Journal of Ambient Intelligence and Humanized Computing (2020) 11:5857–5874
https://doi.org/10.1007/s12652-020-02098-5

ORIGINAL RESEARCH

A microsimulation-based analysis for driving behaviour modelling on a congested expressway

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Received: 30 May 2019 / Accepted: 15 April 2020 / Published online: 20 May 2020

Abstract

Recently, simulation models have been widely used around the world to evaluate the performance of different traffic facilities and management strategies for efficient and sustainable transportation systems. One of the keys factors for ensuring the reliability of the models in reflecting local conditions is the calibration and validation of microsimulation models. The majority of the existing calibration efforts focus is on the experimental designs of driver behaviour and lane-changing parameters. Towards this end, this paper describes the necessary procedure for the calibration and validation of a microscopic model using the VISSIM software, during peak hours. The procedure is applied on Muscat Expressway in the Sultanate of Oman. The calibration parameters and the measure-of-effectiveness are identified by using multi-parameter sensitivity analysis. The optimum values for these parameters are obtained by minimising errors between simulated data and field data. In our proposed model, we used traffic volume and travel speed for model calibration, as well as average travel time for validation of the calibrated model. The achieved results showed that driving characteristics significantly impacted the merging/diverging traffic flow ratio in the merging area, the link length and the distance between on-ramps and off-ramps, as well as the percentage of heavy vehicles. The results also showed that having both the advanced merging and cooperative lane-change settings active, along with safety distance reduction factor, necessary lane change, minimum headway (front/rear), and emergency stop, had a significant influence on simulation precision, especially at on-ramps and off-ramps. Finally, our proposed model can be utilized as a base for future traffic strategy analysis and intelligent transportation systems evaluation to help decision makers with long-term and sustainable development decisions.

Keywords Sustainability · Microscopic simulation · Driving behaviour · Traffic incident management

1 Introduction

The rapid growth of traffic around the word has led to a traffic congestion problem, which negatively impacts the safety, mobility and efficiency of highways. Its negative environmental impacts include increased fuel consumption, air pollution and greenhouse gas (GHG) emissions. Oman is one of the gulf countries that has achieved rapid economic growth, modernization and infrastructure development over the past four decades (Rakesh and Shweta 2010). The rapid urbanization has resulted in a large increase in car ownership and in the number of vehicles, and it has caused serious traffic problems, such as accidents and air pollution (Blair et al. 2018). The Muscat Expressway was opened to reduce the traffic burden on Sultan Qaboos Street, which is the only main road in Muscat at that time. However, due to the unexpected increase in Muscat's population growth in the past 5 years (NTS

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2017; Muscat Municipality 2018), Muscat Expressway users suffer from traffic congestion and other problems every day during peak morning and evening hours (Low and Gleeson 2015). These problems increase with the occurrence of any accidents on a road segment.

Due to the development of emerging technologies, many innovative approaches based on Intelligent Transportation Systems (ITS) are developed in recent years to manage roadway traffic in an efficient way. This is seen as a better alternative to building more roads. These approaches include Variable Message Sign, Car2x Technology, Autonomous Vehicle, Ramp Metric (Carson2010; Nissan and Koutsopoulosb 2011; Simon 2011; OECD 2013; Fountoulakis et al. 2017; Farrag et al. 2020), while estimating and disseminating the traffic information to drivers for emergency management are presented in (Shelke et al. 2019; Su and Sun 2019; Yang et al. 2020).

These management strategies need to be evaluated before being implemented. That said, the practical implications of these facilities come with related legal and financial restrictions (Maheshwary et al. 2019). With the rapid advancement of computer technology, simulation models have played a vital role in the evaluation of traffic management strategies and ITSs (Carson 2010; OECD 2013; Uchiyamaa and Taniguchib 2014; Aria et al. 2016; Himani 2016; Maheshwary et al. 2019). These provide a cost-effective and flexible approach to assessing the safety, mobility and sustainability of transport systems (Nissan and Koutsopoulosb 2011; Dan et al. 2017).

The key to a successful, efficient and acceptable traffic simulation model is its validity and its ability to replicate the local area's network and driver behaviours (FODT 2014; MDOT 2014; WSDOT 2014). This can be achieved by model calibration and a validation process that is defined as selecting the best set of model input parameters; followed by a repetitive procedure, until the desired correspondence between the field data and the model's results are achieved (Fellendorf and Vortisch 2010; FODT 2014; WSDOT 2014). Over the past years, many systematic and comprehensive calibration and validation processes have been developed in order to standardize the calibration process to reduce computational effort and to maximize the reliability of the exported results (FHWA 2004; FODT 2014; MDOT 2014; WSDOT 2014). However, these systematic procedures cannot produce reliable results in all situations. The main reason for this is the high variability and different needs of the traffic models. In each case, there is an inability to set a rule to come up with the exact values of the parameters that must be adjusted in order to precisely model driving behaviour, ranges, and the method for conducting the experimental design. Recently, more microsimulation software packages have become available. The most widely used packages include VISSIM, CORSIM, AIMSUN, SimTraffic, Paramics and INTEGRATION (Ma et al. 2007; Ciulffo et al. 2008; Lee and Ozbay 2009).

Among the software options, VISSIM was found the most efficient (Choa et al. 2002; Raka and Gao 2011; Song and Sun 2016; Srikanth et al. 2017). VISSIM is a stochastic time-step microscopic simulation software package developed by PTV AG in Germany. It is a behaviour-based simulation model that uses a Wiedemann psycho-physical car-following logic to model traffic on urban streets and freeway environments. It contains multiple parameters that provide flexibility in changing the parameters to replicate traffic operations as observed in the field (PTV AG 2016; PTV AG 2017). Therefore, the aim of this study is to develop a framework for the calibration and validation of a VISSIM-based model on the Muscat Expressway in Oman. The intent of this paper is to find the value of a specific set of driving behaviour parameters for prevalent local traffic conditions. In addition, the intent of this paper is to present the procedure followed in the construction of a VISSIM-based model of the Muscat Expressway. This model serves as a base for further traffic strategy analyses and an ITS evaluation to help decision makers in long-term and sustainable development efforts. Although thorough investigations are made in other countries, such important efforts is not yet adequately made in the specific context of Oman.

1.1 Background and related work

1.1.1 Driving behaviour

The fundamental component of any microscopic simulation model is the behaviour of drivers. All driver behaviour models consist of parameters and their respective default values, which allow users to input values within a specified range for driving-behaviour parameters that are based on local traffic conditions. Since it has been observed that drivers' behaviour significantly varies, depending on driving conditions and geographical location, default values for these parameters rarely match local traffic characteristics and conditions for a specific area (Srikanth et al. 2017; Espejel-Garcia et al. 2017). Thus, the default values for such variables should be adjusted for a realistic replication of local driving conditions.

1.1.2 Microsimulation models

Each type of microsimulation software portrays different aspects of driving behaviour as fixed sets of parameters to represent traffic control characteristics and operations (FODT 2014; WSDOT 2014), such as drivers' reaction times, speed acceptance and nine other parameters in AIMSUN (Ciulffo et al. 2008). These include mean reaction time and mean headway in Paramics (Ma et al. 2007;

Lee and Ozbay 2009(, deceleration, acceleration, driver imperfections in a simulation of urban mobility (SUMO) (Kim et al. 2005), the number of observed preceding vehicles, look-ahead distance, average standstill distance, and other Wiedemann coefficients in VISSIM (Menneni et al. 2008). Therefore, researchers have attempted to calibrate different microscopic tools in perspective to different traffic conditions and driver behaviours (Manjunatha et al. 2013; Mehar et al. 2014; Song and Sun 2016; Whaley 2016; Emelie 2016; Henclewood et al. 2017; Srikanth et al. 2017). Researchers have categorized these sets of microscopic traffic simulation parameters into three basic sets or sub-models: a car-following model, a lane-changing model and a gap-acceptance model (Treiber and Kesting 2013; Emelie 2016; Gao 2008).

