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Modelling the impact of wildfire smoke on driving speed

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ABSTRACT

Traffic models can be used to study evacuation scenarios during wildland-urban interface fires and identify the ability of a community to reach a safe place. In those scenarios, wildfire smoke can reduce visibility conditions on the road. This can have serious implications on the evacuation effectiveness since drivers would reduce their speed in relation to the optical density on the road. To date, there is no traffic model which explicitly represents the impact of reduced visibility conditions on traffic evacuation flow. This paper makes use of an experimental dataset collected in a virtual reality environment to calibrate two widely used macroscopic traffic models (the Lighthill-Whitham-Richards and the Van Aerde models) in order to account for the impact of reduced visibility conditions on driving speed. An application of the calibrated traffic model considering the impact of smoke has been performed using the WUI-NITY platform, an open multi-physics platform which includes wildfire spread, pedestrian response and traffic modelling. A dedicated verification test has been developed and performed considering different values of optical densities of smoke and traffic densities to ensure the model has been implemented correctly in WUI-NITY. A case study that demonstrates the applicability of the model to real life scenarios was also implemented, based on data from an evacuation drill. This paper shows that the presence of smoke on the road can significantly decrease movement speed and increase evacuation times thus highlighting the need for inclusion of this factor in traffic evacuation models applied for wildland-urban interface fire scenarios.

1. Introduction

The propagation of wildfires towards urbanized areas may result in mass evacuations. This is typically the case of Wildland-Urban-Interface (WUI) fires, which develop where structures and vegetation merge in a wildfire-prone environment [1]. Besides endangering people and properties in the affected area, WUI fires may also affect infrastructures [1,2], and then influence the outcome of planned or spontaneous evacuations. In this context, traffic evacuation modelling tools can be used to investigate what-if scenarios and perform predictions on the time needed to evacuate a given area [3].

The study of the influence of wildfire smoke on the road network is a crucial concern since private vehicles are largely used for these types of evacuations [4]. However, there is a limited number of studies investigating the strategies and solutions for traffic modelling in case of WUI fire evacuations, compared to other hazards such as hurricanes and floods [5–8]. Recent research attempted at filling this gap by setting the requirements for the coupling of a traffic modelling layer with a wildfire threat [9–11]. In particular, in case of WUI fires, the need for considering a multi-disciplinary perspective (including the relationships between fire spread, pedestrian

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response/movement and traffic evacuation) is evident [12]. However, there are still largely unexplored issues in the specific case of modelling traffic evacuations during WUI fires.

On one hand, fire spread modelling outputs can be used as input for trigger points/buffers [13] defining the time/location at which different areas should be evacuated [14,15]. Those fire spread-dependant trigger models can be integrated with traffic models for simulating the subsequent evacuation stage [10,16,17]. On the other hand, fire spread can progressively result in the closure of some roadway links, which cannot be considered as available links for evacuation purposes [3,12]. However, the evolution of the fire spread is associated with several uncertainties since it depends on several factors, such as fire, vegetation, topography and environmental variables [18]. In addition, evacuation modelling should be manageable in real-time to possibly address decision-making during the event.

On top of the fire-front evolution, smoke propagation and associated visibility conditions should be considered as well. In fact, while the fire spread or the spotting phenomenon (see e.g. Ref. [19], may have not still caused the complete closure of a roadway link, traffic may be influenced by the presence of smoke [11,20]. In fact, smoke affects visibility and visibility, in turn, may affect driving behaviour, i.e., driving speeds [20]. Hence, while the coupling of fire models with traffic models may help in identifying the dynamic evolution of the road network available for evacuation, the influence of smoke on driving evacuation behaviour may be even more complex to assess.

Smoke may have a somewhat similar influence on driving behaviour such as adverse weather conditions, which may impair the driving performance. However, while rainy conditions were consistently found to affect traffic flow variables such as speeds and capacity (e.g. Refs. [21,22], there are mixed results for foggy conditions. In fact, these conditions may result in a decrease in speed and capacity [23], in speed increasing [24], or in a decrease in perceived speed as a function of visibility, effect which can also depend by the simulation environment [25]. However, these studies do not reflect evacuation conditions, which may in turn also affect driving behaviour [26]. In fact, it should be considered that most drivers may be unfamiliar with driving during an evacuation scenario, which can be associated to a decreased speed with respect to familiar environments [27,28]. Moreover, flow capacity drops can also be observed during evacuations [29].

Hence, the knowledge on this topic should be expanded, by studying in detail the influence of smoke on driving behaviour during evacuations. Given the difficulty of acquiring actual data during real-world evacuations, the influence of smoke on driving behaviour may be assessed through simulations, which can provide standardized, easy to collect data even for hazardous driving environments which could expose drivers to risks [30]. [20] evaluated the impact of smoke on driving speeds performing a virtual reality experiment. Their results show that different optical density values due to the simulated smoke were related to a decrease of the average driver speeds.

This preliminary result coupled with previous findings about capacity drops during adverse visibility conditions (see Ref. [23] which could be valid also in evacuation conditions) paves the way towards building a relationship to be used in traffic modelling. This can be based on the collected data and allows exploring this crucial aspect of WUI traffic evacuations. In particular, the influence of adverse weather conditions on traffic flow variables in standard driving conditions was widely studied (see e.g., Refs. [21,22]). In contrast, the influence of smoke on driving speed has not been clearly determined yet. Nevertheless, since the use of traffic modelling may be of particular importance for both evacuation planning and real-time management [18,31]; setting a reduction in speed as function of reduced visibility would allow a more conservative and realistic approach when considering the presence of smoke from WUI fires on the road network.

