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Investigating and calibrating the dynamics of vehicles in traffic micro-simulations models

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Abstract

The accuracy of the micro-simulation model's generated vehicle activity data used in the emissions modelling depends on how the dynamic behaviours of vehicles are being represented in the model. The dynamic behaviour of every single vehicle is constantly modelled during the simulation phase in accordance with different vehicle internal behaviour models. It is therefore imperative that the model reproduces the same variability of these behaviours in the real-world. This research paper investigated two main approaches in studying how car dynamics are represented in AIMSUN traffic micro-simulation model. The first approach was to use field trajectories data in the calibration of car dynamics parameters of the car-following internal behavioural model in AIMSUN, the second approach was to compare the simulated vehicles activity models' outputs with field vehicles activity data obtained from an Instrumented Vehicle (IV) driving along the study route. The field-obtained vehicle trajectories contained second-by-second speeds and acceleration data, which have been utilised in the evaluation of the AIMSUN model performance at both macro and micro levels. The findings showed that the calibration of vehicle dynamics in car-following models has reduced the values of accelerations and decelerations in the simulations. However, this did not influence the vehicle trajectories behaviour that continued to show sharp accelerations and decelerations, which are not representative of the real-world behaviours. The research showed that the use of IV real-world data to evaluate the car-following internal behaviour model provided an effective and computationally efficient validation methodology, which offered a further level of accuracy to the available standard validation procedures.

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1. Introduction

The last decade has witnessed the development of coupling traffic microscopic simulators and instantaneous emission models to be used in the environmental impact assessments of traffic networks. One of the most widely used traffic simulators in the UK is AIMSUN (Advanced Interactive Microscopic Simulator for Urban and non-urban Networks) modelling package. The accuracy of this micro-simulation model's generated vehicle activity data used in the emissions modelling depends on how the dynamic behaviours of vehicles are being represented in the model. The dynamic behaviour of every single vehicle is constantly modelled during the simulation phase in accordance with different vehicle internal behaviour models including the car following, lane changing, and gap acceptance models. It is therefore imperative that the model reproduces the same variability of these behaviours in the real-world. This raises the issue of the calibration and validation of these behavioural characteristics in practice where their aspects are difficult to observe and available data from the field is insufficient. Therefore, this research is primary aimed to examine the use of Instrumented Vehicle (IV) real-world trajectory data to evaluate the car-following internal behaviour model and to enhance the calibration and validation procedures of micro-simulation models.

Section 2 introduces the integration between traffic simulation and emission models. Section 3 summaries a review of the calibration and validation of micro-simulation models. An observation of the car-following internal driver behaviour model in AIMSUN and the identification of study-used model's parameters are presented in section 4. Section 5 explains the research methodology, site and collected data. After this, the model's calibration and validation processes using trajectory data are reported in section 6. Finally, section 7 provides a summary and conclusions.

2. Coupling traffic micro-simulation and emissions modelling

Coupled traffic micro-simulation models with emission models have been used to estimate the environmental impact of real-time transport policies and traffic strategies (Int Panis et al., 2006; Tate, 2013). Reviewed studies showed that the detailed integrated traffic-vehicle emission micro-modelling approach is considered more reliable than any other emission modelling approaches. However, the reliability of this approach is highly correlated with the quality of the generated second-by-second speed trajectory information used by the instantaneous emission models. Therefore, it is critical to ensure that vehicle dynamics in traffic micro-simulation models are replicating these of real-world, and which can be achieved by the calibration and validation of these micro-simulation models (Int Panis et al., 2006; Jie et al., 2013; Tate, 2013).

3. Calibration and validation of traffic micro-simulation models

The calibration and validation of micro-simulation models is important to ensure that the simulated vehicles activity is a true representation of the vehicle dynamics in the real world. Various statistical analysis techniques such as paired or multiple comparison and time series analysis are used in the calibration and validation process where the method selection depends on variables chosen for analysis, the transport system and model data, in addition to their characteristics and statistical behaviour (Barceló, 2010). A variety of guidelines reviewed have recommended the application of a sensitivity testing technique to identify the most influential model parameters based on the situation and task conducted (Antoniou et al., 2014), taking into consideration that global network parameters are calibrated first and followed by the local link-specific parameters to fine tune the result for better fitting of the network conditions (Dowling et al., 2004; Brackstone et al., 2013). The validation process starts once the model calibration process is completed and no further calibration would provide any additional benefit. Validating the calibrated model would confirm its predictive power and is conducted using a new set of independent input data (Hollander and Liu, 2008).

