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Queue Formation and Evacuation Modelling in Road Tunnels During Fires

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This paper illustrates and describes the results of a modelling work on the effect of fire dynamics, queue vehicle formation, tunnel geometry on the evacuation modelling in road tunnels. The modelling approach is based on a CFD simulation of the fire development and interaction with tunnel geometry, the effect of vehicular blockage on smoke movement performed using the FDS code. Several simulations with the EVAC code (an agent-based egress model) are then performed to evaluate the evacuation strategies of the different tunnel users. The queue formation dynamics is evaluated using a specifically conceived model which is coupled with the FDS+EVAC codes to perform the modelling of users' evacuation. Different key aspects have been analysed: 1) the influence of smoke on users' movement speeds 2) the impact of modelling assumptions on the emergency exit choice 3) the effect of the queue formation model and distribution of the vehicles in the tunnel. The model also offers the opportunity to study the effect of emergency ventilation conditions and of the presence of different vehicles (cars, buses). This model approach is here compared and calibrated using the evacuation experiment that was performed in a road tunnel to investigate how occupants behave and respond when exposed to a fire emergency (Nilsson et al., 2009). The complete geometry of this emergency scenario was reproduced, including smoke generation, distribution of vehicles along the tunnel and location of the emergency exits. A satisfactory agreement was obtained, and a sensitivity analysis on model assumptions was performed to extract reference values for the application to new tunnels and different fire scenarios.

1. Introduction

The severe fires in Europe, such as those of the Mont Blanc, Gotthard and Tauern tunnels, have clearly displayed the dramatic urgency of adapting the road and rail tunnels to higher safety standards. Fires in tunnels are a threat not just for the safety of users but also for rescue teams (Borghetti et al., 2017). These issues push public authorities and tunnel designers to take increasing account of risks connected with fires. For a given accident scenario, the set of consequences and their magnitude depend in turn on the instruments and mitigation actions started at the tunnel design and management levels, and involve the following factors: human behaviour, structural solutions, technological systems, management and control procedures.
The process of evacuation from a tunnel in emergency conditions is a complex phenomenon that involves different factors, tied to both physical characteristics such as the tunnel geometry or the distance between the emergency exits, and human behaviour. While the first types of factors are deterministic, the variables tied to human behaviour are more difficult to define and assess because of their intrinsic variability known in the literature as behavioural uncertainty (Lovreglio et al., 2014a) (Ronchi et al., 2014). The literature presents studies that analyse the effects that these factors have on the main parameters and processes of the egress models for buildings and transportation infrastructure such as tunnels (Kuligowski et al., 2005) (Ronchi, 2013). The evacuation time is mainly influenced by the users' speed during evacuation and by their pre-movement time which is the time required for occupants to identify the fire and respond to it (Lovreglio et al., 2015) (Lovreglio et al., 2016a). In addition, the exit choice is another fundamental behavioural process that might

affect the evacuation performance as argued by Lovreglio et al. (2014b), Lovreglio et al. (2016b) and Lovreglio et al. (2016c). Finally, the occupant safety is influenced by the effects of the accident event, such as the propagation of toxic gases and reduced visibility as the occupant movement speed can reduce dramatically in cases of reduced visibility and in the presence of harmful gas (Fridolf et al., 2013). In addition, the presence of systems such as emergency ventilation can have a positive effect on movement speed, slowing the development of smoke in the tunnel.

To date, a key role can be played by evacuation computer models since they can be used to couple fire dynamics and egress models (Lovreglio et al, 2016d). In this paper, Fire Dynamics Simulator (FDS6) and Evac are used for simulation of fire and evacuation inside a tunnel, and coupled with a novel vehicle queue formation model which is implemented in MATLAB. This model automatically calculates the distribution of vehicles inside the tunnel (car, trucks, buses) based on tunnel geometry and traffic conditions for the specific tunnel, allowing for more realistic tunnel evacuation simulations.

