Simulation of Wildfire Evacuation with Dynamic Factors and Model Composition

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Abstract

Wildfires cause devastation on communities, most significantly loss of life. The safety of at-risk populations depends on accurate risk assessment and emergency planning. Evacuation modelling and simulation systems are essential tools for such planning and decision making. During a wildfire evacuation, the behaviour of people is a key factor; what people do, and when they do it, depends heavily on the spatio-temporal distribution of events in a scenario. In this paper, we introduce an approach that enables the behaviour of people and the timing of events to be explicitly modelled through what we term *dynamic factors*. Our approach composes several simulation and modelling systems, including a wildfire simulator, behaviour modeller, and microscopic traffic simulator, to compute detailed projections of how scenarios unfold. The level of detail provided by our modelling approach enables the definition of a new risk metric, the exposure count, which directly quantifies the threat to a population. Experiments for a wildfire-prone region in Victoria, Australia, resulted in statistically significant differences in clearance times and exposure counts when comparing our modelling approach to an approach that does not account for dynamic factors. The approach has been implemented in a high performance and scalable system – the architecture of which is discussed – that allows multiple concurrent scenarios to be simulated in timeframes suitable for both planning and response use cases.

Keywords:
Wildfire, evacuation planning, dynamic factors, model composition, behaviour and risk modelling

1. Introduction

Wildfires cause environmental destruction, property damage and loss of life in various parts of the world. The magnitude of the 2009 Victorian bushfires [1] and the 2007 Southern California wildfires [2] are powerful reminders. Global climate changes further exacerbate this risk, with the predicted increase in heatwaves and prolonged dry periods [3, 4] likely to increase occurrences of such events. In addition, population growth continues to drive urban development further into the wilderness, increasing the number of people in wildfire affected areas.

Enabling emergency services to better understand, plan, and prepare for wildfires is of great importance. To this end, modelling the impact of wildfires on a population and the environment has been a focus of substantial research in recent years [5–9, 11–13]. One factor of particular importance in these models is the departure time of evacuees – the time when they leave their point of origin – which depends on their awareness, beliefs and priorities.

Early work assumed scenarios in which the departure of the population, as a whole, occurs at the instant an evacuation order is issued [14]. This simultaneous evacuation approach however is not representative of real world behaviour. Subsequent works have focused on modelling departure times that better align with the expectations of experts. In general the departure times derived from such approaches follow certain distributions [8, 15, 16], as discussed further in Section 2. While these approaches offer a better model of evacuee behaviour, they do not adequately account for the numerous dynamic factors that would notably influence evacuation decisions of individuals.

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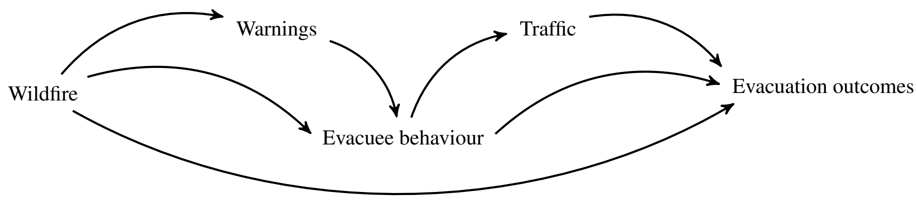


Figure 1: The key factors in an evacuation scenario

For instance, members of a family might leave while others stay to defend, and some people choose to wait until a fire is visible before evacuating.

In this paper we propose a modelling and simulation approach that takes into account some of these dynamic factors. We define dynamic factors as the events connecting the evolution of a fire to the warnings issued, and consequently to the actions of people and evacuation outcomes, as shown in Figure 1. Specifically, we attempt to answer the following research question:

What is the impact of dynamic factors on wildfire evacuation simulation and our ability to assess risk?

We model evacuation scenarios through a workflow consisting of a wildfire simulator, warning generator, behaviour modeller, traffic simulator, and analytics engine. A new metric, exposure count, is introduced in addition to the existing metrics, which represents the number of vehicles that were near the fire during the evacuation (discussed further in Section 4). Our experiments provide insights into the role of dynamic factors in modelling evacuations.