Several recent research studies explored showed that generally, within aggregated calibrated and validated traffic micro-simulation models, the researcher relied on aggregate 'static' flow and speed information while kept using model's default vehicle performance and driver behavioural parameters. This means that these microscopic models were not being calibrated and validated based on the disaggregated and emission-affecting vehicle dynamics parameters such as instantaneous speed and acceleration and simply assumed that each individually modelled vehicle belongs to a group or groups of vehicles sharing the same characteristics (Song et al., 2012; Song et al., 2013). The result of this procedure is that traffic micro-simulation models did not accurately represent the actual vehicle dynamics at the second-by-second level and that the microscopic element of modelling is not validated accurately and hypothetically not statistically valid (Brackstone and McDonald, 1999; Song et al., 2012; Song et al., 2013). Therefore, it was concluded that even if the usual model calibration and validation procedure is good for aggregate results, it might not be accurate or adequate for model performance determined by specific parameters such as traffic emission estimation (Rakha and Crowther, 2002; Jie et al., 2013).

4. Application of micro-simulation modeling

Traffic microscopic simulation models such as AIMSUN and VISSIM, are commonly used to model traffic on road networks, which give the ability to evaluate real-time policies and traffic management strategies with alternative traffic scenarios (Song et al., 2012). In AIMSUN micro-simulation model, the position and speed of every vehicle in the system is updated based on the inspection if lane change is required initially and then applying the car following model if no change in lane occurred. The contribution of this research study considers the longitudinal behaviour of the driver in relation to the lead vehicle (i.e. car-following model) which controls individual vehicle activity in the model.

4.1. Car-following model

The car-following model implemented in the AIMSUN simulation package is based on the safety distance model proposed by Gipps (1981). AIMSUN has a variety of modelling controllable parameters influencing internal behaviour models, these include global, local and vehicle attributes parameters. The car-following model is the major internal behaviour model that depends on vehicle dynamics in limiting the performance of the vehicles and defining the second-by-second speed and spatial position of the vehicle in the simulation. Out of all the controllable parameters in AIMSUN, a main three of the car-following model's parameters (Maximum desired speed, Maximum acceleration, Normal deceleration) have been chosen for calibration process in this research study. For the identification of these parameters, a limited sensitivity analysis has been conducted. Another parameter that influences the desired speed in the model is the speed acceptance parameter (θ) which represents the driver's willingness to comply with the speed limit. However, due to the limited scope of this research and data available, only the abovementioned parameters have been selected for analysis.

4.2. Understanding study model scenarios

The following three scenarios have been modelled:

- Default-CD: Base model with AIMSUN default values
- Option-A: Based completely on the verified version of the model developed by Tate (2011)
- Option-B: Same as Option-A, however the car dynamics parameters have been calibrated from field data

All modelled scenarios in this study share the same global and local model's parameters, in addition to few vehicle attributes parameters, which are all obtained from Tate (2011) developed AIMSUN model and which were all calibrated under the same study. It is important to highlight that the degree of acceptance of speed limits (θ) has been set at a mean value $\theta \geqslant 1$ in all three model's scenarios, which indicates that vehicles will consider a maximum speed value for a section that is greater than the speed limit.

5. Methodology and research data

A calibration and validation methodology of the traffic micro-simulation model has been developed, the conceptual framework of this methodology in presented in Figure 1.

The study site is about one kilometre long stretch of an arterial corridor named Otley Road (A660) situated in the busy Headingley part of Leeds. The study area provides a variety of traffic flow conditions, from free flowing to congestion on a regular basis and which allow the research analysis to focus on the driving behaviour part of the modelling procedure.

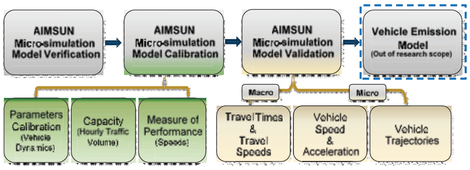

Fig. 1. Research modelling conceptual framework.