A. Car-following model

The car-following model is defined as how the driver of a constrained vehicle responds to changes in the relative position and speed of the leading vehicle. Different car-following models have been developed since the 1950s, such as Greenshields fundamental model and the Van Aerde model in INTEGRATION (Rakha and Crowther 2002; Kehoe 2011), the Pipes model in CORSIM (Treiber and Kesting 2013), the Gipps model in AIMSUN (Gao 2008), and the Wiedemann models in VISSIM (Rakha and Crowther 2002; Olstam and Tapani 2004; Gao 2008; Higgs et al. 2011; Sun and Li 2012; Mathew 2014a; PTV AG 2017).

B. Lane-changing model

Lane changing refers to the act when a vehicle traverses to an adjacent lane from its present lane. Lane changing is a significant component in congested, merging and diverging areas (Moridpour and Rose 2010; Mathew 2014b; Emelie 2016). Two groups of lane-changing models were defined based on the need to change lanes in the Mandatory Lane Changes (MLC) model and the Discretionary Lane Changes (DLC) model (Mathew 2014b; Sun and Li 2012). The first model is used to achieve the origin–destination path, and the second model occurs when drivers change from slow lanes to fast lanes (Mathew 2014b; Sun and Li 2012).

C. Gap-acceptance model

The gap-acceptance model can be defined as the time or available space, or as the accepted speed difference between the trailing and leading vehicles (Hidas 2005; Treiber and Kesting 2013). Gap-acceptance criteria between adjacent vehicles are used to determine whether the drivers are able to change lanes. Gap acceptance is the minimum gap required to commence and finish changing lanes safely. Vehicles presented with a gap greater than the gap acceptance are able to change lanes (Mathew 2014b). We used VISSIM in our study and consequently our focus only on studying driving behaviour in VISSIM.

1.1.3 Driving-behaviour models using VISSIM

The gap-acceptance model is not specified in VISSIM, but merging behaviours can be modelled by adjusting the aggressiveness of the driver (Marczak et al. 2013; Kritsadaniramit et al. 2016). VISSIM works with four different vehicle-behaviour models, namely: Wiedemann, car following, lane change, lateral behaviour, and reaction to the amber signal light (FODT 2014; WSDOT 2014; PTV AG 2017). The car-following, lane-change and lateral-behaviour models are suitable to present the conditions of an expressway.

In VISSIM, car-following behaviour is based on so-called psycho-physical and discrete models developed by Wiedemann—they are the Wiedemann 74 model and the Wiedemann 99 model (FODT 2014; WSDOT 2014). The Wiedemann model assumes that a driver can be in four different driving regimes, including: following, free driving, closing in, or braking. These regimes are defined by thresholds (or action points) that represent the points at which a driver changes his/her driving behaviour (Olstam and Tapani 2004; Gao 2008; Higgs et al. 2011; PTV 2011). The Wiedemann 74 model, used for urban traffic and merging areas, works with only the following three parameters: average standstill distance (ASD), additive part of safety distance (APSD), and multiplicative part of safety distance (MPSD). While the Wiedemann 99 model is a modified version of the Wiedemann 74 model and is used for highways and freeways with no merging areas, it deals with nine parameters (standstill distance (CC0), headway time (CC1), and seven other parameters (CC2–CC8) related to deceleration parameters (Park and Qi 2003; Song and Sun 2016). A mathematical definition of the Wiedemann 74 and 99 model, in VISSIM, is presented by Gao (2008) as:

$$u_n(t+\Delta t) = min\begin{Bmatrix} 3.6 \times \left(\frac{s_n(t)-AX)}{BX}\right)^2, u_f \\ 3.6 \times \left(\frac{s_n(t)-AX)}{BX \cdot EX}\right)^2 \end{Bmatrix} \quad \text{(Wiedemann 74 model)} \tag{1}$$

$$u_n(t+\Delta t) = min\left\{ \begin{array}{l} u_n(t) + 3.6 \times \left(CC_8 + \frac{CC_8 - CC_9}{80} u_n(t) \right) \Delta t,\ u_f \\ 3.6 \times \left(\frac{s_n(t) - CC_0 - L_{n-1}}{u_n(t)} \right) \end{array} \right\} \quad \text{(Wiedemann 99 model)}, \tag{2}$$

where, $u_n(t+\Delta t)$ is the speed of vehicle n at time $t+\Delta t$, $s_n(t)$ is the vehicle spacing between the front bumper of the lead vehicle and front bumper of following vehicle at time $t(m)$, AX represents the desired distance between two standstill vehicles, and BX and EX are random calibration parameters.

The aggressiveness of a driver's behaviour, which is characterized by accepting or rejecting gaps, has a significant effect on lane-change decision making. The lane-changing model in VISSIM is based on the so-called Sparmann model, which was originally developed by Willmann and Sparmann in 1978. According to PTV (2011) and Gao (2008), the Sparmann model is a rule-based model in which lane-changing behaviour is categorized as lane changing to a faster or slower lane. Parameters such as the minimum and maximum deceleration values of trailing vehicles and safety distance reduction factor motivate acceptance or rejection of the decision to change lanes. The safety distance reduction factor decreases the safe distance between trailing and leading vehicles in the desired lanes, as well as the safe distance to the leading vehicle in the current lane. This factor is specified in VISSIM by a default value of 0.6. That means that the safety distance is reduced by 40% during the lane change. Reducing this factor indicates more aggressive behaviour in accepting shorter gaps. Lownes and Machemehl (2006) explain that the parameter in this model plays a significant role in affecting a wide variety of traffic measures (Whaley 2016).

Lateral behaviour settings in VISSIM control the lateral orientation of a vehicle within its current lane, as well as during overtaking. By default, all vehicles are programmed to occupy the entire lane width (Emelie 2016). However, it is possible to assign a vehicle to position itself to the left, right, or in the middle of the lane (PTV AG 2017). The default parameter values are keeping lateral distance to vehicles in the next lanes, diamond-shaped queuing, considering next turning direction and collision time gaining.

To that end, this paper is divided into four sections. A background and the need for the study, and a brief review of the works related to the calibration of driving behavior reference to the VISSIM microscopic simulator is discussed in the introduction section. Section 2 provides a brief description of methodology implementations, including the study area and data collection, the developed model, and detailed discussions about the calibration and validation processes. Section 3 presents discussions based on statistical analysis of the results at different stages of calibration. Section 4 includes a summary of the work, and it highlights major findings and contributions.

2 Methodology

Our proposed model is used as a base model to evaluate different traffic incident management strategies on Muscat Expressway in the Sultanate of Oman utilizing VISSIM platform. From previous studies and based on local conditions, we proposed a framework for calibration and validation processes, as illustrated in Fig. 1. The framework consisted of four basic steps. The first step is pre-modelling, which includes selecting the study area, identifying the study area, identifying Measure-of-Effectiveness (MOE), and data collection. The second step is building a base model that includes network coding. The third step is model calibration, and the fourth step is model validation. Calibration parameters and MOEs are identified by using multi-parameter sensitivity analysis, and the optimum values for these parameters are obtained by minimising the error between the simulated data and the field data. Multiple criteria are included in the optimisation formulation by constraint insertion. A conventional trial and error approach is adopted in order to find the optimal set of driving behaviour parameters.

2.1 Study area

The Muscat Expressway is a 54 km long road that joins Rusail and Qurum. It was opened in 2010 (Muscat Municipality 2018) to reduce the traffic burden on Sultan Qaboos Street, which was the only main road at the time.

For the purpose of our study, a 20 km section of the Muscat Expressway is chosen between the coordinates 23.581077, 58.139735, 23.569872, and 58.407379 that link Qurum and Mubella. The study area is divided into six sections in each direction between Interchange 6 and Interchange 11. The length of these sections vary according to the distances between the interchanges, between 1.8 and 9.8 km (NTS 2017), in which each section is simulated separately in both directions.