The approach described in this work has been implemented in *IBM Evacuation Planner*, a robust multi-model. system offered to stakeholders as a Software as a Service (SaaS), which allows users to easily explore and understand the risk of potential scenarios. Users can control the fire ignition location, wind velocity, shelter capacity and placement to construct hypothetical scenarios to investigate (discussed further in Section 5). In summary, the contributions of this paper are:

- a new modelling approach accounting for dynamic factors,
- analysis of the impact of dynamic factors on wildfire evacuation simulation and our ability to assess risk as a consequence,
- a new metric for evaluating the effectiveness of an evacuation and the risk associated with the affected area, and
- an architecture of a system implementing the complete modelling and simulation workflow through model composition and proof of its viability by construction.

The remainder of this paper is organised as follows. In the next section, we discuss the related work in the area of evacuation modelling and simulation. Section 3 details our modelling approach. Section 4 discusses the risk metrics used in our analysis and formally introduces the proposed exposure count metric. In Section 5 we present the system design and architecture. Section 6 covers our evaluation methodology and results of experiments. We discuss our findings in Section 7 before offering some concluding remarks in Section 8.

2. Related Work

Evacuation modelling is a five step process involving traffic generation, traffic departure time modelling, destination selection, route selection, and evacuation plan setup, analysis and revision [16]. The behaviour of evacuees largely determines their departure time, destination choice, and route selection.

Departure time refers to the time when an individual or family unit leaves their point of origin for their chosen destination. The departure time of an individual or a population has a significant impact on the outcome of an evacuation. For instance, an individual or family unit which decides to evacuate late, would be at a higher risk of exposure to a progressing fire. In fact, Haynes et al. [17] identified that a quarter of all deaths between 1955 and 2008 were a result of late evacuations. On the other hand, a population evacuating early simultaneously could lead to congestion and consequently longer evacuation times.

Accurately modelling the behavioural patterns of a population in disaster scenarios is challenging. Southworth [16] discussed four possible approaches for capturing this information. The first involves the use of data on past evacuations for similar disaster scenarios. This approach is limited however because of the lack of statistically reliable data. A second approach is to conduct a survey to identify people's intended actions during such events. This approach is also limited due to discrepancies between people's stated intentions and their actions during an actual disaster. Another approach involves estimating departure times by understanding how warning information diffuses within the population. Despite a number of studies on this, the process has not yet been adequately studied in the context of modelling wildfire evacuations [8]. Currently, the most widely used approach is to base departure times of a population on the judgement of evacuation planners or experts familiar with the area under study. Trainor et al. [28] argue that human behaviour and transportation systems are intertwined and suggest greater collaboration between engineers and social scientists in the study of evacuations. They proposed applying an interdisciplinary approach to evacuation modelling, which shares many commonalities with the present work.

The general expectation of experts is that fewer people evacuate during the early stages of a disaster and the number grows as the event progresses; ultimately reaching a certain peak then tapering off. This expectation has translated in different ways in existing works. Church and Sexton [19] for instance, directly used such advice, to gradate a population into percentages leaving in discrete time steps after an evacuation order. Other works have assumed that this expectation can be represented as a distribution. Specifically, Cova and Johnson [8] assume the departure events would follow a Poisson distribution, whereas Tweedie et al. [15] assumed the events follow a Rayleigh distribution. On the other hand, research into staged evacuations have indirectly investigated the effect of varying departure times based on the geographic location of small clusters of a population [5, 6, 20, 21]. In contrast to simultaneous evacuations, where the entire population of a region evacuates at the same time, staged evacuations involve the progressive evacuation of sub-regions or 'zones'; thus varying departure time patterns across the region as a whole.

In contrast to these approaches, this paper proposes a more representative approach to modelling departure time behaviours based on a dynamic threat model. The approach integrates three important factors:

1. *Dynamic evacuation triggers based on an advancing fire front*. An advancing fire front generates events over time (proximity warnings, fire-visible event) that are perceived by a subset of the population within the relevant proximity; this in turn triggers the evacuation behaviour of the informed residents. As the fire advances closer to a region, further evacuation triggers are sent out which could subsequently trigger evacuation responses from residents in the area.
2. *Granularity of evacuation triggers*. Unlike existing approaches, the granularity of evacuation triggers could be different. For instance, a warning that a fire would reach a certain area in 6 hours would be perceived by all residents of that area, whereas a fire visible event is more localized and perceived only by individual households within proximity of the fire front.
3. *Levels of severity of evacuation triggers*. Traditionally, departure times are calculated from the time evacuation orders are issued. However, these do not explicitly model how people would respond prior to this trigger, or to events that occur after. Hence, behaviour groups are proposed in this paper to account for the varying degrees of how people respond to warnings with different levels of severity. For instance, while some individuals might be more cautious and choose to evacuate early (e.g., in response to a '6 hour to impact' warning), others might choose to wait until they receive a more severe evacuation trigger (e.g., fire visible). Moreover the actions of individuals in the process of evacuating are also dynamic and may be influenced by new evacuation triggers. For instance, a family preparing to leave in response to an initial warning, could choose to cut their preparation short and leave immediately if a more severe evacuation trigger is perceived (e.g., fire visible).

