate the simulation model performance and how it can produce results similar to reality regarding safety, mobility, and environment. The majority of researchers use more than one MOE to obtain reliable results. Fig. 9 (B) displays different measures and their use values from the literature; delay and travel time have the highest number of uses because these two variables are easy to measure and obtain their exact values. Traffic volume was second, followed by capacity and traffic flow.

Incident variables can describe the characteristics of traffic variation influenced by traffic incidents. Fig. 10 displays the incident variables and their values; the incident duration has been used in the majority of the literature because it has the most influence on traffic operations. The number of blocked lanes is second, and this variable has an extreme effect on the operation of traffic, especially when it is heavy, and there is more than one lane closed. It was observed that the location of the occurrence had the same influence as the number of blocked lanes.

3.4. Heterogeneous traffic simulation with VISSIM

Table 5 for heterogeneous traffic simulation indicates that VISSIM microsimulation is used in four areas: heterogeneous traffic

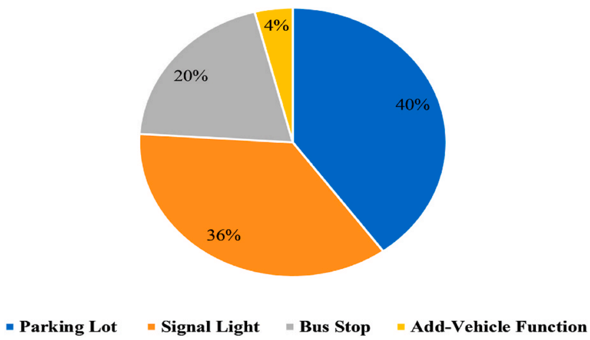

Fig. 8. Display the type of incident simulation method for VISSM software in literature..

