

Simulating civil emergency evaluation with Inverse Generative Social Science

Gayani P.D.P. Senanayake¹ Minh Kieu¹

Department of Civil and Environmental Engineering, University of Auckland, Auckland 1010, New Zealand¹
<http://www.cee.auckland.ac.nz/>

1 Introduction

Emergency evacuations are increasingly becoming problematic and complex in cities (Batty 2008; Borja 2007). It is because the population of the cities and coastal states is steadily growing (Chang & Lo 2016) while transportation infrastructures fail to keep pace with this growth (Dow & Cutter 2002). Under severe emergencies, evacuation is the most important and effective method to save human lives within limited time and space (Lämmel 2011). Mass evacuations often rely on automobiles which usually presents a complex process, sometimes leading to undesirable and chaotic outcomes (Lämmel 2011) where injuries or deaths are caused by crowding, crushing and congestion during emergencies (K. Wang, Shi, Goh, & Qian 2019). The unique characteristics of evacuation traffic; large number of agents, their panic or herding behaviour (Lämmel 2011), and traffic flow including accidents, damaged, and emergency vehicles (Bani Younes, Boukerche, & Zhou 2016) need to be incorporated into the design of generic traffic simulation (Yin, Wang, & Ouyang 2020). This highlights the necessity and significance of a better understanding of traffic flow dynamics, which can be used to facilitate human safety and evacuation management and planning.

Various techniques have been proposed in the existing literature to model and understand the emergency evacuation process (Chiu, Zheng, Villalobos, Peacock, & Henk 2008). Computer simulation has been an effective experimental means for evacuation planning and management due to its low cost and high speed to improve the evacuation process (Zhang, Chan, & Ukkusuri 2014). Among the computer simulation methods, Agent-Based Modelling (ABM) is particularly suitable for simulating individual behaviours and exploring emergent collective phenomena in evacuation. To capture the phenomena and complexities during evacuations, modellers often have to craft the rules of individual behaviours in ABMs from limited post-disaster surveys (Zhao, Lovreglio, & Nilsson 2020) and modellers' knowledge (Zhao et al. 2020). Although the machine-learning-based solutions reduce such a bias and provide better performance in terms of prediction accuracy (K. Wang et al. 2019), these methods fail to provide mechanistic explanations of human evacuation behaviour (Rand 2019), and only a few studies have used machine-learning techniques to investigate evacuation behaviour (Zhao et al. 2020; Şahin, Rokne, & Alhajj 2019). We argue that the existing theoretical understanding of human behaviours during evacuation is insufficient for us to effectively simulate, because of two unsolved challenges:

- Existing data about evacuation behaviours are often scarce and unreliable
- Classical models of complex systems can be highly predictive at the overall system level (i.e. black box) but fail to offer a theoretical explanation of the stochastic human behaviours

This paper presents a work-in-progress research in development of Inverse Generative Social Science (IGSS) (Gunaratne & Garibay 2017; Vu, Davies, Buckley, Brennan, & Purshouse 2021; Vu et al. 2020, 2019) for simulating human behaviours during an emergency. It first reviews the literature on agent-based modelling in simulating human evacuation behaviours and highlights the possibility of credible and falsifiable knowledge discovery frameworks to offer a theoretical explanation and modelling of human behaviours during an emergency evacuation. Instead of crafting the exact equations or rules governing human behaviours (like in classical ABMs), we hypothesise that if we can systematically generate an ensemble of potential human behaviours from the limited observed data that we have, then we can evaluate these propositions to understand how people will behave. We believe that there are still two major scientific challenges that we will address in this research:

- While other IGSS-based frameworks rely on a large volume of aggregated data, where various methods can be used to explore the behavioural space (e.g. genetic algorithms (Smith 2008), conventional genetic programming (Vu et al. 2020, 2019) or regression (Gunaratne & Garibay 2017)), we often have limited data for evacuation scenarios.
- Evacuation scenarios often involve a large number of agents, with a high diversity of behaviours, which lead to computational problems from evaluating many generated behavioural propositions, and from performing expensive bi-level optimisation of both model structure and model parameters.