3. Wildfire Evacuation Model

To accurately capture the effects of dynamic factors on wildfire evacuation simulation we compose a set of specialised models and simulators. Figure 2 shows our modelling workflow and the dependencies between the modelling components. The modelling is initiated with the configuration of a scenario, which includes such parameters as the

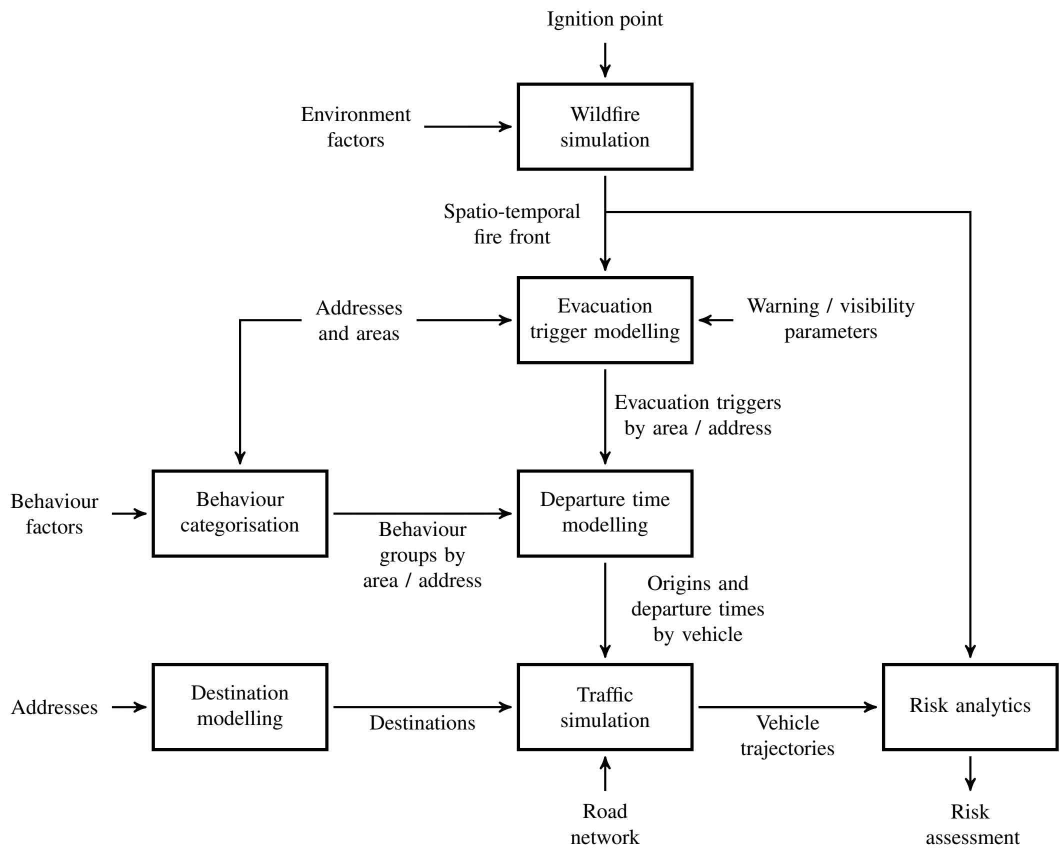


Figure 2: Modelling workflow

wildfire ignition point, environmental conditions (e.g., wind velocity), warning system parameters, and the evacuee behaviour categorisation. Each modelling component is described in detail below.