To our knowledge, there are no attempts in previous research at modelling traffic flow relationships in case of reduced visibility conditions due to wildfire smoke; while this could be a clear contribution to the body of research and practice. For this reason, the main objective of this study is exploring the influence of smoke on the main traffic flow relationships. In particular, the relationship between smoke densities and driving speed obtained experimentally by Wetterberg et al. [20] is used to calibrate two commonly used macroscopic traffic models and estimate changes in the main traffic flow relationships. In addition, the estimated changes in the traffic flow due to wildfire smoke are implemented into an integrated open modelling framework developed by Ronchi et al. [32] to make it available for any interesting parties. The implementation of the newly developed sub-model is demonstrated through a dedicated verification test, in which the variation in travel time is estimated in relation to varying traffic density and optical density conditions due to fire smoke.

The mathematical framework used is presented in the next section, where the macroscopic traffic models considered are briefly described. The experimental smoke-speed relationships are then briefly introduced and their implementation in the integrated framework is presented. Results from the calibration of traffic models whenthere is smoke are then presented, followed by the verification testing of the calibrated models through a test conducted and a case study that demonstrates the applicability of the model to real life scenarios. Finally, results are discussed in light of their possible implications for research and practice in WUI fire evacuation.

2. Calibrating macroscopic models for reduced visibility conditions

The mathematical framework used to model reduced visibility conditions due to smoke is here presented. It is based on two macroscopic traffic models for uninterrupted traffic flow on segments: the Lighthill-Whitham-Richards (LWR) [33,34] and the Van Aerde (VA) [35,36] models. Those models were chosen since they are widely applied for traffic simulation and have low computational constraints. They are therefore deemed appropriate candidates for demonstrating the calibration of a macroscopic traffic modelling framework for reduced visibility conditions.

The LWR and VA traffic models are calibrated as follows, considering the reduced visibility conditions. The adapted Van Aerde model is presented first, since it is more general than the Lighthill-Whitham-Richards, which can be considered as a simplified version of the Van Aerde model itself.

2.1. Adaptation of the Van Aerde traffic model for reduced visibility conditions

The baseline Van Aerde traffic model is reported as follows.

$$\boldsymbol{k} = \frac{1}{a + \frac{b}{v_f - \boldsymbol{v}} + c\,\boldsymbol{v}} \tag{1}$$

where (variables in bold type):

$\boldsymbol{k}$ = vehicular density on the road link (vehicles/km/lane);

$\boldsymbol{v}$ = average vehicular speed (km/h);

v_f = free flow speed (km/h), driver's individual speed unconstrained by other conditions (e.g., traffic);

a, b, c = parametres of the model.

From the fundamental traffic flow relationship:

$$\boldsymbol{q} = \boldsymbol{k}\,\boldsymbol{v} = \frac{\boldsymbol{v}}{a + \frac{b}{v_f - \boldsymbol{v}} + c\,\boldsymbol{v}} \tag{2}$$

where (variable in bold type):

$\boldsymbol{q}$ = vehicular flow (vehicles/h/lane).

The following conditions are applicable:

(1) if the jam density is reached ($\boldsymbol{k} = k_j$), the speed is zero ($\boldsymbol{v} = 0$);
(2) if the flow reaches capacity ($\boldsymbol{q} = Q$), the "speed-at-capacity" value is assumed ($\boldsymbol{v} = v_Q$);
(3) the flow-speed curve reaches its maximum point at (v_Q, Q), then: $q'(v_Q) = 0$.

where:

Q = capacity (vehicles/h/lane), maximum number of vehicles which can cross a given cross section of a road link in an hour, measured per each lane;

v_Q = speed at capacity (km/h), average traffic speed assumed in case of: $\boldsymbol{q} = Q$;

k_j = jam density (vehicles/km/lane) = maximum number of vehicles which could stay within a km of the road, measured per each lane, corresponding to a null average traffic speed in case of congested road conditions (i.e., stopped traffic flow);

$q'(v_Q)$ = first derivative of the $\boldsymbol{q}(\boldsymbol{v})$ function, computed at: $\boldsymbol{v} = v_Q$.

The three conditions above explained lead to the following formulation of the parametres, which can be considered as spacing constants [37]:

$$a = \frac{v_f\left(2v_Q - v_f\right)}{k_j\,{v_Q}^2}\quad\left[\frac{km*lanes}{vehicles}\right] \tag{3}$$

$$b = \frac{v_f\left(v_f - v_Q\right)^2}{k_j\,{v_Q}^2}\quad\left[\frac{km^2*lanes}{h*vehicles}\right] \tag{4}$$

$$c = \frac{1}{Q} - \frac{v_f}{k_j\,{v_Q}^2}\quad\left[\frac{h*lanes}{vehicles}\right] \tag{5}$$

After rearrangements, an explicit version of the Van Aerde Model can be provided:

$$\boldsymbol{k} = \frac{1}{\frac{v_f\left(v_Q - \boldsymbol{v}\right)^2}{k_j\,{v_Q}^2\left(v_f - \boldsymbol{v}\right)} + \frac{\boldsymbol{v}}{Q}} \tag{6}$$

Consequently

$$\boldsymbol{q} = \frac{1}{\frac{v_f\left(v_Q - \boldsymbol{v}\right)^2}{\boldsymbol{v}\,k_j\,{v_Q}^2\left(v_f - \boldsymbol{v}\right)} + \frac{1}{Q}} \tag{7}$$

Under reduced visibility conditions, the following conditions are assumed:

$$Q_s = \alpha\,Q \tag{8}$$

$$v_{f_s} = \beta\,v_f \tag{9}$$

$$v_{Q_s} = \gamma\,v_Q \tag{10}$$

$$k_{j_s} = \delta\, k_j \tag{11}$$

where:

$\alpha =$ coefficient which expresses the reduced capacity under reduced visibility conditions;

$\beta =$ coefficient which expresses the reduced free flow speed under reduced visibility conditions;

$\gamma =$ coefficient which expresses the reduced speed at capacity under reduced visibility conditions.