The map of the study area and the chosen section is illustrated in Fig. 2. Since the main objective of our study is to evaluate traffic incident management (TIM) on the Muscat Expressway, the reason for choosing this study area came from Royal Oman Police (ROP) data that registered the highest number of incidents, especially during peak hours—the

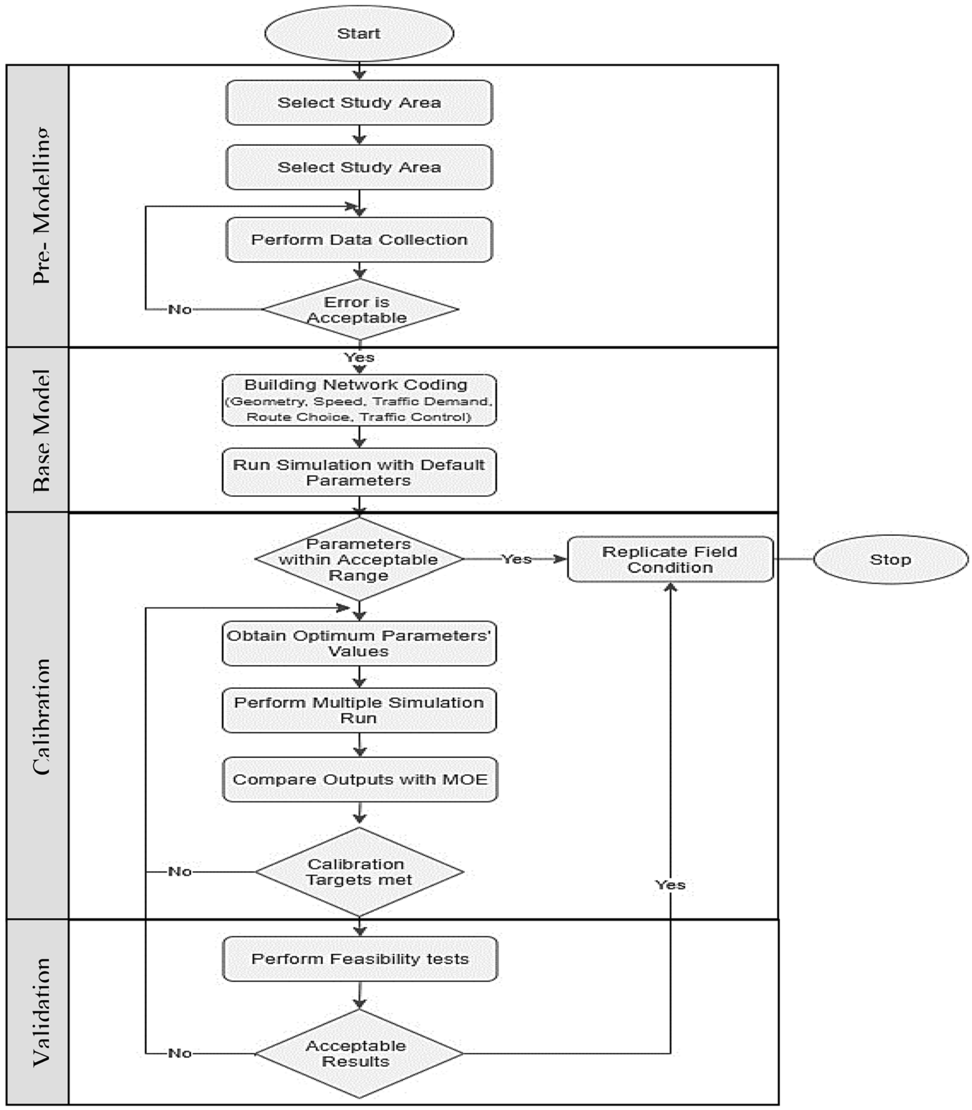

Fig. 1 The proposed framework

topography and length of these sections represent entire sections of the Muscat Expressway. The site provided several challenges in microscopic modelling, including interchange spacing and merging and diverging areas.

Figure 2 shows the route of the chosen section with data collection points. Each section consisted of six lanes, three lanes in each direction. The three lanes were separated by 12 m concrete medians with landscaping and light poles. The posted speed limit was 120 km/h for passenger cars and 100 km/h for heavy trucks (Muscat Municipality 2018).

Mubella is a residential area in Muscat, and most ministry buildings and companies are located in Alkhwaire and Qurum. Therefore, we found that the route between Mubella and Qurum sustains heavy traffic congestion during the morning hours, while the route between Qurum and Mubella (south to north) has heavy traffic congestion during evening hours (Rakesh and Shweta 2010; NTS 2017). Since previous studies (Carson 2010; WSDOT 2014) have shown that incidents have no significant effects on traffic flow during off-peak hours; therefore, for the purpose of our study, the model is tested during morning peak hours on the route between Mubella and Qurum and during evening peak hours on the route between Qurum and Mubella.

2.2 Data collection

For the purpose of our study, two types of data is acquired for building the simulation model. First, we collected basic input data, such as traffic volume data, data on turning vehicles' movement, traffic composition (vehicle mix), vehicles' characteristics, and network geometry (route patterns, such as number of lanes, lane width, shoulder width, road classification and road type, traffic rules). Second, we collected data required for the calibration and validation of the model. For the calibration and validation process, it was essential to

Fig. 2 Map of Oman and route of the chosen sections

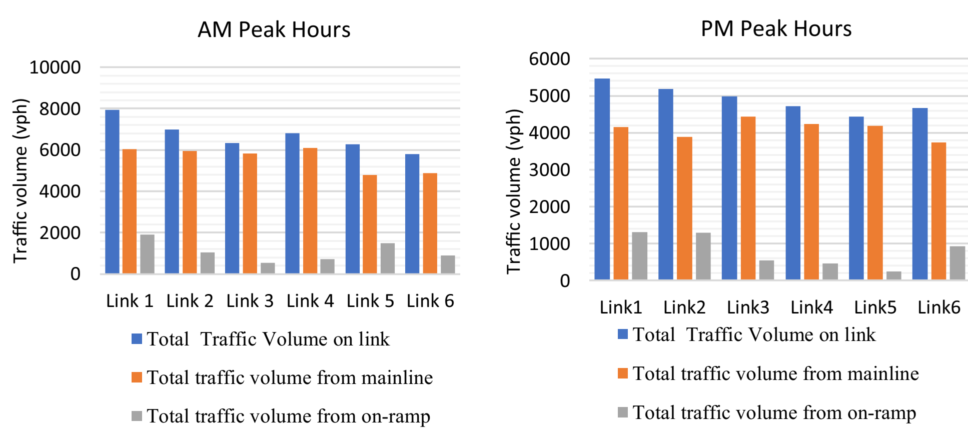

Fig. 3 Traffic volume for mainline and on-ramps

identify MOEs and the appropriate input parameters (FODT 2014).

Geometric data and traffic data were collected from the Supreme Council for Planning and the Muscat Municipality (Muscat Municipality; NTS 2017). From the available data, the average lane width was 3.65 m, with an inner shoulder of 2.5 m and an outer shoulder of 2.0 m (NTS 2017). According to the Omani Highway Design Standard (HDS 2010), the ramp lane or auxiliary lane typically extended between 400 and 800 m. Traffic volume data were determined for both the mainline and for the on-ramp and off-ramp at each link during the two peak hours. Figure 3 shows the traffic volume for the mainline and on-ramp at each section.

The traffic volume for the main links varied between 5795 vehicles per hour and 7495 vehicles per hour during morning peak hours, and it vary between 4430 vehicles per hour and 5470 vehicles per hour during evening peak hours. The

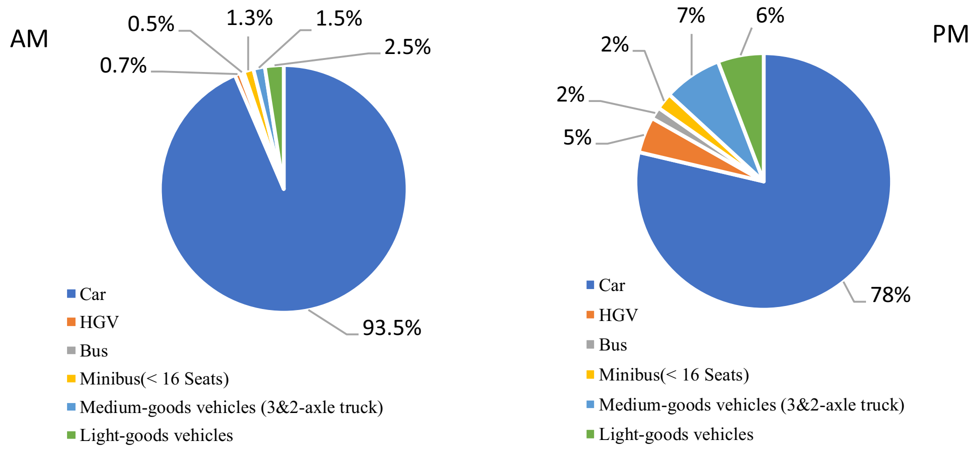

Fig. 4 Traffic composition during morning and evening peak hours

traffic volume on on-ramps varied between 525 vehicles per hour and 1910 vehicles per hour during morning peak hours and between 245 vehicles per hour and 1315 vehicles per hour during evening peak hours.