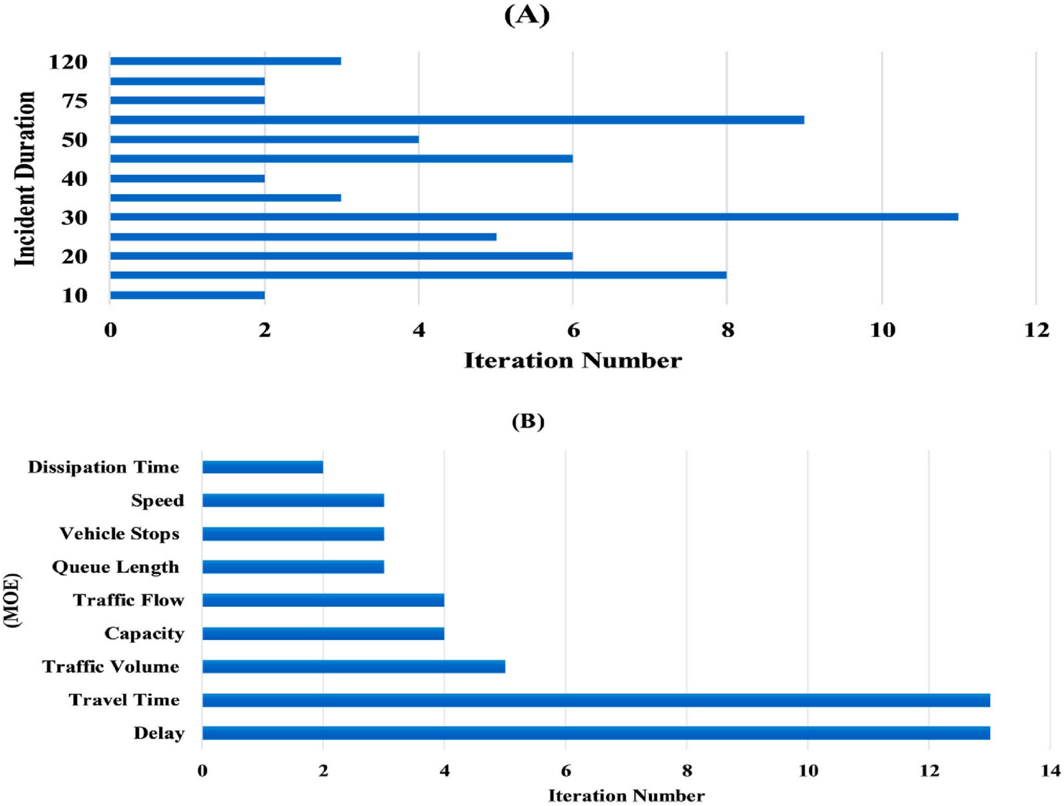

Fig. 9. Display the number of iterations of (A) Incident Duration, (B) Incident MOE for incident simulation in VISSIM software in related studies..

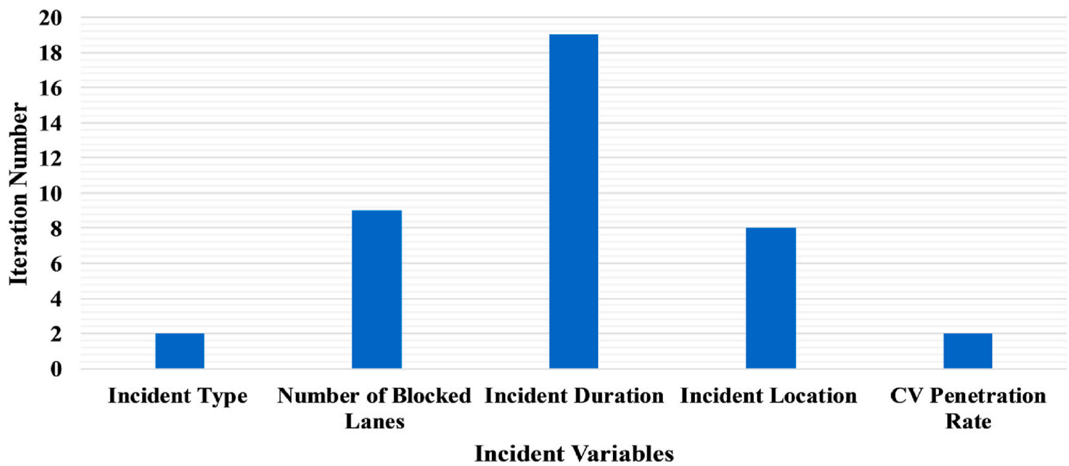

Fig. 10. Display Iterations number incident variables in VISSIM software in literature..

simulation, traffic data generation in a heterogeneous environment, capacity estimation, and contraflow prediction. As indicated in Fig. 11, approximately 70% of VISSIM was used to simulate heterogeneous traffic and study the influence of different approaches in such an environment.

Given the difficulty of collecting traffic data in heterogeneous conditions, 20% of the authors utilised VISSIM to generate traffic data. Based on the complete assessment, VISSIM can be used in four essential techniques; the first approach is simulating heterogeneous traffic [128]. proposed an alternative flyover intersection layout and simulated heterogeneous traffic operations before and after the improvement. Dynamic traffic signal control of heterogeneous traffic was suggested by Ref. [133], who used the VISSIM environment for simulation and validation. To accurately reflect heterogeneous conditions and simulate variable signal timing [133], used a microsimulation model to assess the effectiveness of the displaced left-turn crossover method for an intersection [134]. simulated