$\delta =$ coefficient which expresses the reduced jam density under reduced visibility conditions.

Hence, under reduced visibility conditions, Equation (6) can be rewritten as follows:

$$\boldsymbol{k} = \frac{1}{\frac{\beta\, v_f\, \left(\gamma\, v_Q - \boldsymbol{v}\right)^2}{\delta\, k_j\, \gamma^2\, v_Q^2\, \left(\beta\, v_f - \boldsymbol{v}\right)} + \frac{1}{\alpha\, Q}} \tag{12}$$

The α, β, γ, δ coefficients are estimated from literature studies which attempted at assessing the influence of inclement weather on traffic flow of freeways. In particular, results from the studies by Dhaliwal et al. [22] and Rakha et al. [21] are reported in Table 1. Note that those studies related to rainy and snowy conditions, while studies assessing the influence of smoke were not found in literature. Moreover, the results shown in Table 1 regarding the influence of inclement weather conditions on traffic flow parametres may involve different effects caused by rain and snow, such as wet/icy pavements (and thus reduced friction coefficients), regardless of the lack of visibility.

It is evident from Table A1 that the ranges of variation in v_Q and Q are clearly similar. The average variation in v_f is instead different. The variation in k_j was not significant or even not considered.

For what concerns the variation in v_f, it is possible to use the experimental relationship from Wetterberg et al. [20] presented in the main text of the article, which relates the β coefficient (called fractional speed in the reference study) to the visibility conditions in case of smoke:

$$\beta = -101.57\, D_L{}^3 + 49.43\, D_L{}^2 - 9.28\, D_L + 1 \tag{13}$$

where:

$D_L =$ optical density per m (m^{-1}), which is inversely proportional to the visibility of lit objects (in meters) by a factor of ln 10.

Five visibility conditions (and transition stages between them) were investigated in the study by Wetterberg et al. [20]; listed from the best to the worst visibility conditions, which were useful to develop the above reported relationship:

- no smoke ($D_L = 0\ m^{-1}$);
- light optical density of smoke ($D_L = 0.05\ m^{-1}$);
- medium optical density of smoke ($D_L = 0.10\ m^{-1}$);
- high optical density of smoke ($D_L = 0.15\ m^{-1}$);
- very high optical density of smoke ($D_L = 0.20\ m^{-1}$).

Hence, by applying Equation (9), the variation in the v_f obtained from the experimental relationship (Equation (13)) found by Wetterberg et al. [20] is included between 35% and 70%, depending on the impaired visibility condition (i.e., from light to very high optical density of smoke). This reduction is dramatically different than the percentage drop related to rainy and snowy conditions (Table A1, between 3% and 12%). Hence, it could be difficult to adapt reductions in v_Q and Q from other studies (Table A1) in parallel with the reduction in v_f from the cited experimental study.

However, the variation in v_Q and Q can be assumed as a function of the v_f variation according to previous studies. From Table A1, both reductions in v_Q and Q are computed as being, on average, the 94% of the estimated β coefficient.

Hence, on applying the three following relationships:

$$\alpha = \gamma \tag{14}$$

Table 1
Influence of rainy and snowy conditions on traffic flow parametres [22].

Condition	Estimated parametres[a]					
	α		β		γ	
	Dhaliwal et al. [22] [b]	Rhaka et al. [21] [b]	Dhaliwal et al. [22] [b]	Rhaka et al. [21] [b]	Dhaliwal et al. [22] [b]	Rhaka et al. [21] [b]
Light rain	.900	.895	.940	.970	.880	.910
Medium rain	.880	.895	.930	.925	.880	.890
Heavy rain	.850		.910		.830	
Light snow		.840		.895		.895
Snow		.840		.880		.880
Total range	.850–.900	.840–.895	.910–.940	.880–.970	.830–.880	.880–.910
Aggregate range	.840–.900		.880–.970		.830–.910	
Average value	.870		.925		.870	
Fraction of β	.940		–		.940	

[a] The variation in k_j is not significant and/or it was not considered.
[b] Coefficients are the average value of the suggested ranges, based on several case studies (all values are rounded to the nearest half third decimal).

$$\alpha = 0.94\,\beta \tag{15}$$

$$\delta = 1 \tag{16}$$

the explicit adapted Van Aerde model for reduced visibility conditions can be rewritten as follows.

$$\boldsymbol{k} = \frac{0.94}{\frac{v_f\,\left(0.94\,\beta\,v_Q - \boldsymbol{v}\right)^2}{0.94\,\beta\,k_j v_Q{}^2\,\left(\beta\,v_f - \boldsymbol{v}\right)} + \frac{\boldsymbol{v}}{\beta\,Q}} \tag{17}$$

2.2. Adaptation of the Lighthill-Whitham-Richards model for reduced visibility conditions

The baseline Lighthill-Whitham-Richards traffic model is reported as follows.

$$\boldsymbol{k} = k_j\left(1 - \frac{\boldsymbol{v}}{v_f}\right) \tag{18}$$

where all the variables and parametres have the same meaning defined for the Van Aerde model.

From the fundamental traffic flow relationship:

$$\boldsymbol{q} = \boldsymbol{k}\,\boldsymbol{v} = k_j\,\boldsymbol{v}\left(1 - \frac{\boldsymbol{v}}{v_f}\right) \tag{19}$$

where all the variables and parametres have the same meaning defined for the Van Aerde model.

The following conditions are applicable in this case as well as for the Van Aerde model:

(1) if the flow reaches capacity ($\boldsymbol{q} = Q$), the "speed-at-capacity" value is assumed ($\boldsymbol{v} = v_Q$);
(2) the flow-speed curve reaches its maximum point at (v_Q, Q), then: $q'(v_Q) = 0$.