The traffic is classified into six vehicle classes, namely: cars, heavy-goods vehicles (HGV), buses, minibuses (< 16 seats), medium-goods vehicles (3-axle trucks), medium-goods vehicles (2-axle trucks) and light-goods vehicles (LGV) (NTS 2017; Muscat Municipality 2018). Figure 4 shows the traffic composition of the collected volume data in the two directions during morning peak hours and evening peak hours, which clearly shows that most traffic on the corridor consisted of passenger vehicles.

Figure 4 shows the passenger car saturation is about 93.5% during morning peak hours, while it reaches 78% during evening peak hours. This shows that the percentage of heavy vehicles is increased during evening peak hours.

2.2.1 Selection of measure of effectiveness

MOEs can measure travel time, average speed, traffic throughout, traffic counts, and existing geometry (FHWA 2004; FODT 2014; WSDOT 2015). According to the availability of the data and the purpose of our study, traffic volume was selected for the calibration process, while average speed and travel time were selected for validation of the calibrated model. Average travel speed and average travel time were obtained by using a moving car technique for six runs per link in the study area (NTS 2017; Muscat Municipality 2018). Data were collected during normal working days in daylight hours when the weather was clear (WSDOT 2015). Average values of traffic volume, travel speed and travel time for the study network are presented in Table 1.

The average speed varied between 45.3 and 92 km/h during morning peak hours and between 74.5 and 101.2 km/h during evening peak hours (NTS 2017; Muscat Municipality 2018). We observed that the average speed mainly depends on the distance between the merging area and the diverging

Table 1 Average values of observed traffic volume, travel speed, and travel time

Link	Section length (km)	Time	Total volume on link (vph)	Average travel speed (km/h)	Average travel time (s)
Between Exit 6 and Exit 7 (Link 1)	3.12	AM	7945	68	164
		PM	5470	74.5	148.38
Between Exit 7 and Exit 8 (Link 2)	4.2	AM	6995	92	164.1
		PM	5180	85.97	175.63
Between Exit 8 and Exit 9 (Link 3)	4.88	AM	6345	89.8	196.3
		PM	4985	101.2	174.25
Between Exit 9 and Exit 10A (Link 4)	9.78	AM	6800	86.23	415.25
		PM	4710	99.71	352.88
Between Exit 10A and Exit 10B (Link 5)	1.75	AM	6275	54.3	115.3
		PM	4430	84.5	74.1
Between Exit 10B and Exit 11 (Link 6)	5.44	AM	5795	65.6	299.3
		PM	4675	101.17	194

area, total traffic volume, and the percentage of traffic volume from on-ramps and off-ramps at merging and diverging areas. According to WSDOT in the FHWA's Traffic Analysis Toolbox, the collected data is checked and verified for allowable error. The coefficient of variation (CV) for the freeway is between 9 and 17%, and the percentage error rate is at ± 10%, at t-95 (WSDOT 2015). In our study, all the data is checked and verified, and it showed that percentage error caries is between 1.6 and 7.4% and that CV vagaries between 1.8 and 8.8%.

2.2.2 Selection of model parameters

Selecting the appropriate parameters is important in the calibration process (FODT 2014; FHWA 2004). Researchers have used different parameters in different cases. In the early research by Park and Schneeberger (2003) explained calibration and validation of VISSIM for signalised intersections in the United States based on a linear regression model, using emergency stopping distance, waiting time before diffusion, lane-change distance, standstill distance and minimum headway parameters. Gomes et al. (2004) as well as Lownes and Machemehl (2006) used Wiedemann 99 model and focused on three necessary lane-change parameters (look-back distance, emergency-stop distance, and waiting time before diffusion), and four-car following parameters in calibrating a microsimulation model for a congested freeway by using VISSIM vehicles. Researcher in (Chitturi and Benekohal 2008; Manjunatha et al. 2013) developed a procedure to calibrate simulation models based on the relationship between capacity and two-driver behaviour parameters in VISSIM—its utilised standstill distance and time gap between vehicles. In another direction by Jing et al. (2015) investigated the basic calibration factors for the simulation of traffic conditions within an urban freeway merge/diverge environment. They found that standstill distances vary by location and lead-follow vehicle types. Also, headways and time gaps were found to be consistent within the same driver population and across different driver populations when the conditions were similar. Chitturi and Benekohal (2008) discussed a simulation model of a signalised artery which was calibrated by adjusting Wiedemann 74 car-following and lane-changing parameters in VISSIM. The selection of parameters and optimum values were based on iterations with visual evaluation of results and manual adjustment of parameters. Other researchers selected the optimum values of the calibration parameters by an optimisation formulation using genetic algorithms (Weise 2008; Aghabayk et al. 2013; Manjunatha et al. 2013; Henclewood et al. 2017).

From previous studies, we found that among the driving-behaviour models, the car-following and lane-changing models are the key components in microscopic traffic simulation software (Panwai and Dia 2005; Gao 2008; Treiber and Kesting 2013; Emelie 2016). Among the car-following parameters, Wiedemann 99 (CC0, CC1 and CC8) and Wiedemann 74 (ASD, APSD and MPSD) models are believed to have the greatest impact on the calibration process (MDOT 2014; WSDOT 2014). Also, lane-change parameters such as necessary lane change, minimum headway (front/rear), safety distance reduction factor, and maximum deceleration for cooperative braking have a significant effect on the accuracy of the developed model. For the purpose of our study, Wiedemann 99 model is suitable for an urban expressway, while Wiedemann 74 model is more suitable for merging and diverging.

2.3 Microsimulation model development

The following steps are followed for the proposed methodology of calibration and validation.

2.3.1 Base-model development

The defined base model includes network coding such as coding driveways and merging and diverging sections, and network settings such as model input for time periods, various vehicle types, vehicle classes, traffic data, desired speed, and driving behaviours and simulation assessment periods including the warmup and cool-down periods (WSDOT 2014). All the recommendations are considered for building the model in connectors, links and routes. The connector attributes' emergency stop and lane-change parameters are used to model the lane-change roles of vehicles that followed their route or the path according to the PTV coding manual and the protocol for VISSIM simulation by the Oregon Department of Transportation. The simulation coding guidelines are described in the following subsections from A to G.

2.3.1.1 Network coding The first step in developing the model was building the base model (i.e. network coding). We created a scaled base model in built-in Bing Maps in

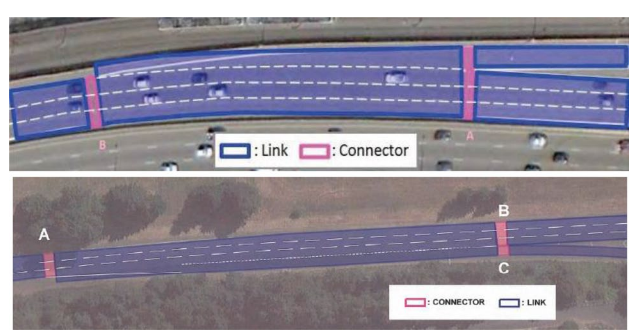

Fig. 5 Coding of freeway with merging and diverging areas

VISSIM 9.14. Links with three lanes, 3.65 m each, were created to represent road segments that carry the specific traffic volume and general curvature of the roadway. Weaving, merging and divergent areas of driver behaviour parameters values are different from basic freeway parameters. Thus, weaving, merging and divergent areas such as entrance ramps, link behaviour types that are separated freeway behaviour types (e.g., free lane selection), and they are controlled by routing through the area and lane-change distance parameters. The effective merging area or entrance ramp included the entire auxiliary lane (or lane drop) to the farthest extent of the auxiliary lane taper, and it captured the full effective length utilised by vehicles, according to the Omani highway design Standard.