The real-world data has been collected using an Instrumented Vehicle (IV) performing repeated circuits of the study network in Headingley. The IV has collected data following the identified study route and for a number of 17 circuits where measurements of second-by-second data under a range of variability in speed, acceleration were reordered at AM (peak/off-peak) and PM peak. The IV data provided GPS system captured second-by-second speed data. Furthermore, the IV equipped CAN system acquired speed data which was found to have more accuracy at its measurements more than the GPS unit due to the loss of GPS system signal at some locations. Therefore, it was decided to use the CAN system captured second-by-second speed data especially that the car-following model is sensitive to accurate speed and acceleration. For the purpose of the calibration and validation of the study model, a set of traffic flow data has been collected during normal traffic conditions. Furthermore, the traffic flow, speed, headways, vehicle fleet composition, PCU units are obtained from the environmental traffic management of Headingley undertaken by Tate (2011). Finally, AIMSUN software provides an Application Programming Interface (API) module has been used to extract model generated second-by-second vehicle speed and acceleration data for each vehicle on the study identified Headingley route.

6. Analysis, results and discussion

6.1. Model car dynamics parameters calibration from field data

A set of car dynamics parameters of the car-following internal behavioural model (maximum desired speed, maximum acceleration, and normal deceleration) has been identified using instantaneous speed and acceleration data obtained from the IV database. These parameters have been optimized and tested under (Option-B) modelling scenario. A total number of (13) trajectories representing study route during the AM peak/Off-peak have been selected and tested for significance. Table 1 presents car dynamics parameters estimated from field data (Option-B) in comparison with other two scenarios.

Table 1. Car dynamics parameters for all three model's scenarios.

Parameter	Default Car Dynamics				Option-A				Option-B			
	Mean	Dev.	Min	Max	Mean	Dev.	Min	Max	Mean	Dev.	Min	Max
Max Desired Speed km/h	110	10	80	150	100	20	80	150	42	4	35	48
Max Acceleration m/s2	3.00	0.20	2.60	3.40	1.85	0.43	1.35	2.75	2.23	0.27	1.76	2.73
Normal Deceleration m/s2	4.00	0.25	3.50	4.50	5.00	0.50	4.00	6.00	1.61	0.18	1.25	1.86

The AIMSUN default parameters values are the highest in terms of speed and acceleration distributions, followed by Options-A in terms of speed and Option-B in terms of acceleration. The AIMSUN default parameters distribution indicated that vehicles would accelerate higher at high speeds and decelerate higher when reducing speed. This description is usually the case on freeways and not on urban arterials such as our study corridor. Finally, the field traffic conditions were well represented in the three measured parameters in Option-B, where the maximum desired speeds of drivers were distributed around the speed limit of the roads in the site. However, it is believed that the pedestrian-vehicle conflicts in the site have established a more careful driving behaviour, which might have influenced the normal deceleration estimated parameter values where its distribution occurred far left to both Default-CD and Option-A distributions with higher peak and smaller variation indicating possible under estimation of the vehicle attribute of normal deceleration.

6.2. Model calibration and validation

The calibration process showed that using model's default car-dynamics parameters in AIMSUN, the morning peak model was not able to represent activities of vehicles driving on the study route. However, the calibrated Option-B model was not only valid for the measures of performance but also valid in terms of representing emission sensitive vehicle dynamics using both aggregated and disaggregated data. However, until now there is no certainty that the model is accurately representing the actual vehicle dynamics at the second-by-second level and that the microscopic element of modelling is validated accurately and hypothetically statistically valid. Therefore, a model validation at the disaggregated level has been conducted.

6.2.1. Macro scale validation

The macro scale validation involved route level analysis where travel times and travel speeds estimated by the models were compared with disaggregated field-observed data using visual and statistical analyses. For each model scenario, the arithmetic mean travel time, standard error from the mean, standard deviation, mean average percentage error (MAPE), minimum and maximum travel time of vehicle trajectories have been estimated. Similarly, the same have been calculated from the site database for the 13 vehicles trajectories as shown in Table 2.

Table 2. Route travel time comparisons between field-observed and model scenarios.