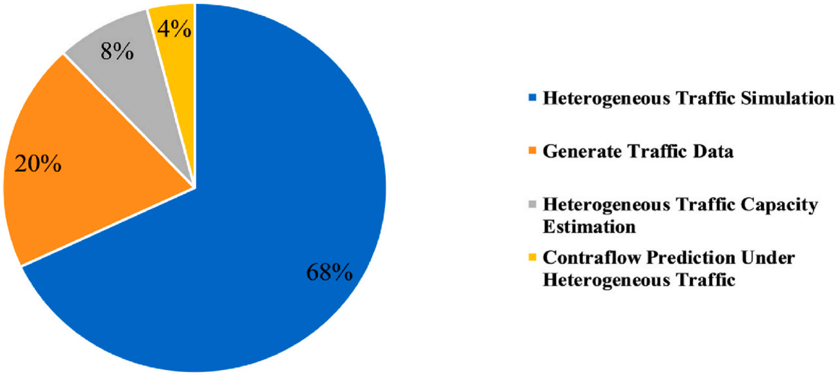

Fig. 11. Display the VISSIM utilisation for heterogeneous traffic simulation..

heterogeneous traffic under varying traffic conditions to incorporate urban mobility dynamics for real-time decision-making for congestion relief.

A microsimulation environment was used by Ref. [135] to simulate heterogeneous traffic, assess the level of service (LOS), and investigate the implications and operational performance of selected intersections [136]. replicated heterogeneous traffic on motorways using VISSIM to extract flow parameters and analyse the effects of traffic composition and paved emergency lane usage on capacity [140]. used the microsimulation environment to simulate a heterogeneous traffic flow and test liner parameter-varying for ramp control. A microsimulation environment was used by Ref. [142] to investigate unconventional alternate intersection layouts under heterogeneous traffic flow [143]. simulated the influence of increased driver acquiescence on roadway capacity under a heterogeneous environment. Using VISSIM [144], investigated the assessment of unsignalized intersections using proximal safety indicators. Using a simulation scenario [145], demonstrated the efficacy of signal regulation for heterogeneous traffic under vehicle-to-infrastructure (V2I) communication. A microsimulation environment was presented in Ref. [146] to reproduce the stream characteristics and represent field behaviour to understand the influence of changes in two-wheeler composition on the capacity of a roundabout in heterogeneous traffic. In Ref. [147], using microscopic traffic simulations, the effects of constructing distinct lanes for motorised two-wheelers were assessed [148]. used VISSIM to evaluate and analyse CAV's influence and performance on fuel consumption in a nonhomogeneous environment at various market penetration rates. Through simulations [149], examined the dynamic behaviour of an optimisation model for traffic-light control under heterogeneous traffic conditions [123]. used VISSIM to analyse and study the traffic patterns of different transportation facilities under heterogeneous traffic conditions in a network [150]. explored the queue-jumping phenomenon using car-following and lateral behaviours to recreate heterogeneous traffic conditions.

The second most common approach is to generate traffic data [130]. estimated link travel time under a heterogeneous traffic flow using VISSIM for simulations and data generation [138]. employed VISSIM to extract traffic data and validate a heavy-truck movement limitation methodology in a heterogeneous traffic network [139]. coded a traffic network and gathered data for signal pre-emption for EVs in heterogeneous traffic situations using a microsimulation model [141]. estimated LOS thresholds using simulation outputs (speed, flow, and density) and a microsimulation environment to predict the capacity and evolution of the speed–flow diagram under heterogeneous conditions [151]. used the PTV VISSIM software to generate traffic data and calibrate the present field conditions to optimise traffic operations using different traffic management measures under heterogeneous traffic conditions [129]. used a third approach for capacity estimation in heterogeneous traffic and employed a simulation to determine the capacity of a roundabout in the presence of heterogeneous traffic [131]. employed VISSIM to model heterogeneous traffic conditions and used the output results for