The merging and diverging section was set as one link, with the number of lanes equal to the number of lanes on the main freeway (three lanes), plus the number of lanes merging onto or diverging from the freeway (one or two lanes), with one connector downstream and two connectors upstream of the merge link, as shown in Fig. 5. Figure 5 demonstrates the link coding and link behaviour adopted for a three-lane section merging with one lane ramp.

To avoid unrealistic lane changes from the mainline into the acceleration lane, and to reflect the driving behaviour and lane discipline observed on-site and according to Omani Highway Design Standard Section 9 (HDS 2010), the default values of emergency stop and lane-change parameters in the lane-change distance in the connector dialogue box were changed. The look-back distance defines the distance at which vehicles begin to attempt to change lanes. At this distance, a driver is able to change lanes successfully. The default value for lane-change distance is 200 m. In VISSIM, the emergency stop distance defines the last possible position for a vehicle to change lanes. At this position, the vehicle will stop to wait for an opportunity to change lanes. The default value is 5 m in VISSIM. The new values were set to 5 m and 30 m in merging areas and 60 m and 200 m for diverging areas (WSDOT 2014; OMG 2018), as shown in Fig. 6 (in some links, such as link between Exit 6 and Exit 7, or to 'no lane change' for the appropriate lane in some links, such as links between Exit 10 and Exit 11).

Heavy vehicles were observed to only use the right lane. Therefore, lane closures were used to ensure that correct lane-use vehicles were added to the network by using flow data from field observations.

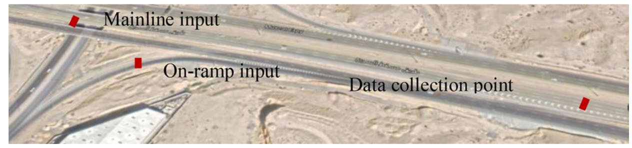

Fig. 7 Traffic input and data collection points

2.3.1.2 Traffic input and composition Two separate input traffic flows were assigned—one for the mainline and one for the on-ramp, as shown in Fig. 7. For each link, the total flow and vehicle composition were set. Simulation models