The two conditions above explained lead to the following relationships:

$$Q = k_j\,\frac{v_f}{4} \tag{20}$$

$$v_Q = \frac{v_f}{2} \tag{21}$$

Under reduced visibility conditions ($D_L > 0\ \mathrm{m}^{-1}$), the following conditions (along with the condition in Equation (9)) are assumed considering Equations from 8 to 10 and from 14 to 16:

$$Q_s = \alpha\,Q = 0.94\,\beta\,Q \tag{22}$$

$$v_{Q_s} = \gamma\,v_Q = \alpha\,v_Q = 0.94\,\beta\,v_Q \tag{23}$$

$$k_{j_s} = \delta\,k_j = k_j \tag{24}$$

Hence, the two conditions (Equations (20) and (21)) become:

$$Q_s = k_j\,\frac{\beta\,v_f}{4} \tag{25}$$

$$v_{Q_s} = \frac{\beta\,v_f}{2} \tag{26}$$

It is evident that, in this case, the only parametre needed for the calibration of the LWR model is the β parametre, which can be assumed according to the results of Equation (13), depending on visibility conditions. Once the β parametre is estimated, both an explicit version of the LWR model in reduced visibility conditions and an estimation of the other traffic parametres in reduced visibility conditions (Equations (25) and (26)) can be performed.

The explicit adapted LWR model for reduced visibility conditions can be rewritten as follows.

$$\boldsymbol{k} = k_j\left(1 - \frac{\boldsymbol{v}}{\beta\,v_f}\right) \tag{27}$$

where all the variables and parametres have been previously defined.

2.3. Calibrating parametres based on experimental data

Based on Equation (13), the parametre β to be introduced into Equations (17) and (27) is obtained. In the study by Wetterberg et al. [20]; four reduced visibility conditions due to fire smoke were investigated, corresponding to low ($0.05\ \mathrm{m}^{-1}$), medium ($0.10\ \mathrm{m}^{-1}$), high ($0.15\ \mathrm{m}^{-1}$) and very high optical density ($0.20\ \mathrm{m}^{-1}$). The β parametres can be calculated for each of those conditions. Given the previously defined relationship between the parametres α and β, the α parametre can be calculated as well in the four above defined reduced visibility conditions. The resulting α and β parametres are presented in Table 2.

Once α and β parametres are defined, both the s-LWR and s-VA models are determined.

Please notice that by means of the fundamental traffic flow relationship, the traffic flow rate q (vehicles/hour/lane) can be obtained in both cases (LWR and VA models) by multiplying Equations (17) and (27) by the average speed v.

3. Exemple of application of calibrated models

In this section, the results of the application of the reduced visibility conditions to the LWR and VA traffic models, leading to the calibrated s-LWR and s-VA models (Equations (17) and (27)) are presented.

In particular, the updated fundamental diagrams are exemplified in the following Figs. 1 and 2. Note that they were developed considering the following input parametres:

- the capacity Q in standard conditions was assumed to be equal to 1300 vehicles/h/lane, which is the value suggested by the Highway Capacity Manual [38] for minor two-lane highways. Those highway types are comparable with the v_f experimentally found by Wetterberg et al. [20] in clear conditions (72.4 km/h) for this road type.
- v_Q in clear conditions was assumed to be equal to the value suggested by the Highway Capacity Manual [38] for minor two-lane highways (52.3 km/h).

It should be noted that those input values are related to two-way two-lane rural roads, while the LWR model and similar frameworks are generally applied to multilane highways and freeways. However, in evacuation conditions, lane-reversal of arterial two-lane roads are generally operated to allow evacuation from the endangered area (see e.g., Ref. [8]. Hence, uninterrupted flow conditions can be deemed in this case as generally applicable to segments of the evacuation routes not affected by intersections and operated as one-way two-lane roads.

Following these hypotheses, k_j in clear conditions was derived from the relationships between the LWR model parametres and used as baseline value for the VA model.

The calculated values of the model for different optical density levels are reported in Table 3.

4. Implementation and verification of the model adaptation considering the impact of smoke

The calibrated model considering the presence of smoke is demonstrated through its implementation in a freely accessibly platform, namely WUI-NITY [32,39], briefly described as follows.

4.1. The WUI-NITY platform

The WUI-NITY platform is based on the game engine Unity 3D (Unity Technologies, San Francisco CA, USA) with built-in Virtual Reality (VR) capability acting as a host for different modelling sub-components. In fact, WUI-NITY allows the coupling of the following different modelling layers:

- a fire spread model;
- a pedestrian response and movement model;
- a traffic model.

The platform is intended as model agnostic to allow the implementation of different modelling tools for each modelling layer depending on the given intended application. In its first implementation, the tool includes macroscopic sub-models for all three modelling layers.

To keep the possibility of being used in real-time in case of evacuation management, a trade-off between the simulation granularity/detail and the reasonable overall computational time should be kept for each modelling sub-component. However, given the scope of this study, which attempts at modelling the impact of wildfire smoke on driving speed, only the effects of smoke on traffic evacuation are considered, thus focusing on the traffic modelling layer in the WUI-NITY platform.

For the given application and given the exemplary scope of this work, a simple macroscopic traffic model (the LWR model) was used to represent the traffic evacuation on the egress routes, neglecting the influence of delays at intersections. This is deemed a reasonable assumption for this application as queuing on segments is predominant in case of large-scale evacuation. In addition, intersections could be differently operated during evacuation (e.g., turning off traffic signals), thus reducing their impact on evacuation time.