2 Literature Review

There is a considerable amount of research that has proposed solutions to model pre-evacuation decision-making during an emergency (Zhao et al. 2020). Of them, several Agent-Based Models (ABMs) have been developed to investigate emergent evacuation scenarios (Dawson, Peppe, & Wang 2011; Lovreglio, Ronchi, & Nilsson 2016; Wood & Schmidtlein 2013; Zhang, Chan, & Ukkusuri 2009). Although existing ABMs can capture the dynamics during an evacuation process and offer a detailed analysis of agent interactions, each agent’s evacuation decisions are based on a set of rules (Dawson et al. 2011; Zhang et al. 2014). However, the possible linear or nonlinear trends of each factor of the model outcomes need to be specified by the modellers (modeller’s bias), and this may reduce the possibility to investigate the actual trends (Zhao et al. 2020). Under evacuation circumstances, drivers and pedestrians act in an unexpected panic situation and the traditional driver behaviour models such as car-following and lane-changing behaviour might fail to capture the conditions in emergency Li and Wang (2020). Apart from that, ABMs are not designed to produce behaviours that the designer can interpret and require intensive computational power with the complexity of the simulation (Cummings n.d.).

A very small literature exists on the “model discovery” (Gunaratne & Garibay 2017), and “inverse generative social science” (Vu et al. 2019)) of mechanism-based models. Both approaches use evolutionary computing (EC) methods to steer the search for good model structures. In a handful of studies on IGSS, evolutionary computing has also been used to search for ABM structures recently – the agents’ internal rules and structuring computational architectures. In an early study, Smith used a genetic algorithm to evolve the rules in a classifier to reproduce the observed social assortativity of birds (Smith 2008). More recently, Zhong and colleagues used gene expression programming to optimise the structure of a reward function used by agents to evaluate behavioural choices, such that the ABM could better reproduce empirically observed crowd behaviours (Zhong, Luo, Cai, & Lees n.d.). Later, Gunaratne and Garibay used genetic programming to evolve agents’ farm selection rules to identify new model structures for a NetLogo implementation of the seminal Artificial Anasazi ABM to reproduce the archaeological population demography of Long House Valley, Arizona (Gunaratne & Garibay 2017). Vu et al. (2019) develop an IGSS approach using genetic programming, decision trees, causal state modelling, and machine learning and artificial intelligence. It used multi-objective genetic programming to identify alternative situational mechanisms for a social norms model of alcohol use, aimed at both improved representation of observed drinking patterns in the US over 15 years and theoretical interpretability. The application of multi-objective genetic programming represents a starting point for building the tools needed to perform the model discovery process of IGSS. Further, IGSS is a new approach, its applicability in traffic simulation to model complex human behaviour has not yet been tested and is the most difficult aspect of the evacuation process and hard to model in mathematical equations (Mas, Imamura, & Koshimura 2011). IGSS is situated to offer meaningful insights into the mechanisms and evolve the rules to best fit the decision-making processes under pressure and panic.

Given this background, this study mainly focuses on dynamic traffic conditions among the agents during the evacuation process. The objective of this study is to build the preliminary evacuation simulation model to prove the applicability of the IGSS concept in capturing and discovering the rules of agents’ evacuation behaviours and interactions between them under data scarcity. This toy simulation model will be the base to develop a complex IGSS model that tests and analyses different case study scenarios and grasp the characteristics and effects of human traffic behaviours during the evacuation.

3 Methodology

Preliminary analysis of the study are made to simulate traffic evacuation with limited empirical data by establishing the form of the basic algorithm and determining the range of the various system parameters. The evacuation toy model uses a NetLogo modelling environment (Tisue & Wilensky 2004). We adapt the agent-based tsunami evacuation model developed by H. Wang, Mostafizi, Cramer, Cox, and Park (2016) for a case study in Auckland, New Zealand. Figure 1 shows a snapshot of the developed toy model.