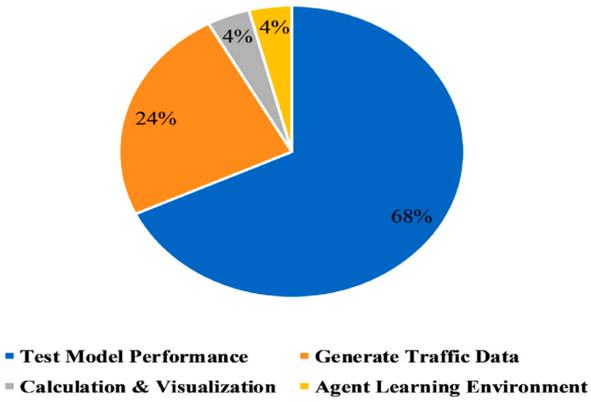

Fig. 12. Displays utilisation of VISSIM in the AI review..

capacity estimation [137]. used VISSIM to determine the optimum contraflow alternative path under heterogeneous traffic conditions by employing dynamic assignment.

3.5. AI with VISSIM software

The use of VISSIM simulations in this review differs from one approach to another, as indicated in Table 6. These approaches have four primary uses for VISSIM: approximately 70% for test model performance, 24% for generating traffic data, and the remainder for an agent-learning environment, in addition to calculations and visualisations, as displayed in Fig. 12.

The approaches to testing model performance are as follows [170]. used VISSIM to examine the performance of (TRASCR-c) as an adaptive traffic signal control [171]. employed a neural network to establish lane-change probability and assess its performance in a simulation scenario. Focusing on mainstream speed and travel time [172], evaluated the effectiveness of ramp-metering control based on the Q-learning algorithm [175]. employed VISSIM to evaluate the influence of queue warnings in a CV environment using the back-of-queue algorithm [174]. established a local ramp-metering model using the ALINEA algorithm and evaluated the suggested methodology using VISSIM. Metaheuristic algorithms [176] optimised the upstream flow, and VISSIM tested the performance. To regulate a traffic light system [180], employed an adaptive fuzzy neural network and tested its performance in a microsimulation scenario [154]. used adaptive GA to coordinate traffic signal control; the performance was evaluated through the VISSIM COM interface [181]. assessed the effectiveness and robustness of calculating queue length using CV data based on the perceptron neural network [183]. optimised the traffic signal using estimation of distribution algorithms and tested the obtained result using a simulated environment. After developing an adaptive neuro-fuzzy inference system (ANFIS) model to estimate the extent of traffic emissions and optimise the cycle time [184,190]. used VISSIM simulation to evaluate the performance of intersections both before and after optimisation [186]. used the max-pressure algorithm to optimise signal control performance and assessed it through simulation. PANNAL was utilised to regulate traffic and EV guidance; VISSIM was employed for simulation and assessment [185]. Using the COM interface [188], evaluated the intersection signal control based on graph theory-based algorithms [191]. used microsimulation to verify the efficiency of the optimisation signal settings based on (MFAC) algorithm [192]. used the reversible lane control algorithm to address the imbalance in traffic flow at a junction and the COM interface to test the performance.

For generating the data [173], employed VISSIM to create the data required for signal timing optimisation using GAs [177]. used ANFIS to predict the (PCUs) of different vehicle types and traffic-flow data from a simulation environment to assess the capacity and perform model analysis. A simulation was utilised to extract the queue lengths, delays, and stops employed by Ref. [179] to manage intersectional traffic disruptions. A microsimulation environment was used by Ref. [182] based on a backpropagation neural network (BP-NN) to obtain data containing vehicle to vehicle (V2V) information to predict the velocity of intelligent CVs [187]. generated data for training the ANN to estimate traffic delays using a VISSIM simulation [193]. created the necessary data using a microscopic simulation model to estimate the dynamic path flow based on a convolutional neural network [178]. used VISSIM as an agent-learning environment by employing the deep Q-learning algorithm to control a signal at an isolated intersection. The simulation environment allowed the agent to learn before being subjected to a real-world test [189]. used the final approach for calculation and visualisation to regulate the fluctuating headway in a highway work zone region by utilising VISSIM COM interface and multi-agent reinforcement learning algorithm and a simulation platform to visualise real-time trajectory for each vehicle optimisation.