In particular, the LWR traffic model is implemented in WUI-NITY using a time-step discretisation, as shown in Equation (28).

$$k_j(T+1) = k_j(T) + \frac{\Delta t}{L_j n_j}\left(q_{j,IN}(T) - q_{j,OUT}(T)\right) \tag{28}$$

where:

$k_j(T)$ = average traffic density in the road section j at the time T (vehicles/km/lane);
$\Delta t = (T+1) - (T)$ = Time step (s), set by default as equal to 1 s;
L_j = length of the road section (km);
n_j = number of lanes;

Table 2
Parametres α and β derived as a function of the optical density in reduced visibility conditions.

D_L (m^{-1})	0.05	0.10	0.15	0.20
β	0.65	0.47	0.38	0.31
$\alpha = 0.94\,\beta$	0.61	0.44	0.36	0.29

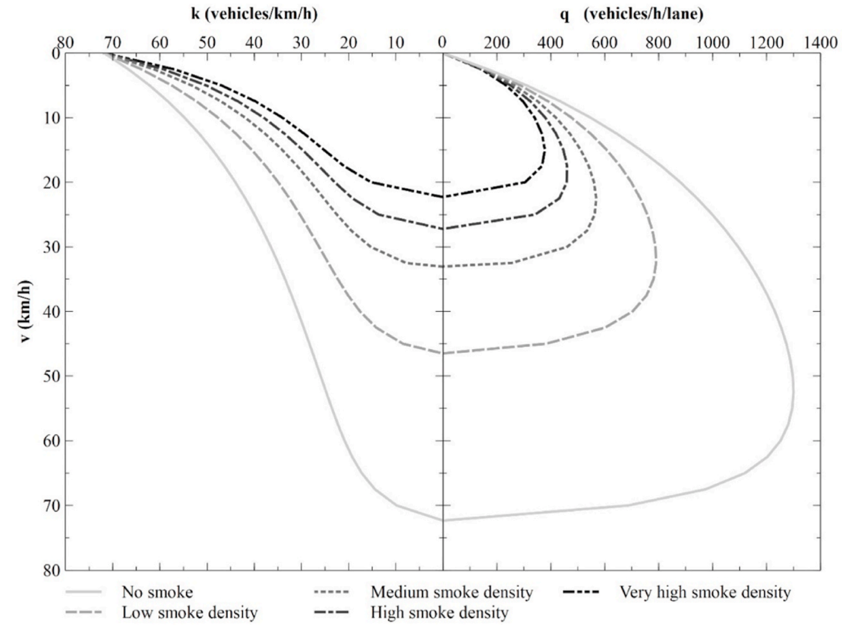

Fig. 1. Diagram of the s-VA traffic model in different visibility conditions.

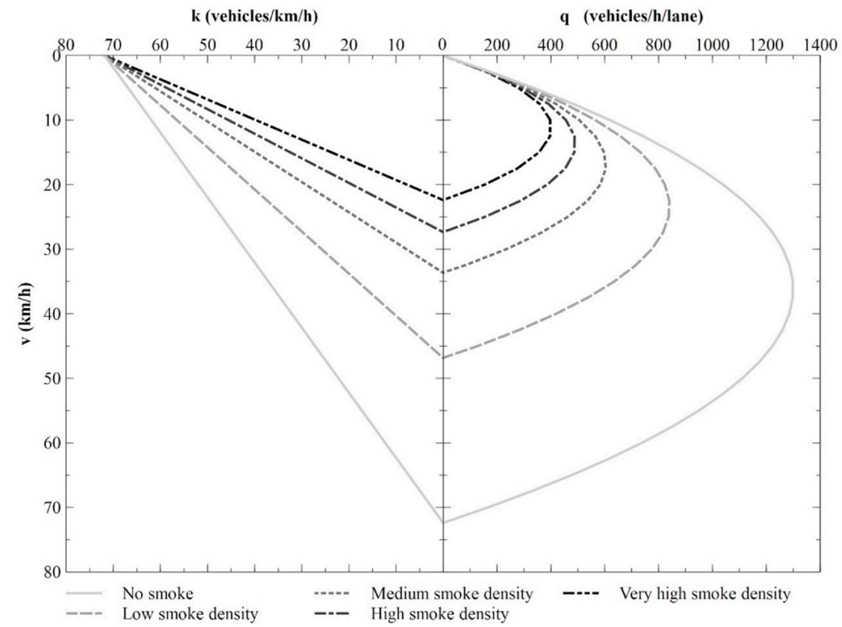

Fig. 2. Diagram of the s-LWR traffic model in different visibility conditions.

Table 3
Calculated key values in reduced visibility conditions based on the experimental data by Wetterberg et al. [20].

D_L (m^{-1})	0*		0.05		0.10		0.15		0.20	
Traffic model	LWR	VA	s-LWR	s-VA	s-LWR	s-VA	s-LWR	s-VA	s-LWR	s-VA
v_f *(km/h)*	72.4	72.4	46.9	46.9	33.7	33.7	27.4	27.4	22.4	22.4
Q (vehicles/h/lane)	1300	1300	841	803	605	578	491	469	402	384
v_Q *(km/h)*	36.2	52.3	23.4	32.3	16.8	23.2	13.7	18.9	11.2	15.5
k_j *(vehicles/km/lane)*	71.8	71.8	71.8	71.8	71.8	71.8	71.8	71.8	71.8	71.8

LWR = Lighthill-Whitham-Richards model, VA= Van Aerde model.

$q_{j,IN}(T)$ = traffic flow entering in the section j at the time T (vehicles/hour/lane);
$q_{j,OUT}(T)$ = traffic flow exiting from the section j at the time T (vehicles/hour/lane).

Another feature concerning the traffic sub-component is the route choice model, computed by adopting the open source tool Itinero[1]https://www.sciencedirect.com/science/article/pii/S0925753520305415-fn5, which is able to represent dynamic route choice in relation to the availability of the target location (e.g., in case of fire/smoke affecting the evacuation routes). The integration between traffic simulation and fire spread is implemented by an algorithm which consider the possibility of destinations being blocked by the fire and traffic management solutions such as lane reversal on road links. The main outputs of the traffic simulation for each time step are: the number of vehicles which arrive at destination or in the road network, the vehicular density, the evacuation time curves at each destination and the number of residents, evacuees and those who reach shelters.