Fig. 1: Toy Model on Tsunami Evacuation

The above tsunami evacuation model platform includes five components: the transportation network, the population distribution, the evacuation shelters, the tsunami inundation, and casualty model. The simulations are capable to capture evacuees' socio-demographic characteristics which are related to the evacuees' decisions, such as choice of evacuation mode, milling time which marks the start time of their evacuation, and walking speed which represents the physical ability of the evacuee. The platform is capable of simulating a tsunami evacuation scenario with variable tsunami and behavioral characteristics. In addition, the city of Auckland has been used as a case study because of its high risk of experiencing a tsunami in the foreseeable future.

Figure 1 depicts the agents behaviour after several minutes of simulation process. At the beginning of the simulation, at time $(t) = 0$, it shows the distribution of initial population in brown. The ocean is on the top, and the evacuation shelters (yellow) are placed outside the inundation zone on the bottom and left. There are fictitious six horizontal evacuation areas located outside of the tsunami inundation zone and three fictitious vertical evacuation structures within the inundation zone where they are optional for the user to add. After the earthquake, depending on the milling time, people evacuate either by car

(blue) or on foot (orange), and the tsunami inundates the city causing casualties (red). We focus on the consequences of the tsunami hazard on the road infrastructure, by providing options to break the road link during tsunami, and not on the building infrastructures.

The model can simulate several options related to human decisions and mobility characteristics. For instance, evacuation mode choice (foot, car) is one of the critical decisions, independently made by each agent, which have major impacts on the overall evacuation life safety. Equally important, and especially for near-field tsunami evacuations with less preparation time, milling time is another critical variable that is associated with evacuees' decision-making process. To capture the evacuation preparation time, as suggested by Mas et al. (2011), departure times in this work follow a Rayleigh distribution where values of t and s respectively represent the minimum milling time and the spread of the departure times. The larger is s , the larger the tail of the distribution towards later departure times will be. Further, the model provides option for the user to select immediate evacuation in which evacuees start the evacuation immediately after the tsunami alarm. Two other mobility characteristics affecting the efficiency of evacuation and the mortality rate of the scenario are the walking speed of the pedestrians and details of vehicular movement such as the maximum driving speed and other traffic flow variables (Wood & Schmidlein 2012). In this work, the movement of vehicles is governed by a classic car-following model, the General Motors model, the details of which are documented by Mostafizi, Wang, Cox, Cramer, and Dong (2017). In addition, it is assumed that walking speeds follow a normal distribution with varying mean.

3.1 Study Site

The Auckland city is chosen as the study site for this work, mostly because of its special geographical and topographical characteristics and higher population of Seaside which is estimated to be 205,608 (*Population of North Shore in 2021 2022 - statistics* n.d.). The close proximity of the Auckland, within the next 10 years, there is a 10 percent to 60 percent chance (best estimate is 30 percent) of a magnitude 7 or higher earthquake occurring in the area (*GeoNet Earthquake forecasts* 2017), which makes this city prone to tsunami evacuation in the foreseeable future. On top of these, the flat topography of the city would allow the tsunami inundation to reach a long distance inland in a relatively short time.

3.2 Data for the simulation

The model uses GIS data as input for transportation network, population distribution and evacuation shelters in the shape-file format.

4 Future Plan and Conclusion

This toy model is developed to investigate the feasibility of using IGSS to simulate individual's behaviours in an emergency, where we would need to overcome data scarcity and modeller bias. We will use the toy model to provide the *pseudo-truth* data for an machine-learning-based IGSS model to learn the action rules used in the toy model. If the model can systematically generate the hypothesised evacuation behaviour in the developed agent-based model using IGSS concepts, then these preliminary model propositions can be evaluated to understand how people will behave in an emergency, while addressing major scientific challenges of using existing IGSS-based frameworks with limited data for evacuation scenarios and computational problems with a high diversity of behaviours.

With its success, a complex IGSS model will be developed in the future to continue this research. It will execute several simulations on different scenarios and test the influence of the evacuation behaviour of agents. Hence, this toy model will be the base to consider more realistic evacuation actions in the future.

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