Data Source	Sample Size	Route Travel Time (Sec)					
	(no. of trajectories)	Mean	Std. Error Mean	Std.	MAPE	Max	Min
Site	13	183.9	15.04	±54.23	-	278.0	108.0
Default-CD	1207	156.1	1.26	±43.72	17.81%	254.5	51.0
Option-A	911	162.4	1.49	±45.10	13.24%	268.5	42.5
Option-B	1018	178.2	1.30	±41.50	3.20%	262.0	57.5

The comparison between travel times in site and models showed that all simulated vehicles had lower average travel times than the site observed average travel times. A two-sample t-test showed the average travel times of simulated vehicles are not significantly different from the field-observed vehicles, where the Option-B had the highest P-value. Travel time distribution forms a significant basis for modelling travel time variability and reliability. The Shapiro-Wilk normality tests showed that the field-observed values are found to be normally distributed with P-value of (0.284). Conversely, the simulated vehicles travel times are found to be non-normally distributed with very low P-values. A Kolmogorov-Smirnov statistical test confirmed that there is no significant difference between the travel times of field-observed and simulated vehicles so it is reasonable to assume that they come from the same distribution.

The relationship between the travel time/speed have been studied. Table 3 provides a summary of vehicle dynamics for all trajectories including field and extracted from model's scenarios, the maximum values represent the highest value between all of the studied trajectories and are not based on averages. The table showed that vehicles in both Default-CD and Option-A model scenarios have travelled at an approximate mean speed of 28 km/h. Furthermore, some vehicles have reached high travel speeds, which vehicles in the field or Option-B model could not achieve. The maximum travel speed attained in both model scenarios (Default-CD and Option-A) was over 60 km/h. The field and Option-B vehicles have travelled on similar average speeds ($\approx$ 22–24 km/h, MAPE 5.26%) and with maximum achievable travel speeds just below the roads' speed limit borderline of 48 km/h. Furthermore, the maximum acceleration values for Field and Options A&B were similar, while the Default-CD scenario maximum acceleration achieved was higher than the field-observed one. On the other hand, Field and Option-B deceleration mean values (average of all negative acceleration values) were very close and lower than the Default -CD and Option-A values.

When comparing Options A and B, the simulated vehicles in Option-A model have higher maximum speeds because vehicles speeds were mostly controlled by the accepted speed limit of the drivers which is set at values between a minimum of 48 km/h (θ=1.0) and maximum of 67 km/h (θ=1.4) and which in all cases are lower than the desired maximum speed which is set at minimum of 80 km/h as shown in Table 1 earlier. In Option-B, the maximum speeds of the simulated vehicles were mostly controlled by the maximum desired speed (i.e. ⩽ 48 km/h) since it is lower than the accepted speed limit by the drivers which set at values between a minimum of 48 km/h (θ =1.0) and maximum of 67 km/h (θ =1.4). This justifies why simulated vehicles in scenarios Default-CD and Option A have higher speeds and lower travel times than filed-observed and Option B model vehicles.

Table 3. Vehicles dynamics summary of field-observed and simulated trajectories.

Data Source	Vehicle Dynamics for all trajectories							
	Average Speed km/h (Std.)	Average Speed km/h (Std.)	MAPE	Max. Speed in all (km/h)	Max. Acc. in all (m/s2)	Mean Dec. m/s2 (Std.)	Max. Dec. in all(m/s2)	% Over Field Max. Dec
	Excl. Stationary	Inc. Stationary						
Field	23.9 (±4.67)	15.6 (±4.43)	-	47.8	2.73	0.55 (±0.52)	3.29	-
Default-CD	27.8 (±5.93)	16.84 (±6.83)	14.03%	61.9	3.39	1.19 (±1.16)	27.07	2.68%
Option-A	28.0 (±7.84)	16.64 (±8.73)	14.64%	66.9	2.74	1.24 (±1.39)	20.99	3.26%
Option-B	22.7 (±4.76)	14.53 (±5.7)	5.29%	47.9	2.72	0.66 (±0.65)	19.82	0.23%

6.2.2. Micro scale validation

This section examines vehicles activities and dynamics from field and simulated vehicles based on similar travel times of individual trajectories. Based on the trajectories data obtained from IV, the 13 vehicles' travel times varied between 108 and 278 seconds. A stratified sampling method has been used to group the travel time's cumulative distribution into five equivalent intervals and the consistent 'models' simulated vehicles trajectories have been identified. Out of these, samples of five vehicles from each model scenarios trajectories have been randomly selected for the analysis. Statistical tests showed that average travel times of simulated vehicles are not significantly different from the field observed ones (t-test, H0[a]), furthermore, the distribution of travel times between modelled and real--world trajectories were similar (K-S test, H0[b]). Table 4 presents a summary of the selected trajectories vehicle dynamics.