2. Modeling Approach

The Fire Dynamics Simulator (FDS) (McGrattan et al., 2013), developed at NIST, is a CFD model of fire-driven fluid flow. FDS solves numerically a form of the Navier-Stokes equations appropriate for the low-speed, thermally-driven flow with an emphasis on the smoke and heat transport from fires. FDS model solves the equations for the conservation mass, species, and momentum, taking into account conductive and radiative heat fluxes. The overall computation is treated as a Large Eddy Simulation (LES). Further details on the model are described in McGrattan et al. (2013). Evac (Korhonen, 2017) is the evacuation module of FDS capable of modelling the impact of fire on evacuees' behaviour, movement and escape strategies. Each evacuee is treated independently and is characterized by its own personal properties and escape strategies. The movement of each agent is modelled using 'social' forces acting on the agents consisting of both physical forces, such as contact forces and psychological forces exerted by the environment and other agents. The agents' escape strategies are influenced by familiarity with exits, visibility of exits and effects of smoke and obstacles. The interaction between fire and evacuation models and direct access of Evac to the fire information are the main strongpoints of FDS+Evac, which also calculates FED (Fractional Effective Dose) index and the agents' intoxication and incapacitation. The evacuation simulations of the FDS+Evac are stochastic, for instance, it uses random approach to generate the initial positions and properties of the agents. In addition, there are small random forces and torques on each agent's equation of motion. Thus, same results are not obtained for a given input file if multiple simulations are done and proper convergence criteria are needed (Ronchi, 2014). A queue formation model is developed and implemented in this work to evaluate the length along which the queue of vehicles extends in each i-th lane from the accident (fire) to the tunnel entrance. Estimation of the queue length is needed to evaluate the number of people potentially involved in the event, their distribution inside the tunnel, and the time needed to queue. An automatic tool was developed to write the FDS+Evac input files on the basis of tunnel geometry and traffic data such as flow of vehicles and traffic composition). The proposed module allow the modelling of cars, buses and trucks by assembling different solid parts, including the wheels and transparent windshield (see Figure 1). In this way it is possible to simulate their effect on smoke movement, visibility of the emergency exits and movement of the agents. All the vehicles are initially placed inside the tunnel, and the queue formation dynamics is modelled adding an extra pre-movement time to the users.

3. Case Study: the Göta Tunnel

The investigated scenario refers to the experimental results of the Göta Tunnel (Nilsson et al., 2009). One bore of the tunnel was considered, for a total length of 295 m, and all the 29 cars were placed in the same position as reported during the experiments (Figure 1). A delay time was assigned to each agent in accordance with what measured during the experiment. Although there was no real fire in the experiment, artificial smoke used to alarm the participants and force them to start the evacuation towards the exits. Figure 2 shows the results of the experimental test. Most of the users escaped using bypass #2, followed by #1 while a few chose #3. All the model results are obtained in several simulations (up to 40, to ensure convergence), treated with a statistical approach and discussed in terms of mean and variance. Box plots were used to better highlight the distribution of results. Figure 3a shows that the model is able to predict that bypass2 and bypass 3 are predominantly chosen by tunnel users as escape routes. Despite the inherent uncertainty in model prediction, evidenced by the size of the box plots, it is important to observe that the experimental results are inside the box plot and close to the mean value (red line). Panel b shows that the indecision on which bypass to choose is associated to the users that are at a comparable distance between two bypasses. Users 3-7 used randomly bypass 3 or 2, and users 17-21 did the same for bypass 1 and 2. The choice depends on many factors, including view factors and social interaction.