4. Discussion

In this section, the obtained findings for all proposed aspects are presented. Additionally, the limitations and implications of the common approaches employed in each review section are discussed. VISSIM has numerous unique features that make it one of the best microsimulation platforms. However, as with any software, it has limitations and drawbacks. For example, VISSIM does not have a dedicated model for lateral movement within a lane. The vehicle maintains its lateral position when entering a network. Thus, VISSIM cannot simulate two-dimensional traffic flow. Furthermore, during the modelling of mixed traffic, lower-speed vehicles rapidly produce a bottleneck, which is uncommon in practice. Moreover, new users find it challenging to navigate the output capabilities as well as sophisticated input of VISSIM, as the data coding and input processes are time-consuming. Furthermore, VISSIM does not realistically simulate vehicle trajectories, as vehicles in the simulation follow links and connectors. Preventing the possibility of head-on collisions between left-turning vehicles can be accomplished by programming two opposing left turn connectors at an intersection with no overlap. Moreover, left-turning vehicles may sometimes stray from lane markings and execute either wide or narrow turns. These uncertainties in vehicle-turning radius need to be appropriately addressed in current simulation tools to prevent biased SSAM results.

Certain parameters in VISSIM cannot be directly measured in the field, including driver-behaviour parameters that have a significant influence on the output and must be calibrated to accurately replicate on-field conditions. The model with calibrated parameter values demonstrated an acceptable fit, whereas the model with default parameters differed considerably from the observed data. Thus, the importance of the calibration step is evident. Nevertheless, calibrating a microsimulation model is challenging because of the numerous user-defined parameters it contains, all of which need adjustment to achieve suitable levels. Similarly, calibrating a VISSIM model is problematic because of the numerous user-defined parameters that must be tuned to attain the desired accuracy levels. A review of the literature revealed that the main approach for calibration was manual. The manual calibration process adopts an iterative trial-and-error methodology, employing intuitive discrete values for each parameter and exploring plausible amalgamations of multiple parameters until the desired outcomes are realised. Nevertheless, this method is susceptible to a perpetual cycle of addressing one issue at the expense of introducing another, thereby rendering manual calibration a time-consuming undertaking in academic contexts. It is recommended to employ manual calibration only when dealing with a small number of parameters. However, when the calibration parameter set is substantial, it is advisable to utilise automated techniques such as metaheuristic algorithms to pinpoint the ideal set of parameters that closely align with real conditions. It has been noted in the literature that the genetic algorithm (GA) has been extensively employed in metaheuristic approaches, whereasParticle Swarm Optimisation (PSO) and tabu search (TS) have been employed on a limited basis.

Driving behaviour is the main component of VISSIM microsimulation. An examination of the existing body of literature reveals that the significance of incorporating driving-behaviour simulation into various approaches can greatly assist decision makers in modelling, assessing, and evaluating the applied methods. As discussed in the previous section, 60% of the studies were performed on highways because highways significantly influence traffic operations. In comparison, 36% utilised W 99 because it has implemented parameters that can reflect a better understanding of the traffic environment. However, this model also has drawbacks that must be considered. For example, W 99 could not accurately represent traffic phenomena when linked to unusual driving behaviour and, therefore, could not replicate forced driver manoeuvres that can lead to conflict. Vehicle acceleration can be reduced from its maximum value for numerous reasons, such as proximity to the intended speed or a slower vehicle ahead. The lane-change model of VISSIM helps identify the primary traffic characteristics that cause frequent traffic lane changes, and by utilising driving-behaviour simulation, it is possible to enhance our understanding of the risk associated with lane changing and develop more effective strategies for road safety on freeways. The W 99 lane-change model has issues that must be addressed. Lane changes and merging could be more problematic in congested flows. By utilising driving-behaviour simulation, it is possible to enhance our understanding of the risk associated with lane changing and develop more effective strategies for road safety on freeways.