Table 4. Vehicles dynamics summary of field-observed and selected simulated models' trajectories within the same travel times on the route.

Trajectories	Average Travel Time Sec (Std. error)	Average Speed km/h		Mean Max. Speed km/h (Std.)	Max Acc. m/s2 (Std.)	Mean Dec. m/s2 (Std.)	Max Dec. m/s2 (Std.)
		Excl. Stationary	Inc. Stationary				
Field	183.92 (±15.04)	23.9 (±4.67)	15.6 (±4.43)	41.63 (±4.13)	2.23 (±0.27)	0.55 (±0.05)	2.18 (±0.45)
Default-CD	183.58 (±9.85)	24.8 (±4.76)	13.7 (±3.84)	49.84 (±4.13)	2.77 (±0.29)	1.12 (±0.27)	4.16 (±0.94)
Option-A	176.45 (±9.62)	26.5 (±7.12)	14.2 (±3.65)	52.27 (±4.67)	1.79 (±0.29)	1.33 (±0.53)	4.77 (±1.28)
Option-B	185.0 (±9.82)	22.6(±3.73)	13.8 (±3.98)	39.6 (±3.47)	2.07 (±0.34)	0.63 (±0.19)	2.24 (±1.56)

From Table 4, the comparison of the observed and selected modelled average vehicles' dynamics values showed similar findings to the ones found at the macro level when the complete sets of modelled vehicles samples were used in the comparison and similarly Option-B presented the nearest fit to the field-observed mean and maximum vehicle dynamics values. However, this section aims to examine the vehicle dynamics at a more detailed level.

6.2.2.1. Speed and acceleration distributions analyses

Since the desired speeds and accelerations in the microscopic simulation model are defined as distributions between minimum and maximum values, the comparisons of the distributions of speeds and accelerations for the field-observed and simulated vehicles have been conducted. Figure 2 illustrates the simulated speed and acceleration distributions of the selected trajectories from the Default-CD, Option-A and the calibrated Option-B models compared with those of the field data excluding periods where the vehicles were stationary. The figure shows that modelled distributions of speeds tended to take a bimodal shape where the modelled speed data have clearly followed different distributions than the field-observed one. Out of the three model scenarios, Option-B speeds distribution illustrated the slightly closer fit to field-observed values. The acceleration distributions showed that the majority of vehicles acceleration values on the study route fell into the acceleration bin-range of (-0.5,0.5 m/s2). Under this bin, the Option-B acceleration distribution did not match the field distribution entirely, however the two distributions almost matched perfectly out of this bin's range boundaries. Furthermore, in the Default-CD and Option-A models, a bigger number of vehicles tended to decelerate at higher deceleration values ranged between (-4.0, -1.0 m/s2). The figure also showed that modelled acceleration/deceleration data tended to have a wider range of values than the field observed one, however a moderate fit can be considered between the general shape of the calibrated Option-B and the field-observed acceleration density plots where in general the percentage of higher and lower acceleration/deceleration values are fairly small. The wider range of model's acceleration/deceleration data can be explained by the fact that the modelled traffic represents various drivers.

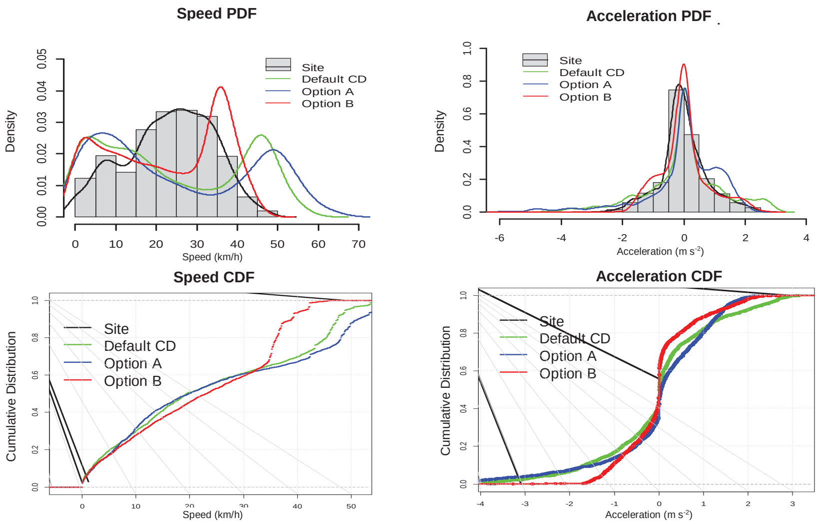

Fig. 2. Comparison of simulated speed and acceleration PDF/CDF distributions with observed ones.