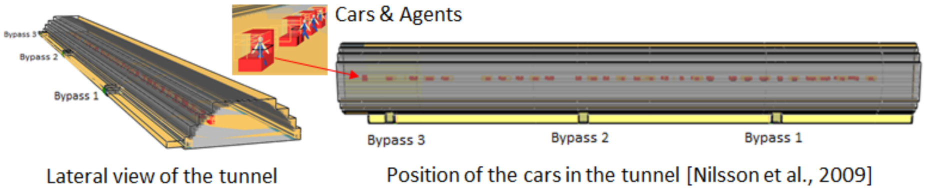

Figure 1: Göta Tunnel geometry and scenario

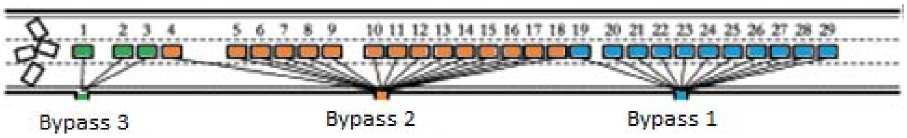

Figure 2: Göta Tunnel experimental egress choices

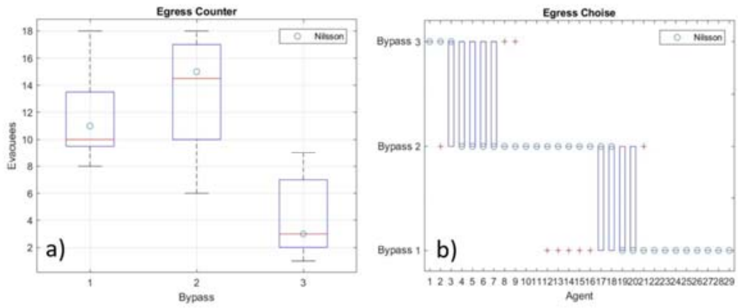

Figure 3: Panel a) comparison between experimental egress choices and prediction of FDS+Evac. The red line indicates the median, lower and upper limits of the box plot indicate the 1st and 3rd quartiles. Minimum and maximum data are also shown (black lines). Panel b) Choice of the bypass used by each agent in the entire set of simulations performed.

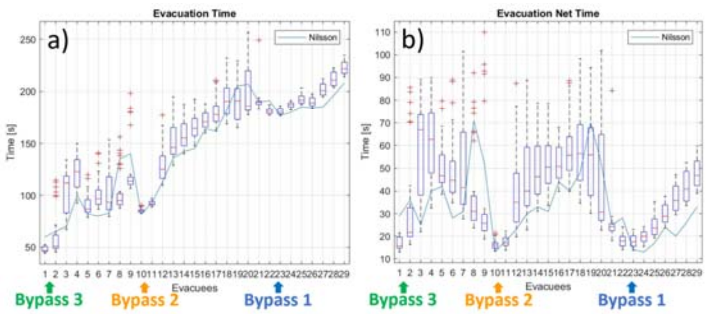

Figure 4: Comparison between measured (line) (Nilsson et al., 2009) and predicted (boxplots) evacuation times. Panel a) Total evacuation time. Panel b) Net evacuation time. Crosses indicate outliers.

Figure 4 shows a comparison with the measured total and net evacuation times. The net times were obtained by subtracting the pre-evacuation times from the evacuation times. It is possible to observe that the total evacuation times in general increase moving away from the accident, since users require more time to become responsive. However, total time also depends on the net time needed to evacuate (Panel b). In this case the time needed is clearly depending on the distance between the initial position of the agents and the nearest bypass. The agreement between prediction and experimental observations is remarkable, however some discrepancies with the experimental results were observed. For example, Figure 5 shows that in one of the 40 simulations some of the users chose a different bypass to escape than what done experimentally.

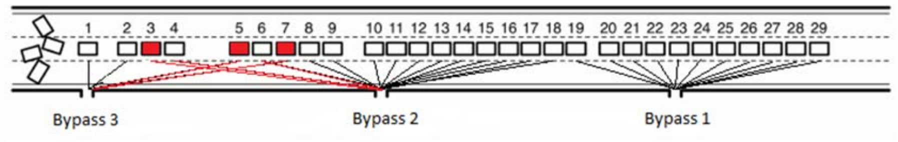

Figure 5: Emergency exits (bypasses) choice in one of the EVAC simulations. Red cars highlight agents that behaved differently from the experimental observations.

3.1 Effect of Modelling the Egress Affinity Parameter

To better understand this discrepancy, it was decided to assign an affinity parameter to each exit, weighed according to the distance that separates each agent from it. FDS+EVAC provides the possibility to define the variable KNOWN_DOOR_PROBS with a value between 0÷1. For each participant an affinity parameter was then calculated the three-emergency exit, depending on the position of the car, in this way: all users in cars stopped after a bypass were assigned value of one (assuming that passing the bypass the users are aware of it). This assumption is reasonable if the bypass is well indicated and there is adequate visibility. For the other emergency exits (bypasses) the affinity parameter of the user was calculated in inverse proportion to his/her distance from the bypass up to a maximum distance of 30 m, above which the affinity is zero. As an example, the affinity parameters for user in car #16 are 1.0 (bypass1), 0.568 (bypass2) and 0.0 (bypass 3).