4.2. Verification of the sub-model considering the impact of smoke on speed

Given the functionalities offered by WUI-NITY, a set of verification tests were developed and run to perform an implementation of the developed sub-model in reduced visibility conditions. This verification test is an ideal scenario designed to investigate the current and any future implementation of sub-models concerning driving speed in reduced visibility conditions. The structure and format of the test is in line with the existing verification and validation adopted for evacuation models adopted in building fire safety engineering applications [40].

The test was run by focusing on the implementation of the s-LWR model in the traffic simulation layer of the WUI-NITY platform. In this example, a single carriageway road (having speed limit equal to 70 km/h) was considered, by allowing the traffic moving on a single lane for a total length of 1 km (see Fig. 3). In this scenario, one vehicle traveling at the assigned maximum speed corresponding to the speed limit (70 km/h) was made moving along the road (from start to destination), with a given set visibility value. The test was repeated by varying the initial vehicular density on the road (e.g. using 5 different levels of vehicular density from the isolated vehicle scenario to the stopped traffic condition, which for this scenario was equal to 75 veh/km/lane) and the visibility (in 5 conditions: no smoke, and visibility corresponding to an optical density per m of 0.05 m^{-1}, 0.10 m^{-1}, 0.15 m^{-1}, 0.20 m^{-1}). This allowed testing the competing impact of traffic density and reduced visibility conditions on traffic flow.

The following assumptions were adopted while performing the test:

- The LWR model was implemented considering 5 km/h as a minimum speed. This assumption could be modified by the user in WUI-NITY, it was here used for simplicity given the scope of the analysis (i.e., to avoid complete congestion by having speed values equal to 0 km/h in this ideal test).
- The given optical density (which can be used to calculate visibility) is here assumed uniform across the whole road segment.
- Using an agent-based modelling approach, an IF conditions was set up so that when the two concurring variables causing speed reduction would occur (e.g., traffic density and reduced visibility), the minimum speed adopted would be based on the minimum speed driven by the visibility variable rather than the minimum speed due to traffic density (e.g., 1 km/h in this example). This issue has been widely investigated in other evacuation contexts [41].
- The time-step adopted in the calculation was equal to 1 s.

As a result of the test, the evacuation times obtained by applying the s-LWR model and by using the WUI-NITY platform were compared, by calculating percentage differences, reported in Table 4. Please notice that the calculated evacuation times at density equal to 75 vehicles/km/lane always correspond to 3600 given the assumptions made on minimum speed. The differences between simulated and calculated times were all below 3.3%. In particular, the stall speed was approximated to 1.08 km/h in WUI-NITY rather than 1 km/h adopted in the hand calculations. The long runtime at the highest vehicle density level makes this small difference in assumed speed more visible. The overall difference in results is caused by the approximation of the speed-density relationship equation implemented in the simulator and hand calculations.

4.3. Case study

In this section the implementation of the sub-model concerning the impact of smoke on vehicle speed in the WUI-NITY platform is presented through a case study (see Fig. 4). The chosen case study is the Roxborough Park wildland-urban interface community in Colorado, USA. This community has been selected since an evacuation drill has taken place at this location on the 27th of July 2019. Evacuation response and movement data were collected within the scope of the WUI-NITY project [32] and have been used here for the

[1] (https://www.itinero.tech/).

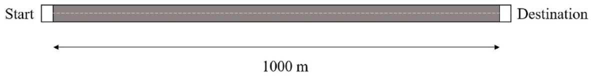

Fig. 3. Geometrical configuration of the verification test.

Table 4
Differences between calculated and simulated evacuation times.

Density *k (vehicles/km/lane)*	Input Calculation -C-or Simulation -S-	Simulated versus calculated evacuation times (s) (% difference in parenthesis)			
D_L (m^{-1}) →		**0.05**	**0.10**	**0.15**	**0.20**
1	C	81	112	138	168
	S	80 (1.2%)	112 (0%)	137 (0.7%)	168 (0%)
19	C	106	147	180	219
	S	105 (0.9%)	146 (0.7%)	179 (0.6%)	219 (0%)
38	C	158	217	265	322
	S	157 (0.6%)	217 (0%)	265 (0%)	321 (0.3%)
56	C	295	400	483	577
	S	294 (0.3%)	399 (0.2%)	482 (0.2%)	576 (0.2%)
75	C	3600	3600	3600	3600
	S	3479 (3.3%)	3514 (2.4%)	3530 (1.9%)	3544 (1.6%)