Incidents have the most significant influence on traffic operations, particularly during peak hours. Moreover, the execution of traffic organisation under incident situations is intricate and costly in terms of time and resources. By contrast, VISSIM simulation offers the advantage of flexible adjustment of traffic organisation schemes at a low cost and unlimited iterations, making it a highly valuable analysis tool. When faced with various traffic control schemes, VISSIM simulation could be employed to compare the options and select the optimal scheme quantitatively. The VISSIM software lacks incident simulation tools. Researchers have suggested alternative approaches to simulate incidents inside the VISSIM environment to overcome this issue and investigate their influence on traffic operations. One thing that was noticed during the literature review was that using VISSIM in this capacity is unrelated to the incident location.

Heterogeneous traffic, characterised by the presence of various vehicle types, among which motorcycles, trucks, cars and buses, each with distinct characteristics and driver behaviours, is more intricate than homogenous traffic. The interactions between these different kinds of vehicles, including their varying speeds, sizes, and maneuverabilities, lead to complex traffic patterns. The literature review reveals that VISSIM can stimulate heterogeneous traffic to an extended level. The only limitation to consider is that the calibration step significantly impacts the model's accuracy. Consequently, Augmenting the count of calibrated parameters can significantly improve model accuracy. The accuracy of calibration is intricately linked to both the number and the calibre of the amassed data. The availability of precise datasets facilitates the robust objective function, thereby enhancing the precision of the model. As VISSIM is inherently a microscopic traffic-flow model, its calibration can be accomplished using microscopic variables. Nevertheless, employing distinct sets of class-wise microscopic variables at the network level could escalate the computational demands associated with the calibration process.

A thorough investigation into the relevant literature reveals that VISSIM has a robust environment for evaluation, data generation and agent-learning platforms for applying AI and ANN in different approaches. There are points to be considered when using VISSIM software for AI and ANN applications. During the ANN training employing VISSIM and to prevent the network from overfitting, there is a requirement to use an independent group dataset for validation to increase the prediction ability of the ANN. The max-polling technique reduces the special size and number of parameters and prevents overfitting during polling. This polling technique employs a method of selecting the most significant subzone value and indicates a notable level of activation. However, the slow convergence requires a solution, for example, revising the optimisation algorithm. Conventional weight-update techniques frequently encounter challenges in escaping local optima and exhibit sluggish convergence towards optimal solutions. To address these limitations, a revised iteration of a nature-based method integrating metaheuristics with the weight-updating technique of ANNs has been employed. The slow convergence issue necessitates the development of strategies to address this challenge. In cases where a neural network fails to converge, it is frequently feasible to enhance convergence by augmenting the dataset and updating and modifying the shape membership functions (MF) to replicate this relationship and minimise inaccuracy during training.

As mentioned previously, the phase is iterated multiple times, referred to as epochs, until the required level of convergence is achieved. Despite the fact that ANN proves to be a robust technique for modelling various real-world problems, it does possess a number of limitations. In cases where the data input exhibits ambiguity or is subject to a relatively high degree of uncertainty, there exist potential solutions that can be implemented to address this particular issue. The process of incorporating observational uncertainty into the network requires the addition of a supplementary layer and modification of the loss function. Techniques such as weight decay can control overfitting for large neural network models, which can assist in minimising the uncertainty. As acknowledged, local minima can trap the optimisation process, preventing it from finding the global minimum in ANN training. There are strategies to overcome local minima, such as random initialisation, which is the simplest method in which the weights of the network are randomly initialised. Different initialisations lead to different solutions; the momentum technique serves as a means to expedite the gradient vectors in the correct direction, thereby facilitating faster convergence. This method stands as one of the most widely utilised approaches for eliminating local minima.