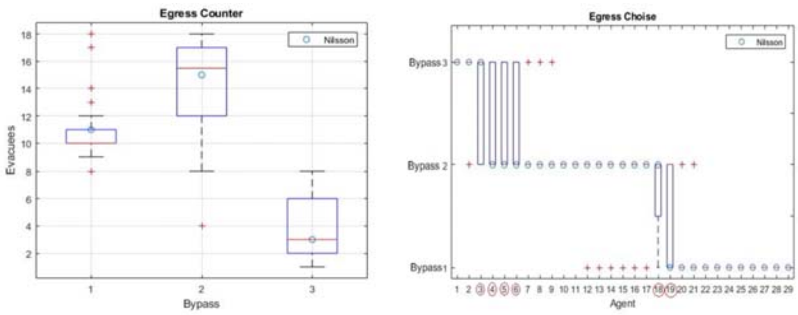

Figure 6: Effect of the Egress Affinity Parameter on the results of Figure 4.

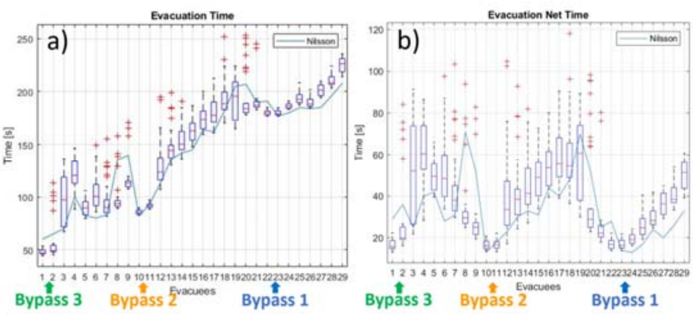

Figure 7: Effect of the Egress Affinity Parameter on the results of Figure 5.

Figure 6 and 7 show that the effect of the affinity on the variability of the predictions is significant, especially for bypass 1, which is closer to the tunnel entrance. Overall, the use of the egress affinity parameter, evaluated as described above, allowed reducing the standard deviation for the total evacuation time of ~22%.

3.2 Validation of the queue formation model

The queue formation process was treated as a stochastic process, i.e. the distances between the various vehicles, once stopped, belong to a Gaussian distribution whose parameters (mean and variance) were estimated using the Nilsson experiments. The distance is then evaluated $\boldsymbol{\delta_{stop}} = \boldsymbol{\delta_{stop,mean}} + \boldsymbol{\sigma}$ *randn(1). The same assumptions were be taken for the braking reaction times and the hesitation time, that is the time necessary to open the vehicle door. From the Nilsson's experiment, it emerged that hesitation time follows a gamma distribution, while for the reaction time a lognormal distribution is adopted t_react=lognrnd(μ, σ)

(Taoka, 1989). Due to this statistical approach, there is the possibility that the reaction times is not sufficient and an accident can occur. In the case of a collision between the two vehicles, the two cars are is positioned in the tunnel one immediately after the one other and an accident is recorded using a counter that estimates the frequency of collisions during the queue formation (this is beyond the scope of this work). Finally, buses and trucks are randomly sampled in proportion to their % inside the traffic of the specific tunnel. Table 1 summarizes the model parameters for the queue formation.

Table 1: Queue model parameters and assumptions

Variable/Parameter	Description	Value/Distribution recommended
$\boldsymbol{f_{traffic}}$	Traffic frequency	Constant Value
$\boldsymbol{f_{BUS}}$	Probability of a BUS presence	Constant Value
$\boldsymbol{v_{main,k}}\ (\boldsymbol{n_{lane}})$	Average speed of the k-th lane	Uniform $\boldsymbol{v_{main,k}} = \boldsymbol{v_{main,k}}(\boldsymbol{f_{traffic}})$
$\boldsymbol{\delta_k}\ (\boldsymbol{n_{lane}})$	Distance between moving cars	Uniform $\boldsymbol{\delta_k} = \boldsymbol{\delta_k}(\boldsymbol{v_{main,k}})$
$\boldsymbol{\delta_{stop}}$	Distance between cars stopped	Gaussian
$\boldsymbol{t_{react}}$	Braking reaction time	Lognormal
$\boldsymbol{t_{hesitation}}$	Time to open vehicle door	Gamma