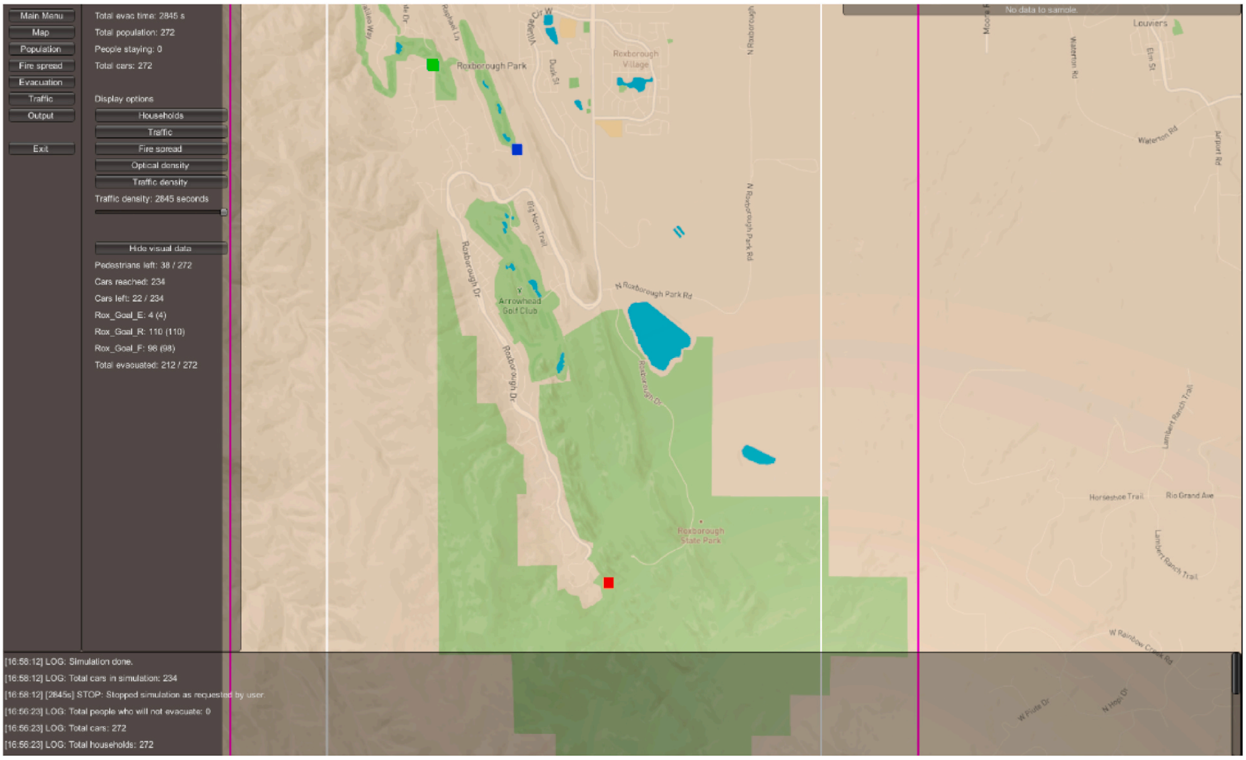

Fig. 4. Screenshots from the Roxborough scenario implemented in WUI-NITY. The blue/red/green squares indicate the destinations of the vehicles (i.e., shelters).

calibration of the inputs.

Roxborough Park is a community in an area of 8.98 Km^2. During the evacuation drill it was possible to collect data concerning human behaviour such as route and destination choice and pre-evacuation time distributions. The readers are referred to the WUI-NITY report and associated publications presenting the data for further information concerning the data collection methods in use during the drill [32,39].

In order to appreciate the differences in results due to the impact of smoke, two scenarios have been simulated in WUI-NITY. Scenario 1 assumes a preventive evacuation without smoke. Scenario 2 assumes a hypothetical global visibility corresponding to an optical density D_L equal to 0.20 m^{-1}. The main inputs of the simulation are presented in Table 5. It should be noted that the input of the scenarios have been selected to resemble the conditions observed during the drill.

Table 5
Input configuration for Roxborough Park case study.

Variable	Input
Population	272 people distributed in the location according to the drill data
Route choice	Destinations and paths chosen according to the drill (3 possible destinations: South, North-West and North-East, see [32]
Pre-movement time	Distribution according to the drill data [32]
Background traffic	None
Visibility conditions	$D_L = 0$ m^{-1} in scenario 1 $D_L = 0.20$ m^{-1} in scenario 2

Since the WUI-NITY model makes use of pseudo-random sampling from distributions to account for variability of possible human responses [42] multiple repeated simulations are conducted and convergence of results is assessed. This is performed using an acceptance criteria that the average evacuation time remains below 2% for at least 10 consecutive runs and a minimum of 50 runs.

The average total evacuation time in scenario 1 is 6610 s (approximately 1 h and 50 min) and in scenario 2 is 7213 s (approximately 2 h), with a resulting increase of 9% for scenario 2. WUI-NITY allows obtaining the number of vehicles in the scenarios during the passage of time and calculate the total evacuation time. These results provide an example of how reduced visibility conditions can impact total evacuation time in case of WUI fire scenarios.

5. Discussion

Two macroscopic traffic models have been calibrated to include the impact of wildfire smoke on driving speed. This was performed to represent an evacuation condition in case of WUI fires, using an example of a two-lane road section as egress route. This condition can be frequent, especially considering that there are several communities (even in densely populated areas) endangered from a possible WUI fire which can rely on few and low-capacity egress routes [43].

An experimental relationship between smoke density and individual speed [20] was adopted to calibrate two macroscopic traffic models. This was performed by implementing an updated speed-flow relationship considering the impact of wildfire smoke on driving speed. In fact, previous research assessed the negative influence of rain [21,22] and fog [23] on traffic flow variables; while the influence of wildfire smoke is still largely unexplored. However, smoke can affect traffic flow in different ways, especially in case of evacuations, where some links can be blocked due to the presence of smoke [11,12], thus dynamically affecting in turn the evacuation operations or speed increase may affect evacuation times. Compared to evacuation times in clear conditions (which for the case under consideration would correspond respectively to 52 s, 89 s, 103 s, 205 s and 3600 s considering the vehicle densities reported in Table 3), evacuation times are doubled or even tripled in case of low traffic density and low visibility conditions than in clear conditions. This means that in case of scarcely populated rural areas affected by evacuations in case of WUI fires, the effect of smoke can dramatically increase network clearance times, due to the high capacity drop due to the presence of smoke, even in presence of relatively few vehicles entering a given road section.