In general, the distributions showed that the calibrated vehicle dynamics parameters used in Option-B have made the simulated and filed-observed vehicles' speeds and accelerations fairly more consistent. Nevertheless, differences between both simulated and field-observed data still exist particularly considering the speeds distribution. As expected, the Default-CD model scenario speed and acceleration distributions have the highest differences when compared with the field-observed distributions. Comparing the distributions using statistical K-S test showed that these tests would reject the hypothesis that the statistical distributions of simulated vehicles' speeds and accelerations for all scenarios are similar to the field-observed distributions. These tests are considered too strict in the evaluation of microscopic vehicle dynamics such as speeds and acceleration due to the stochastic properties of micro-simulation traffic models process. Therefore, it would be infrequent to get full consistency between simulated and field-observed microscopic traffic characteristics, which has been also confirmed by Jie et al. (2013).

Since the research scope is more interested in inspecting the second-by-second speed-acceleration relationship taking into consideration that vehicles release higher emissions in the acceleration phase. Figure 3 presents a comparison of the frequency distribution of the field-observed speeds and accelerations with the simulated vehicles' speeds and accelerations distributions of the selected vehicles in the three-modelled scenarios excluding any times where vehicles were stationary. The frequency distribution of speeds and accelerations of vehicles under the default and Option-A parameters have travelled along the route at the roads' speed limit of 48 km/h with very little speed variability and acceleration values consternated in the range of (-0.25, 0.25 m/s2). The frequency distribution figures also showed that in the calibrated model (Option-B) most of the vehicles have travelled along the route and accelerated to reach speeds around the maximum desired speed mean of 42 km/h, which is representing the same speeds range that similarly most vehicles in the field stopped accelerating beyond, besides, the field data have wider overall acceleration variability and fairly close deceleration variability to Option-B.

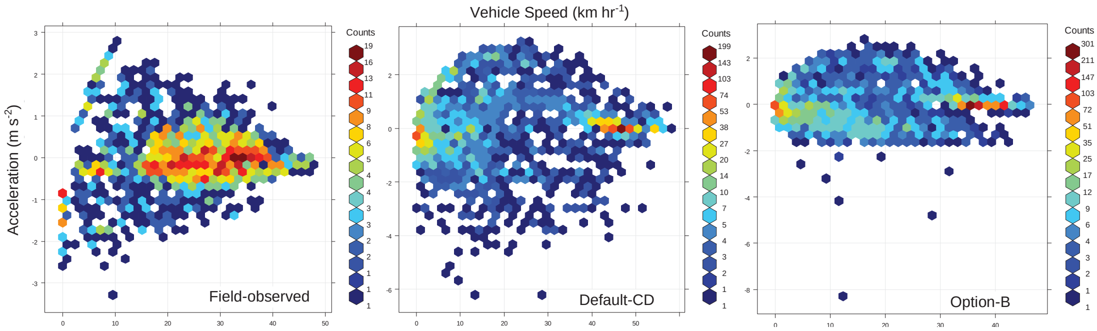

Fig. 3. Frequency distributions of field & modelled passenger vehicle speed and acceleration distributions (hexagonal binning).

The difference between both is that the modelled vehicles have a very limited speeds variability where most of their cruising speeds ranged between 33 to 42 km/h, while the field-observed vehicles cruising speeds are much more variable with wider cruising speeds ranged between 18 to 40 km/h. Additionally, most of the modelled vehicles acceleration frequencies at those cruising speeds are consternated in the range of (-0.25, 0.25 m/s2) which is less variable than the accelerations in the field concentrated at a range of (-0.8, 1.0 m/s2). The above findings show that in the real world, the surrounding environment has influenced the vehicle dynamics where driver lean to negotiate different minor events during driving whereas in the microscopic models vehicles have accelerated much more smoothly to reach the desired cruising speed with much less distortions. Finally, all the modelled vehicles showed aggressive deceleration behaviour which occurred more frequently in the Default-CD and Option-A models. Generally, the above facts show that at the second-by-second level, vehicles speeds and accelerations in the Default--CD and Option-A model scenarios showed a distorted pattern when compared with the field-observed data. On the other hand, the calibrated Option-B represented the vehicle dynamics in a better way; however, the differences of speeds and accelerations variability ranges are believed to influence vehicle emissions estimations because of their significant dependency on the speeds and accelerations of the vehicles.