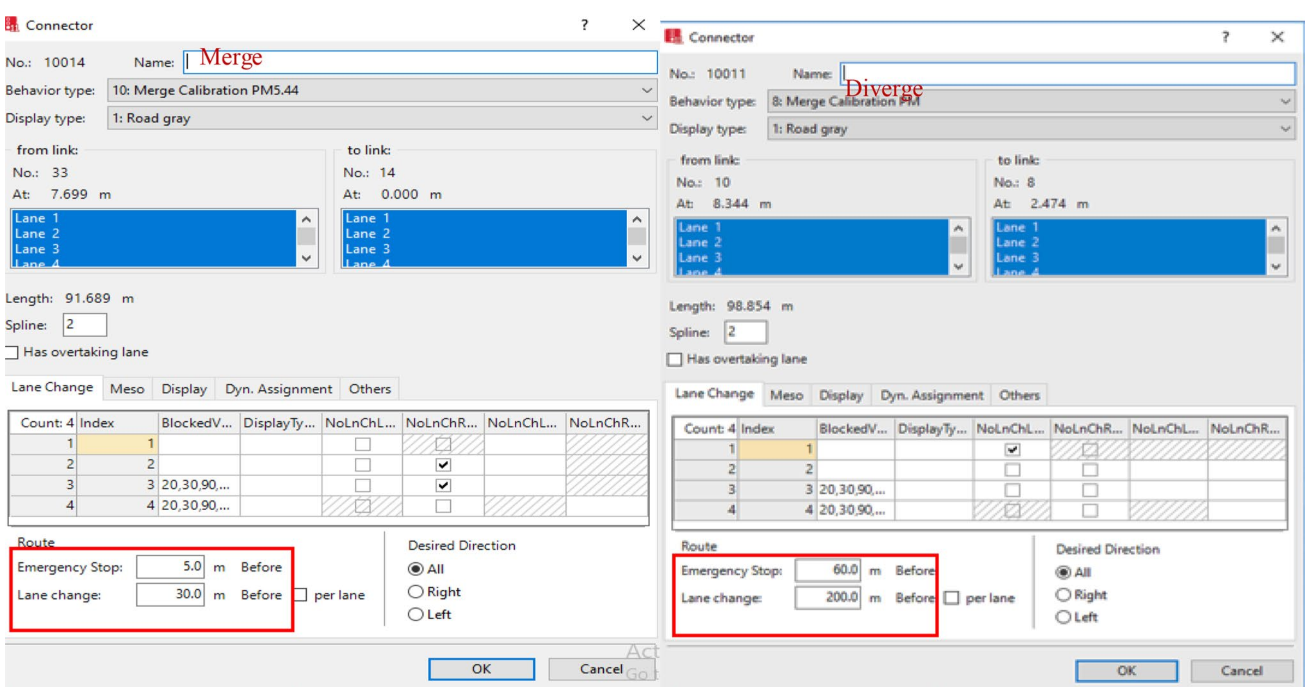

Fig. 6 Lane-change parameters for diverging and merging links

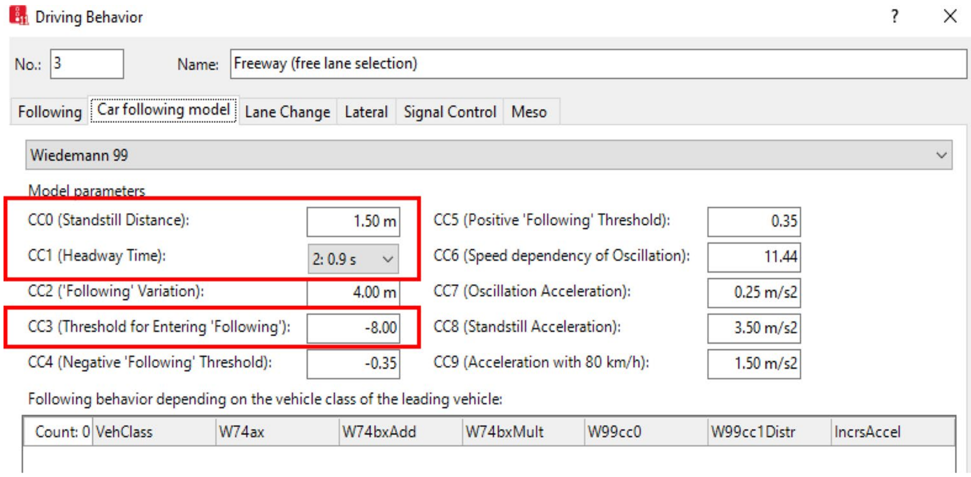

Fig. 8 Car-following parameters

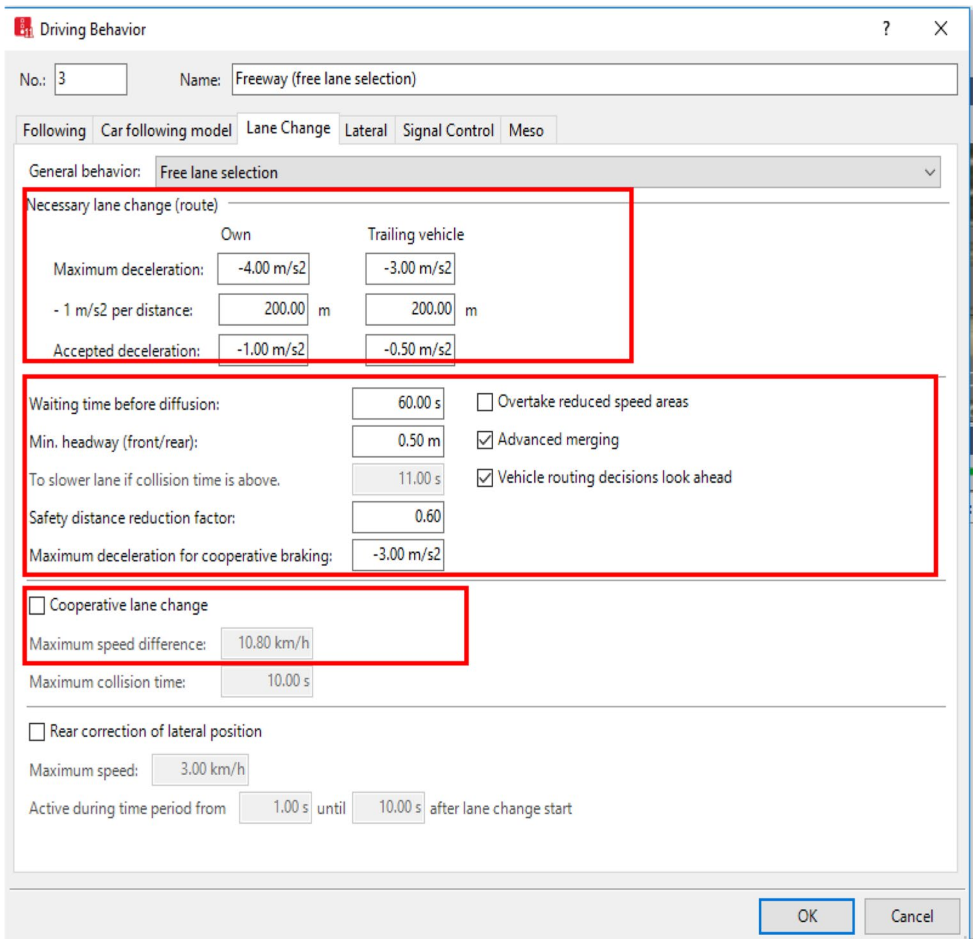

Fig. 9 Lane-change parameters

typically come with a set of standard types of vehicles such as cars, buses, trucks and motorcycles. In our case, more non-standard vehicle types were defined in terms of static and dynamic characteristics.

2.3.1.3 Vehicle routing A set of static vehicle routes was defined on the mainline, as well as a route for run-through traffic in merging and diverging areas.

For the purpose of our study, the Wiedemann 99 model was used for the mainline. In weaving, merging and diverging areas, driver behaviour parameter values are different from basic freeway parameters (MDOT 2017; OMG 2018).

Thus, along with default link behaviour types (Wiedemann 99 model), additional link behaviour types with adjusted parameters were defined in the model to reflect the traffic behaviours observed on-site. Adjustable parameters for car-following behaviours and modelling lane changing behaviour in VISSIM can be seen in Figs. 8 and 9 (PTV AG 2011, 2017).

2.3.1.4 Simulation period The peak period, along with warmup and cool-down periods are also defined. The peak period was set for 1 h (as 3600 s), and warmup and cool-down periods vary between 900 and 1800 s.

2.3.1.5 Speed control coding We used the default desired speed distributions, and the desired speed decision was set at the posted speed limit at 120 km/h for passenger cars and 100 km/h for heavy trucks (Muscat Municipality 2018). Several speed categories were formed in order to reproduce the desired speeds coming from the processed data. The range of the speed values, as well as the distribution in every category, was decided based on the speed profile of every segment.

2.3.1.6 Network settings On Omani motorways, overtaking on the inside is prohibited. Therefore, driving behaviour was set to 'right-side rule (motorised)'. A number of multiple simulation runs that were required to minimise the impact of the stochastic nature of the model on the results were computed according to Eq. (3):

$$n = \left(\frac{s \times t_{\alpha/2}}{\mu \times \varepsilon} \right)^2 . \tag{3}$$

where, n is the required number of simulation runs, s is the standard deviation of the system performance measure (such as total traffic volume) based on previously conduced simulation runs, and $t_{\frac{\alpha/2}{2}}$ is the critical value of a two-sided Student's t statistic at the confidence level of α and $n - 1$ degrees of freedom. An α of 5% is typical, μ is the mean of the system performance measure, and ε is the tolerable error that is specified as a fraction of μ. A 10% error re is desired. Averages and variances of the MOEs from data collection were calculated, and the number of simulation runs was computed as seven. However, 10 simulation runs were considered according to the recommendation provide in (WSDOT 2015) with 199 in the 'random seed' and 210 as the 'random seed increment'. A simulation resolution of 10 timesteps per simulation second was used.

2.3.1.7 Data collection points To enable data collection on vehicle flow and speed, the data collection points were placed at the middle before diverging and after merging of each section (Fig. 5). The vehicle travel times and locations were set between the beginning and the end of each link, with the help from the vehicle travel time measurement function in VISSIM.

2.3.2 Calibration and validation targets

2.3.2.1 Calibration targets Since the process of adjusting calibration parameters is iterative, calibration tolerances or targets were set to curtail the process of the Traffic Analysis Toolbox Volume III. The calibration targets presented in Table 2 were developed by the Wisconsin Department of Transportation for its freeway modelling program.

*GEH is an empirical formula expressed as

$$GEH = \sqrt{\frac{2 * (M - C)}{(M + C)}}, \tag{4}$$

where, M is the simulation model volume and C is the field counted volume.

A statistical t test was used to determine whether the difference between simulation output and field-measured data was statistically significant.

Statistical hypothesis tests such as Student's t tests, z tests and analysis of variance (ANOVA) were used to compare simulation output and field-measured data to determine

Table 2 Calibration targets

Calibration item	Calibration target/goal
Traffic volume	Simulated and measured link volumes for more than 85% of links to be: Within 100 vph for volumes less than 700 vph Within 15% for volumes between 700 vph and 2700 vph Within 400 vph, for volumes greater than 2700 vph. Simulated and measured link volumes for more than 85% of links to have a GEH* statistic value of five (5) or lower
Travel time	Simulated travel time within ± 1 min for routes with observed travel times less than seven (7) minutes for all routes Simulated travel time within ± 15% for routes with observed travel times greater than seven (7) minutes for all routes
Speed	Modeled average link speeds to be within the ± 10 mph of field-measured speeds on at least 85% of all network links
Visualization check	Check consistency with field conditions of the following: on- and off-ramp queuing; weaving maneuvers; patterns and extent of queue at intersection and congested links; lane utilization/choice; location of bottlenecks; etc.

whether their difference was statistically significant (FODT 2014). Other sensitivity analyses were reported in the literature to find out significant calibration parameters. Park and Qi (2005) reported that the use of a Latin hypercube experimental design along with one-way ANOVA analysis to find sensitive parameters. Factorial design by Ciulffo et al. (2008) and elementary effects by Ge and Menendez (2012) were alternative methods used to find sensitive parameters.

2.3.2.2 Validation targets To check for the validity of the calibrating model, three goodness-of-fit measurements were computed, including root mean square error (RMSE), correlation coefficient (CC) and mean absolute percentage error (MAPE)—these have been used for validation (FDOT 2014).

MAPE measures the size of the error in percentage and is expressed as:

$$Mean\ Absolute\ Percent\ Error\ (MAPE) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{isim} - y_{iobs}}{y_{iobs}}\right| \times 100, \tag{5}$$

where, n is the total number of traffic measurement observations, Y_{isim} and Y_{iobs} are simulated and observed data points at a time–space domain, and Y_{isim} is an average of the total number of simulated outputs.