It should be noted that reliable real world data concerning reduced visibility due to smoke at driver's height are lacking. In other words, data concerning evacuation speeds during wildfires exist (e.g. Ref. [44], but those are not coupled with visibility conditions at driver's height. The use of virtual reality data allows a systematic investigation of the reduction of speed at varying smoke densities which would currently not be possible due to the lack of data. The assumed visibility conditions were chosen in order to provide a wide range of values of optical densities (from 0 to 0.2 m^{-1}) which can be considered representative of a varying set of conditions. Very high visibility represents standard driving conditions unaffected by the presence of smoke, while very poor visibility may strongly affect driving behaviour.

The present model is calibrated on data collected from individual driving behaviour in smoke. Future research should experimentally investigate how driving in smoke is affected by the concurrent presence of other vehicles and reduced visibility. In the meanwhile, it is recommended to adopt the models presented in this work, as they yield more conservative results compared to current predictions which completely omit the impact of smoke on driving speed.

Results from the model calibrations show a traffic flow which is severely slowed down (free flow speed below 40 km/h) once the smoke optical density is below 0.05 m^{-1}, considering a no-smoke free flow speed of about 70 km/h. This is not dependent on the model used for the calibration (i.e., s-LWR or s-VA). This is evident by observing the results presented in Figs. 1 and 2 and in Table 3. This result highlights that considering the presence of smoke is crucial for modelling traffic evacuation from an endangered area. In fact, the traffic flow variables can dramatically change once the visibility conditions get worse. For example, if a very low visibility condition is taken into account (e.g., smoke density below 0.05 m^{-1}), traffic congestion until vehicles moving through stop-and-go typical of traffic jams can be reached much quicker than in clear conditions, leading to a more rapid unavailability of a given road link.

This information is crucial for both evacuation planning and real-time management [18,31]. In the first case, those concepts can be applied to define trigger points/buffers [13,44] for the aim of defining the time and/or the location at which an evacuation order should start [14]; Li et al., 2015). In the second case, the evolution of fire and, consequently, smoke, can be taken into account while managing the evacuation, predicting the possible unavailability of given links due to the presence of smoke. It should be noted that the current model makes use of simplified assumptions concerning global visibility conditions in a given road link. Future work should focus on coupling such updated traffic models with a more accurate prediction of smoke spread which accounts for varying visibility during the passage of time and within a given road link.

The present work demonstrates that 1) the integration between different modelling layers is fundamental (i.e., combining fire spread models, evacuation response and traffic models) to achieve reliable predictions of evacuation clearance time; 2) such modelling layers should be able to communicate and produce credible outputs in real-time, relying on an appropriate trade-off between computational time and accuracy. For this reason, the use of the WUI-NITY platform allowing for the simulation of multiple layers affecting WUI fire evacuation [32,39] was selected.

Introducing the models calibrated for taking into account reduced visibility conditions in such platforms may indeed pave the way for an enhanced planning and real-time management of evacuations due to wildfires in WUI areas, as demonstrated in this study. Clearly, this is a first attempt of filling a gap in research and practice, which surely needs further study and development. In fact, the underlying data on which the current mathematical framework is based [20] were collected in a driving simulation task in a virtual environment. Future studies should be conducted to investigate a wider set of behaviour for different drivers' population and road types, and possibly relying on data from real events (e.g. using trajectory and speed data from evacuating vehicles, e.g. making use of GPS data or traffic sensor datasets).

In this paper, a simple macroscopic traffic modelling approach was used, which is deemed suitable with real-time management, but which may need further refinement for planning purposes. In the latter case, the switch to microscopic or mesoscopic modelling can be justified [3]. Moreover, the comparison between simulated evacuation and real case studies in presence of smoke from wildfires could help in assessing the validity of such approach.

Another important limitation of this work is the consideration of a two-lane rural road scenario only in the case study. On one hand, this could be a very common scenario in WUI fires, especially in case of small and isolated communities close to the wildland, but also for large areas in specific cases (see e.g., Ref. [45]. On the other hand, especially for planning purposes, the different composition of the road network should be taken into account and more data are needed for different road types. In fact, for large areas, considering the freeway/main highway network is the main core of the problem (see e.g. Ref. [8], and this is a different case than the two-way two-lane rural road case. However, even the two-way two-lane rural road case can be practically operated as a one-way corridor with intersection control in evacuation conditions.

Moreover, the effects of smoke on traffic evacuation are not limited to the impact on traffic flow (i.e., on travel times and congestion), but they may also cause crashes, especially during evacuation in large wildfires. Several examples of such events are reported by Blanchi et al. [46]; Diakakis et al. [47]; McLennan et al. [48] in Australia and Europe during large wildfire evacuations. However, while most of research on wildfire evacuation cite the occurrence of traffic crashes during evacuation also due to reduced visibility conditions this aspect is still not studied from a prevention perspective, such as in safety studies focused on other specific driving conditions (e.g., Refs. [11,49,50]. This should be based on the analysis of causes and circumstances of traffic crashes during evacuation. An attempt in this sense was made by Abioye et al. [51]; who developed a set of indicators to consider driving behaviour during evacuation from a safety perspective. This particular aspect is worth of future investigations.

6. Conclusion

This paper presented the calibration of two widely used macroscopic traffic flow models for their use in reduced visibility conditions through data from a virtual reality experiments. An implementation of those new calibrated model has been done through the WUI-NITY platform, an open multi-physics tool which allow considering the impact of wildfires on traffic evacuation. Results show the need of considering the impact of smoke on driving speed, given the expected reduced speeds and subsequent higher evacuation times.

This study represents a first attempt at modelling driving behaviour in wildfire smoke during evacuations and it is based on a set of simplified assumptions, such as considering simple macroscopic traffic modelling, a two-lane rural road scenario, a global visibility reduction for all the road links and an average driving behaviour based on results from virtual reality experiments and previous literature on inclement weather. Those aspects should be deepened in future research, pointing out that, however, the models presented in this work provide more conservative results compared to current predictions in which the effect of smoke is practically neglected.

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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