6.2.2.2. Detailed trajectories analyses

A detailed analysis of the trajectories for five-selected vehicles from the field and each model scenario, where the selected samples represent the five travel time intervals presented earlier. The speed-distance and acceleration distance profiles presented in Figures 4 and 5 show that different traffic conditions were present along the route in both real world and simulations. The start of the route experienced stop-and-go movements with vehicles travelling at low speeds and fluctuating between acceleration and deceleration as shown in Figure 4. The modelled vehicles in Option-B accelerated and decelerated sharply before the first junction and then maintained constant speeds at the middle block of the route and finally decelerated steeply before the junction at the end of the route, the same behaviour was replicated with similar rapid changes of speeds in the other two model scenarios. Considering this, the simulated vehicles' speeds seem to be controlled by the traffic condition and road geometry more than the desired speed or speed limit at the beginning of the route (congested part).

On the other hand, vehicles in the field had a different behaviour where vehicles hardly ever maintained constant speeds and accelerated and decelerated gradually with no sharpness such as the modelled ones did. This aggressiveness of the modelled vehicles' acceleration and deceleration behaviours can be directly related to the mechanism of the Gipps safe distance car-following behaviour model. In the modelled trajectories, the vehicle tends to choose speeds that can avoid potential collision with the leading vehicle; however, the model performs a restriction on the vehicle to travel at the exact safe-following distance from the vehicle ahead. Therefore, when the distance between the two vehicles is over the safe distance, the following vehicle move at its current speed or accelerate to reach its identified desired speed, whereas if the distance between the two cars is decreasing and approaching the safe distance (i.e., the leading vehicle is stopping or reducing speed), the vehicle begins to brake abruptly in accordance with a model identified driver's reaction time (fixed and equal to the simulation step) which allows the driver to sense the vehicle ahead. The inconsistency with the field-observed vehicles is that in the real world, the driver cannot estimate the safe distance accurately such as the model where the value is always either over or under estimated. For instance, vehicle 3 of the field-observed trajectories has experienced mainly slow flows and traffic congestion conditions. The trajectory and speed/acceleration profiles show that driver tended not to highly accelerate to reach his/her desired speed and when a stop is expected the driver started to decelerate gradually and reduced speed from a fair distance ahead maintaining a smooth transition into the stop. A proposed resolution of the Gipps car-following restriction is by making the safe following distance as a variable based on the differences between the speeds of the leading and following vehicles, this concept would make the safe distance more flexible and would reduce the aggressiveness of the acceleration/deceleration behaviours making the car-following model more representative of the real-world driving characteristics.

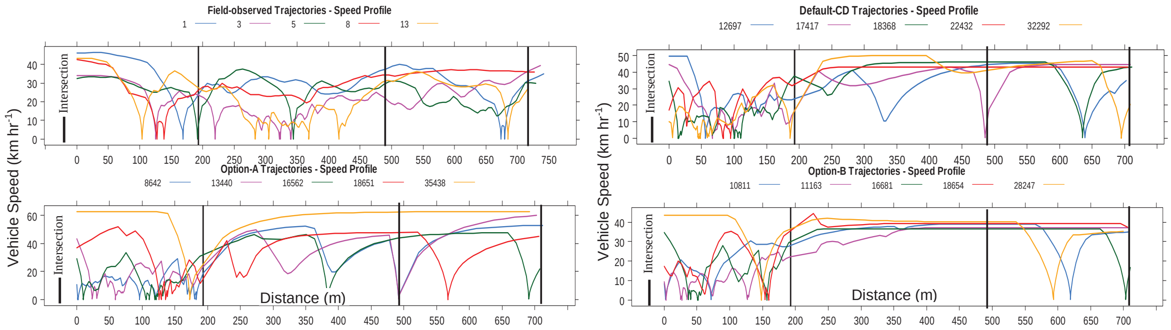

Fig. 4. Field and modelled trajectories speed-distance profile comparison on Headingley route.