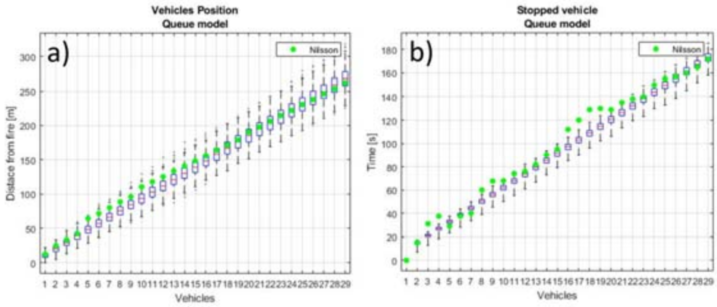

Figure 8: Göta Tunnel. Comparison between experiments (green symbols) and queue model predictions. Panel a) vehicle position. Panel b) Time to stop the vehicle [s]. ($\boldsymbol{t_{react}}$ is lognormal distribution with μ=1.3 s and σ=0.74 s, $\boldsymbol{\delta_{stop}}$ is Gaussian with μ=8.91m and σ=3.11 m, $\boldsymbol{t_{hesitation}}$ is a gamma distribution with $\boldsymbol{t_{hesitation}}$ μ= 2.16 s and σ= 6.23 s).

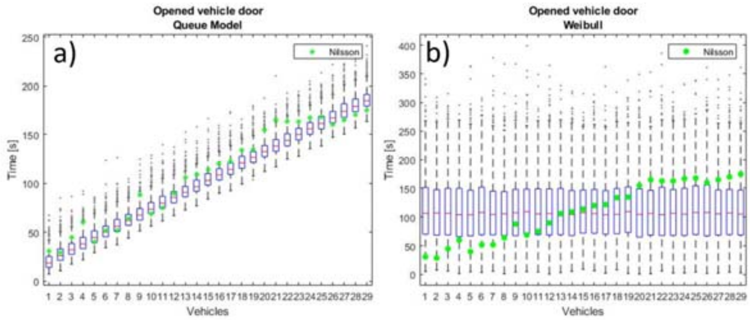

Figure 9: Göta Tunnel. Time to open vehicle door. Comparison between experiments (green symbols) and queue model predictions. Panel a) this work. Panel b) assuming a Weibull distribution.

Using the queue model it is possible to simulate the formation of queues by evaluating the position of the vehicles and their stopping time. 1000 simulations of the Göta tunnel experiment were performed and compared to experimental results. The position of the fire was set at 284 m from the tunnel entrance. The average travel speed was set at 50 km/h in accordance with the limit imposed during the experiment, while the traffic frequency was reduced to 850 vehicles/h to simulate a low traffic condition. Figure 8 shows that a good agreement can be observed in terms of both distances (deviations of about 10÷18 m) and stopping times (deviations 14÷18 s). Finally, using the previously estimated gamma distribution for the hesitation time, it was possible to evaluate the time when agents leave their vehicles. The increasing linear trend, shown in Figure 9, takes into account the fact that the time to leave the vehicle is largely influenced by the time needed to stop the vehicle, which can be evaluated only using a queue formation model. On the contrary, a common approach is to assume a distribution (for example a Weibull distribution). Figure 9 shows the substantial difference between these two approaches, always referring to the Göta tunnel experiments.

Conclusions

In this paper an innovative vehicle queue formation model is coupled with FDS+EVAC codes to model the emergency evacuation process inside a tunnel in the presence of a fire. The model automatically calculates the distribution of vehicles inside the tunnel based on tunnel geometry and traffic conditions. Using the queue model it is possible to evaluate the position of the vehicles and their stopping time, allowing for more realistic tunnel evacuation simulations. The results showed that the time needed to leave the vehicle is largely dictated by the time needed to stop the vehicle, which can be evaluated only using a queue formation model. Since both the queue formation model and EVAC code are not deterministic approaches, a statistical analysis of the results of numerous simulations was performed to determine averages and variances. This model approach is validated using a literature tunnel evacuation experiment. The complete geometry of this emergency scenario was reproduced, including smoke generation, distribution of vehicles along the tunnel and location of the emergency exits. A satisfactory agreement was obtained, and a sensitivity analysis on model assumptions was performed to extract reference values for the application to new tunnels and different fire scenarios.