5. Research gap and future direction

This particular section provides a concise summary of the findings derived from the existing literature, presenting five key contributions, and identifying associated gaps in knowledge. First, the VISSIM model calibration mainly approaches the VISSIM microsimulation model calibration under heterogeneous traffic conditions, focusing on cars, buses, and motorcycles. Nevertheless, this method can be enhanced by incorporating additional vehicle types and diverse scenarios of heterogeneous traffic operations. This can be achieved through the development of a saturation headway model that considers factors such as the number of through lanes as well as exclusive right/left-turn lanes. By calibrating the microscopic simulations at signalised crossings, this model can be utilised effectively. The review consistently observed the application of GA. To further optimise its utilisation, it is recommended that an auto-tuning approach be incorporated for the hybrid GA and GA parameters, encompassing the mutation and crossover rates. The incorporation of metaheuristic algorithms in an automated calibration procedure for the driving-behaviour models would result in substantial advantages.

Calibration is a prolonged process, particularly while dealing with a substantial number of parameters. To reduce the calibration time, it is suggested to use parallel computing technologies with multicore/multiprocessor systems for individual simulations or divided cores for several parallel simulations. Alternative goodness-of-fit functions to mean square normalised error optimisation techniques should be investigated, including slap swarm optimisation and multi-objective grey wolf optimiser for VISSIM parameter calibration. Secondly, in driving-behaviour simulations, the hysteresis phenomenon could be used to investigate the stability and attentiveness of vehicles in traffic flows and develop new ITS-based approaches.

The study examined the distributions pertaining to time headway and standstill distance. Subsequently, these distributions were incorporated into algorithms for car-following to predict travel time reliability. This prediction took into consideration various factors, including weather conditions, special events, and work zone effects. Furthermore, the study examines the influence of AV on-demand changes on the potential conflicts that may arise at unsignalised intersections, and the rules for changing lanes on the on-ramp should be studied and tightened in an intelligent (ICV) environment. Differences in vehicle behaviour were observed before and after traffic control installation in an ICV environment, and vehicle-group behaviour characteristics were optimised during the strategy implementation. VISSIM microsimulation can be effectively utilised to determine the optimal parking bay capacity based on specific parking frequencies and flows. This analysis also takes into account the complexities associated with vehicle movements in situations where no parking spaces are accessible.

Moreover, the gaps in incident simulation using VISSIM include testing the operation of the onboard lane-change advice system of an intelligent vehicle in the real world to investigate driver compliance and its overall influence on driving behaviour. The automation of heavy-goods vehicles and the implementation of messaging devices have the potential to bring about Incident number reduction and improve traffic safety and commuter mobility, as well as a decrease in gas emissions.

Factors such as driver network familiarity, land use, weather situation, and the pedestrian's presence may be employed to evaluate the susceptibility of an intersection to how an incident affects the nearby road system. The driver's reaction to implementing active traffic management (ATM) was examined because ATM tactics rely on the understanding of the driver and attitude across the ATM approach employed. It is imperative to establish practical guidelines, recommendations, and frameworks that assist in the selection of optimal strategies for different contexts. To determine connected vehicles (CVs) influence on secondary crash risk and road network safety, it is necessary to evaluate various factors, including various CV penetration rates, performance measurements, time intervals, incident locations, lane obstruction lengths, roadway networks, and/or traffic distributions.

Furthermore, in a heterogeneous traffic simulation, the formulation of the error function includes a component related to the travel time of links. It is important to address the calibration of model parameters at both the class level and the link level in order to achieve more precise network modelling in a heterogeneous environment. Mathematical models have been developed to represent the phenomenon of motorcycle queue jumping at signalised intersections in heterogeneous and undisciplined traffic flows. This capability (mathematical models) could be added to existing simulation packages by developing a plug-in or add-on, creating and calibrating a microscopic model capable of simulating 100% two-wheelers and defining priority and conflict zones accordingly in heterogeneous traffic.