Root mean square error (RMSE) is used to measure the deviation of the simulation output from observed data. For traffic model calibration, an RMSE of less than 0.15 is considered acceptable:

$$Root\ Mean\ Square\ Error\ (RMSE) = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(\frac{O-M}{O}\right)^2}. \tag{6}$$

A correlation coefficient (CC) indicates the degree of linear association between simulated and observed data. A CC of 1 indicates a perfect and direct relationship, while a CC of − 1 indicates a perfect and inverse relationship. For model calibration, a CC of 0.85 is considered acceptable:

$$Correlation\ Coefficient\ (CC) = \frac{1}{n-1}\sum_{i=1}^{n}\frac{\left(y_{sim} - \bar{y}_{sim}\right)\left(y_{obs} - \bar{y}_{obs}\right)}{S_{sim} \times S_{obs}}, \tag{7}$$

where, n is the total number of traffic measurement observations, and Y_{sim} and $\bar{y}_{obs}$ are means of the simulation and observed measurements. S_{sim} and S_{obs} are the standard deviations of the simulated and observed measurements.

3 Results analysis

3.1 Calibration results

The simulation runs were executed with the default parameters of VISSIM for each link separately. We run the model on different times with changing the VISSIM parameters until the calibration target was acceptable. The parameters were manually adjusted according to the literature, practitioner's experience, and/or similar models to determine the optimum parameter set. The traffic volume and average speed used MOEs for the calibration process. The consistency with field conditions of on- and off-ramp queuing, weaving manoeuvres, patterns and extent of queues at congested links, lane utilisation/choice, location of bottlenecks, etc., were visually checked and were significant. A comparison of MOEs obtained from the field to those yielded by VISSIM default values and those given by adjusting candidate calibration parameters are summarised in Table 3.

Table 3 Calibration results

Link	Time	Traffic volume			Average travel speed	Average travel time
		GEH statistic	GEH check < 5	Difference (vph)	Difference (kmph)	Difference (s)
Between Exit 6 and Exit 7 (Link 1)	AM	4.108	Yes	362	8.5	37.3
	PM	0.108	Yes	8	5.70	− 16.43
Between Exit 7 and Exit 8 (Link 2)	AM	3.797	Yes	315	− 15.1	− 22.3
	PM	0.042	Yes	− 3	6.77	− 9.18
Between Exit 8 and Exit 9 (Link 3)	AM	0.012	Yes	1	0.52	− 26.84
	PM	0.184	Yes	− 13	6.80	− 17.25
Between Exit 9 and Exit 10A (Link 4)	AM	0.631	Yes	52	− 9.39	− 5.97
	PM	0.189	Yes	− 13	0.21	− 3.96
Between Exit 10A and Exit 10B (Link 5)	AM	0.670	Yes	53	− 2.7	8
	PM	0.001	Yes	0	− 3.60	− 17.10
Between Exit 10B and Exit 11 (Link 6)	AM	0.1445	Yes	11	11.35	26.9
	PM	0.660	Yes	45	0.89	− 37.00

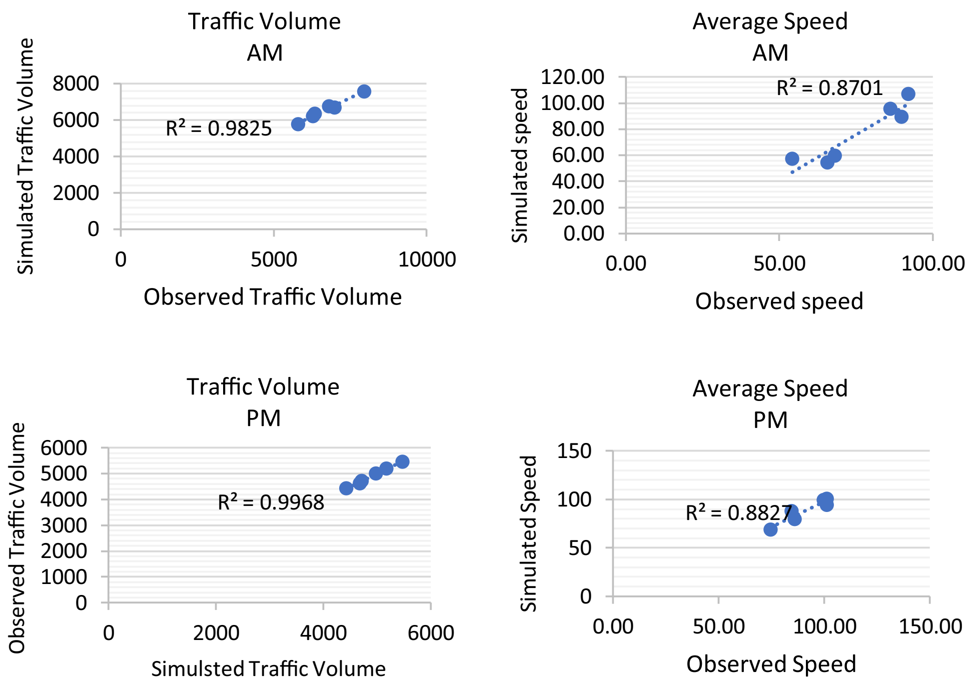

Fig. 10 T-test of similarity comparison of observed and simulated counts

(1) The statistics of the calibrated model indicate a significant improvement over the results of the default model.
(2) As per our case study, all traffic volume was greater than 2700 vehicles per hour. We found that all simulated and measured link volumes for more than 85% of the links were found to be within 400 vehicles per hour.
(3) The simulated and measured link volumes for more than 85% of the links have a GEH* statistical value of lower than 5.
(4) The travel time in all the links was less than 7 min, and we found that simulated travel time was within ± 1 min for observed routes.
(5) Modelled average link speeds were within ± 16 kmph of field-measured speeds on at least 85% of all network links.
(6) Finally, the hypotheses *t* test of similarity comparison of observed and simulated counts for the selected network is shown in Fig. 10.

From Fig. 10, it can be seen that the simulated average traffic volume and average travel speed of the calibrated model, when compared to observed results, show reasonable matching between simulated and observed MOEs. The hypotheses of similarities were accepted, and the model calibration was considered to be successfully completed. However, the calibration process was achieved by trial and error until the target was reached. Generally, the results fit better when the traffic volume was less than the capacity and where the distance between entrance and exit (merging and diverging areas) was higher. The major factors that affected the calibration process were traffic volume, link length and distance between on-ramp and off-ramp areas, as well as sharing percentage of traffic flow of on-ramps and off-ramps to the traffic flow of the mainline. Therefore, we found that the results were much better during morning peak hours, especially at longer links, such as between Exit 9 and Exit 10A and between Exit 10A and Exit 10B. However, the link between Exit 7 and Exit 8 during morning peak hours had the highest traffic volume that exceeded the capacity. Moreover, the distance between merging and diverging areas was overlapping.

It was also found that the percentage of sharing merging and diverging traffic with the mainline at merging and diverging areas had a strong effect on the mainline traffic flow and driver characteristics, such as driving behaviour and lane change and lateral parameters. For example, driving behaviours at the link between Exit 6 and Exit 7 were more aggressive (e.g., CC0 [standstill distance] = 0.5 and maximum deceleration = – 8 m/s). The percentages of on-ramp and off-ramp traffic volume to the mainline were about 24% and 21%, respectively, compared to other links, such as between Exit 10B and Exit 11. Driving behaviours were less aggressive (e.g., average standstill distance = 1.0 and maximum deceleration = – 6.5 m/s), in which the percentages of on-ramp and off-ramp traffic to the mainline were about 15% and 17%, respectively.

Finally, driving behaviours were more aggressive when the heavy vehicle percentage was higher on the same connector; for example, the on-ramp connector between Exit 10B and Exit 11. Driving behaviours during morning peak

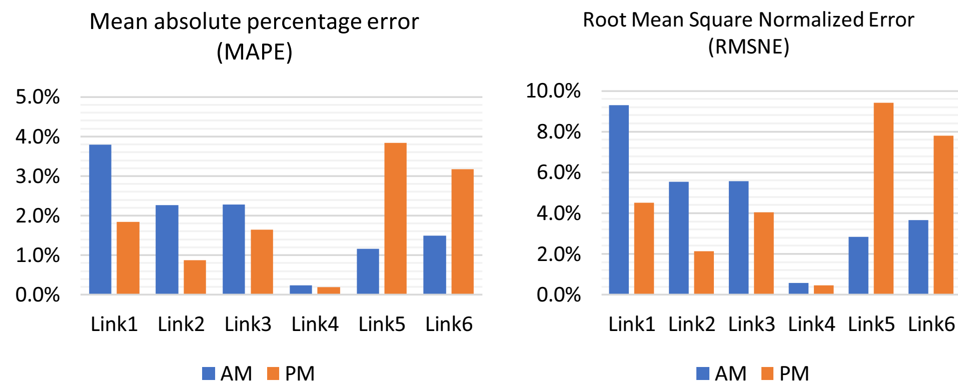

Fig. 11 Results of measures of goodness-of-fit (MAPE, RMSNE)

hours when the heavy vehicle percentage was around 22% were more aggressive (average standstill distance = 1 and maximum deceleration = 7.5) than the same connector during morning peak hours when the heavy vehicle percentage was around 6.5% (average standstill distance = 1.5 and maximum deceleration = 6.5).