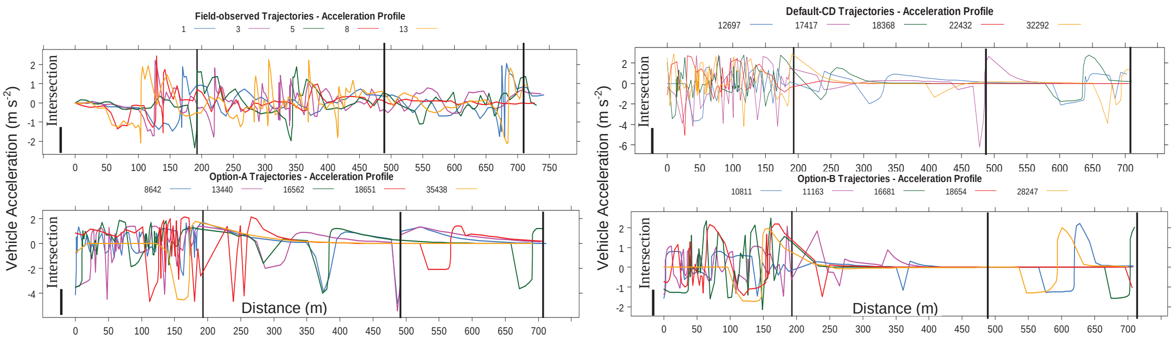

Fig. 5. Field and modelled trajectories acceleration profile comparison on Headingley route.

Furthermore, the profiles show that vehicles speeds start to increase at approximately 160 m from the start of the route and after crossing the signalised intersection with St. Anne's Road where the distances between junctions increase and vehicles tend to accelerate under free-flow conditions. The profiles under these traffic conditions confirmed the pervious findings about the maximum desired speed similarity between Option-B and the field-observed vehicles, in addition to other model scenarios' vehicles tendency to reach high speeds as per their modelled driver acceptance of the speed limit. However, despite of the closeness between the Option-B and the observed trajectories under the free flow conditions, the field-observed vehicles' desirable speeds seemed to be lower than the modelled ones where the vehicles achieved the desirable speeds and maintained their acceleration fluctuating at low levels around the centreline such as vehicles 1 and 8. Whereas the modelled vehicles accelerated abruptly to approach their maximum desired speeds and then decrease their acceleration rate to almost zero and maintained the same speed through the route as far as not being interrupted by the traffic as in the case with vehicles (18654) and (28247). This represents the car-following behaviour when the vehicle is free and not constrained by a leading vehicle as explained earlier in section 4.

7. Conclusions

In this research paper, the distributions of vehicle dynamics parameters identified by the maximum desired speed and acceleration in addition to the 95th percentile of normal deceleration have represented a realistic vehicle behaviour as a result of being constrained to the values observed in the real-world. The findings from the macro scale validation approach confirmed reviewed literature conclusions that default vehicle dynamics parameters of micro-simulation models are not able to replicate real-world observed travel time and speeds without being calibrated and validated. Additionally, the failure of Option-A model in replicating the vehicle dynamics at the macro level highlights the importance of validating models using different sets of disaggregated data to identify problems in the model, which are not observed when model is being validated, by aggregated data. On the other hand, the validation of the simulated vehicles speed and accelerations data against real world measurements at the micro level showed inconsistency between the speed and accelerations distributions and distributions frequencies at the second by second level. This highlights the deficiency of the methodologies and conclusions of various past case studies, which considered that attaining a close match between the acceleration frequency distribution plots of micro-simulation modelled and observed trajectory data (such as Figure 2 produced in this study), along with achieving a satisfactory time-distance comparisons to be enough evidence that the detailed vehicle dynamics in the model are suitably representative of reality and that model's outputs can be used in emissions estimation. Even with attaining close fit and consistency between vehicle dynamics frequencies distributions of the field and the model, the detailed analysis of the trajectories at the second-by-second levels might revile significant discrepancies in the vehicle dynamics between the model and reality. Thus, model outputs would not be suitable for the use in emissions estimation.

Overall, the calibration of vehicle dynamics in car-following models has reduced the values of accelerations and decelerations in the simulations. However, this did not influence the vehicle trajectories behaviour that continued to show sharp accelerations and decelerations, which are not representative of the real-world behaviours. The research showed that the use of IV real-world data to evaluate the car-following internal behaviour model provided an effective and computationally efficient validation methodology, which offered a further level of accuracy to the available standard validation procedures.

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