References

Borghetti F., Derudi M., Gandini P., Frassoldati A., Tavelli S., 2017, Tunnel Fire Testing and Modeling, The Morgex North Tunnel Experiment, Springer International Publishing, ISBN: 978-3-319-49516-3, DOI:10.1007/978-3-319-49517-0.

Fridolf K., Ronchi E., Nilsson D., Frantzich H., 2013, Movement speed and exit choice in smoke-filled rail tunnels, Fire safety journal 59:8-21, DOI:10.1016/j.firesaf.2013.03.007.

Korhonen T., 2017, FDS+Evac Technical Reference and User's Guide.

Kuligowski E.D., Peacock R.D., Hoskins B.L., 2005, A review of building evacuation models NIST.

Lovreglio R., Ronchi E., Borri D., 2014a, The validation of evacuation simulation models through the analysis of behavioural uncertainty, Reliability Engineering & System Safety 131:166-174, DOI:10.1016/j.ress.2014.07.007.

Lovreglio R., Borri D., dell'Olio L., Ibeas A., 2014b, A discrete choice model based on random utilities for exit choice in emergency evacuations, Safety Science, 62:418-426, doi: 10.1016/j.ssci.2013.10.004.

Lovreglio R., Ronchi E., Nilsson D., 2015, A model of the decision-making process during pre-evacuation, Fire Safety Journal, Vol. 78:168–179, DOI:10.1016/j.firesaf.2015.07.001.

Lovreglio R., Ronchi E., Nilsson D., 2016a, An Evacuation Decision Model based on perceived risk, social influence and behavioural uncertainty, Simulation Modelling Practice and Theory, 66:226–242, DOI:10.1016/j.simpat.2016.03.006.

Lovreglio R., Fonzone A., dell'Olio L., Borri D., 2016b, A Study of Herding Behaviour in Exit Choice during Emergencies based on Random Utility Theory, Safety Science, 82:421–431, DOI:10.1016/j.ssci.2015.10.015

Lovreglio R., Fonzone A., dell'Olio L., 2016c, Mixed Logit Model for Predicting Exit Choice during Building Evacuations, Transportation Research Part A, Vol. 92:59-75, DOI:10.1016/j.tra.2016.06.018

Lovreglio R., Ronchi E., Maragkos G., Beji T., Merci B., 2016d, A dynamic approach for the impact of a toxic gas dispersion hazard considering human behaviour and dispersion modelling, Journal of hazardous materials 318 758-771, DOI:10.1016/j.jhazmat.2016.06.015.

McGrattan K., Hostikka S., McDermott R., Floyd J., Weinschenk C, Overholt K., 2013, FDS Technical Reference Guide Volume 1: Mathematical Model, NIST Special Publication 1018 Sixth Edition, FDS version 6.1.1.

Nilsson D., Johansson M., Frantzich H., et al., 2009, Evacuation experiment in a road tunnel: A study of human behavior and technical installations, Fire Safety Journal 44:458–468, DOI:10.1016/j.firesaf.2008.09.009

Ronchi, E., 2013, Testing the predictive capabilities of evacuation models for tunnel fire safety analysis, Safety science 59:141-153, DOI:10.1016/j.ssci.2013.05.008.

Ronchi E., 2014, The need for a verification and validation protocol for evacuation models, Fire and Evacuation Modeling Technical Conference (FEMTC), Gaithersburg, MD (US).

Ronchi E., Reneke P.A., Peacock, R.D., 2014, A method for the analysis of behavioural uncertainty in evacuation modelling, Fire Technology 50.6:1545-1571, DOI:10.1007/s10694-013-0352-7.

Taoka G.T., 1989, Brake Reaction Time of Unalerted Drivers, Institute of Transportation Engineers (ITE) Journal, 59(3), 19–21.