3.2 Validation results

Validation of a simulation model is the next stage after ensuring that the model is well-calibrated. In this study, travel times were selected as MOEs for model validation. Three error measurements were used to evaluate the quality of the calibrated model, namely: MAPE, RMSNE and correlation coefficient (CC). Figure 11 shows that all the error measurements were below 10%, which indicates reasonable matching between simulated and observed travel times.

(1) From these results, it can be seen that the error measurements from MAPE are below 5%, which indicates a reasonable matching between simulated and observed travel times.
(2) RMSNE for all links was found to be less than 10%, which is considered acceptable for traffic model validation.
(3) Finally, correlation coefficients (CC) for morning and evening were 0.97 and 0.99, respectively (more than 0.85). This signifies a perfect and direct relationship, where a CC of 0.85 is considered acceptable for model calibration
(4) Overall, all validation results were satisfactory, with minimal errors. Therefore, it can be concluded that the model was successfully calibrated and validated.

3.3 Adjusted parameters

In our simulations, a number of driver behaviour parameters were adjusted to achieve an acceptable simulation output. Two driving behaviours were defined in VISSIM: mainline, which represents main link, and merging and diverging connectors for both morning and evening. A conventional trial and error approach were adopted in order to find the optimal set of driving behaviour parameters. The final set of driving behaviour parameters and their corresponding values differ from the default settings, as listed in Table 4. It should be noted that only parameter values that differ from the default are included in the table.

4 Conclusion and future work

Calibration and validation of microscopic simulation models were demonstrated through a case study on the Muscat Expressway in the Sultanate of Oman in order to find the optimal value of microscopic driving behaviour parameters. In this paper, we outlined a complete methodology for constructing, calibrating and validating a simulation model of the Muscat Expressway, along with merging and diverging areas. A total of 20 km of the Muscat Expressway was calibrated in two directions during peak hours (morning and evening peak hours). The case study presents different challenging features: six on-ramps and six off-ramps in each direction, different types of traffic composition, and an uncontrolled freeway connector during peak hours that create several interacting bottlenecks, especially on on-ramps and off-ramps.

The required procedures were demonstrated, which included gathering/processing field data and microscopic simulation using the VISSIM software. The field data was retrieved and verified in a proper way to be used in software. The model was developed by building the base model and then calibrated using traffic volume and average speed. The calibrated model was validated by using

Table 4 Driving behavior parameters and their corresponding values

Mainline link parameter	Default		Calibrated AM		Calibrated PM	
1. Car Following model (Wiedemann 99)						
CC0 (standstill distance)	1.5 m		0.5 m: 1.5 m		1.0 m: 1.5 m	
CC1 (headway time)	2:0.9 s		1:0.5 s: 2:0.9 s		1:0.5 s	
2. Lane change						
Necessary lane change (route)	Own	Trailing vehicle	Own	Trailing vehicle	Own	Trailing vehicle
Max deceleration	$-4.0\ m/s^2$	$-3.0\ m/s^2$	$-5.5\ m/s^2$: $-8.0\ m/s^2$	$-4.5\ m/s^2$: $-7.5\ m/s^2$	$-5.0\ m/s^2$: $-7.5\ m/s^2$	$-4.0\ m/s^2$: $-7.0\ m/s^2$
$-1\ m/s^2$	200 m	200 m	30 m	30 m	30 m	30 m
Accepted deceleration	$-1.0\ m/s^2$	$-0.5\ m/s^2$	$-2\ m/s^2$: $-4\ m/s^2$	$2\ m/s^2$: $-4\ m/s^2$	$-2\ m/s^2$: $-4\ m/s^2$	$2\ m/s^2$: $-4\ m/s^2$
Min. headway (front/rear	0.5 m		0.3 m: 0.5 m		0.3 m: 0.5 m	
Safety distance reduction factor	0.60		0.10: 0.30		0.10	
Max deceleration for cooperative braking	$-3.00\ m/s^2$		$-7.0\ m/s^2$: $-8.0\ m/s^2$		$-7.0\ m/s^2$	
Cooperative lane change	X		√		√	

Connector parameter (merging/diverging area)	Default		Calibrated AM		Calibrated PM	
1. Car following model (Wiedemann 74)						
Average standstill distance	2.00 m		0.50 m: 1.50 m		1.0 m: 1.50 m	
Additive part of safety distance	2.00 m		1:00 m		1:00 m	
Multiple part of safety distance	3.00 m		1:00 m		1.0 m: 2.0 m	
2. Lane change						
Necessary lane change (route)	Own	Trailing vehicle	Own	Trailing vehicle	Own	Trailing vehicle
Max deceleration	$-4.0\ m/s^2$	$-3.0\ m/s^2$	$-5.0\ m/s^2$: $-8.0\ m/s^2$	$-4.0\ m/s^2$: $-7.5\ m/s^2$	$-5.0\ m/s^2$: $-8.0\ m/s^2$	$-4.0\ m/s^2$: $-7.5\ m/s^2$
$-1\ m/s^2$	200 m	200 m	30 m	30 m	30 m	30 m
Accepted deceleration	$-1.0\ m/s^2$	$-0.5\ m/s^2$	$-2.0\ m/s^2$: $-4.0\ m/s^2$	$2.0\ m/s^2$: $-4.0\ m/s^2$	$-2.0\ m/s^2$: $-4.0\ m/s^2$	$2.0\ m/s^2$: $-3.0\ m/s^2$

Table 4 (continued)

Min. headway (front/rear	0.5 m	0.3 m: 0.5 m	0.3 m: 0.5 m
Safety distance reduction factor	0.60	0.10: 0.30	0.10: 0.30
Max deceleration for cooperative braking	$-3.00\ m/s^2$	$-7.0\ m/s^2$: $-8.0\ m/s^2$	$-7.0\ m/s^2$
Cooperative lane change	X	√	√
3. Lateral			
Observe adjacent lane(s)	X	√	√

average travel time. It was concluded that the VISSIM microsimulation model with default parameter values was incapable of replicating the field conditions. After multiple simulation trials with different parameter values, the results showed the superiority of our calibrated model. Then, different error measurements were computed to assess the validity of the model. The achieved results showed all the errors were below 10%, which was reasonable matching between the observed and simulated MOE.

In conclusion, several important findings result from this calibration—they can be summarised as follows:

(1) Good accordance between measured and predicted values was obtained for all the combinations of design characteristics and traffic demand patterns.
(2) It was found that 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.
(3) The main parameters affecting the simulation precision the most are car following parameters in the Wiedemann 99 (CC0 and CC1) and Wiedemann 74 (ASD, APSD and MPSD) models; lane-change parameters such as necessary lane change; minimum headway (front/rear); safety distance reduction factor; and maximum deceleration for cooperative braking.
(4) 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.
(5) In general, the calibrated parameter values indicate that drivers in Oman are more aggressive in lane changing and car following compared with the default values in VISSIM under congested conditions.

In this paper, we were able to identify some important driving behavioural parameters that can be used later as benchmarks for other studies to simulate different scenarios in VISSIM prior to their field implementation.

In the future, we plan to utilize this model as a base model to evaluate different Traffic Incident Management Strategies to provide the most effective strategy in different situations. This may help decision makers in long-term and sustainable development.

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