The traffic signal control scheme and optimisation model considered different types of vehicle penetration under heterogeneous traffic flow. Dynamic cycle durations were developed, and the offset for signalised crossings within a non-lane-based traffic network was optimised. An establishment of a concept of stochastic capacity has been made, aiming to estimate the impact of heterogeneous traffic conditions on motorways. Certain attention is given to vehicle composition within traffic flow in these assessments. The analysis of post-encroachment time has been conducted through the utilisation of microscopic simulation in order to identify vehicular-type combinations and critical directional conflicts (offending and conflicting vehicles) involved in near-crash situations. This analysis considers all nodes and all possible vehicular movements. The safety evaluation of an intersection takes into consideration the heterogeneity of traffic and encompasses factors such as visibility at nighttime, extreme weather conditions, and other abnormal events. This evaluation is conducted using a microsimulation approach.

Finally, the literature offers insight into the benefits of utilising ANNs and states the research gaps. Probing vehicle and feature sounds (e.g., missing detection phenomena in an automatic vehicle identification (AVI) system) should be used to measure their influence on market penetration. Adaptive signal control must be developed for corridors with heterogeneous CVs lacking lane discipline. The latency with mixed traffic of conventional and CVs at signalised intersections could be optimised under different penetration rates.

An adaptive technique for an ANFIS could be used to adapt traffic signal operations to diverse traffic scenarios at different intersections. The trajectory optimisation of cooperative lane change, merging, and car-following behaviours can be combined in a multilane highway bottleneck region.

6. Conclusion

The present study carried out a comprehensive review and synthesis of international studies and practical applications pertaining to the use of PTV VISSIM software. The focus was on the calibration process and examining driving behaviour through different approaches, including incident simulation within VISSIM, modelling heterogeneous traffic scenarios, and assessing the integration of AI methodologies. This review expands upon the existing knowledge by presenting contemporary methods across all evaluated sections, conducting comparative analyses within each domain, and delineating the evolutionary trajectory of these techniques.

Despite the valuable insight gained from this review, several knowledge gaps were identified, underscoring the requirement for further research and technological advancements. In addition, this review covers recent research that demonstrated the integration of VISSIM driving-behaviour models in conjunction with optimisation algorithms and AI models. Through rigorous evaluation, GAs have emerged as the most effective method for calibrating driving-behaviour parameters, offering a robust solution to complex problems without requiring intricate programming. However, it is worth noting the GA requires numerous simulation runs to achieve reliable results. This study revealed that the Wiedemann 99 driving-behaviour model, with its ten adjustable parameters, provides a more nuanced representation of field conditions than the Wiedemann 74 model.

Consequently, it has been more frequently employed, as validated by the findings of this review. Addressing incidents on highways, known for their profound influence on traffic operations, presents a unique challenge within VISSIM. Although the software is not specifically designed for incident simulations, researchers have devised different methods to address this issue. The most straightforward approach involves simulating traffic incidents within parking lots, thereby offering flexibility for lane selection. Moreover, this study investigated the influence of heterogeneous traffic on traffic operations through a microsimulation of driving behaviour across diverse scenarios, leading to valuable insights into optimal solutions given the inherent complexity.

Finally, as a potential recommendation for future research, although VISSIM has proven to be a potent tool for simulating heterogeneous traffic conditions, integrating optimisation algorithms and AI models across current applications could have a pivotal role in addressing intricate problems. Researchers have relied on VISSIM to generate essential data and assess the effectiveness of their approaches under varying circumstances. Improved performance could be achieved by integrating VISSIM with optimisation algorithms or AI models. This collective body of work underscores the significance of the interplay between advanced simulation tools and innovative methodologies in enhancing our understanding and management of dynamic traffic systems.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Haitham Al-Msari: Writing – review & editing, Writing – original draft, Visualization. **Suhana Koting:** Writing – review & editing, Supervision. **Ali Najah Ahmed:** Writing – review & editing, Visualization. **Ahmed El-shafie:** Writing – review & editing, Visualization, Supervision.

Declaration of competing interest

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.

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