To aid discussion of various aspects of our modelling we introduce here some formal definitions. Considering a metric space (M, d) where d is the regular Euclidean distance, we define $X_t \subset M$ as the set of points under threat at time t. Let P be the total population in a scenario. Let p_{it} be the position of person i at time t. We define $A_k \subset M$ as an area, K as the set of areas in our scenario, and $U_k \in P$ as the set of people originating from A_k. We also define $T = t_0, t_1, \ldots, t_n$ to be the set of times over which we simulate.

3.1. Wildfire Simulation

As a part of our modelling workflow, a wildfire simulator has been implemented following the cellular automata model for forest fire spread prediction proposed and validated by Alexandridis et al. [22]. In particular, this model captures the effects of the type and density of vegetation, wind speed and direction, ground elevation, and spot fires. In addition, our implementation includes models of the Forest Fire Danger Index (FFDI)[2] and fire suppression efforts. In Australia, FFDI values are used as the basis for issuing warnings and advice to the population but not as triggers for evacuation. For instance, during high FFDI days, residents and tourists are advised to avoid going to high-risk areas. In this investigation weather conditions are statically applied (see assumptions in section 6.6). The output of the simulator is the spatio-temporal fire front that is fed to the evacuation trigger model.

[2]Forest Fire Danger Index. `http://en.wikipedia.org/wiki/McArthur_Forest_Fire_Danger_Index`

3.2. Evacuation Trigger Modelling

In response to the fire front progression and its projected state, several types of events are modelled and serve as evacuation triggers to the population. In particular, three types of impact warnings are modelled: 24-hour warning, 6-hour warning, and 2-hour warning. Although a 24-hour impact warning is the least urgent, it encourages residents to make appropriate preparations and leave early if they have mobility issues. A 24-hour warning may be issued before a fire begins based on forecasts of high-risk conditions. The portion of a popuulation that responds to such a warning is typically quite low (e.g., ∼ 5%).

Warnings are sent out on the per-area basis, e.g., if the fire front is projected to impact an area in 6 hours, all the residents of that area receive a 6-hour impact warning. Formally, at time w_k^τ, people in area A_k are sent a warning that the fire will impact in τ hours:

$$w_k^\tau = \min_t \{t : A_k \cap X_{t+\tau} \neq \varnothing\}, \quad t \in T. \tag{1}$$

Based on (1), the three warning types listed above can be modelled by setting τ to 24, 6, and 2 respectively. People who are in the behaviour group that responds to the broadcast warnings then initiate their evacuation procedure, as discussed in Section 3.3. Higher-priority warnings take precedence over lower-priority warnings, e.g., a 6-hour warning is considered more urgent than a prior 24-hour warning, or similarly a 2-hour warning is more urgent than a 6-hour warning received earlier. This is necessary since the departure time of an evacuee responding to a 24-hour warning may be later than the departure time of the same evacuee responding to a warning of a more imminent threat.

We also model *fire visibility* triggers (the priority of these triggers exceeds all warnings), which cause affected people to evacuate when the fire front is within visible range of their initial location. Let the visibility distance be ϵ, then the trigger time v_h due to a threat for a household $h \in M$ is defined as:

$$v_h = \min_t \{t : d(h, X_t) \leq \epsilon\}, \quad t \in T. \tag{2}$$

Fire visibility events have greater spatial granularity when compared to impact warnings, since they are triggered for each household (address) independently as opposed to the area broadcast approach used for warnings.

3.3. Behaviour Categorisation

Private vehicles are the primary form of mobility for people living in wildfire prone areas. We therefore focus on capturing vehicle use and vehicular traffic in our modelling. Assuming the initial location of the population within the area is known, we first assign people at addresses to vehicles. Recalling that P is our set of people and letting V be our set of vehicles, we can then treat the vehicle assignment as a function ψ that maps people to vehicles: $\psi : P \to V$.

Assuming κ is the average number of people per vehicle (set to 1.5 in our experiments), we use this parameter to transform a set of people at each address to a set of vehicles with the initial location equal to the address location. A set of people in each vehicle forms a group that makes collaborative decisions. Each group is assumed to make a decision regarding what events trigger the group to evacuate, where events include warnings and fire visibility, should they occur. A set of evacuation triggers E_g that will make a group g evacuate specifies the behaviour of that group. These behaviours are configured for a scenario by setting a proportion of evacuee groups that will respond to each event. This proportion is referred to as the *participation rate*. The participation rates used in our evaluation for each evacuation trigger are provided in Section 6.2. We further assume that household members are together at the time of the fire; no special trips are made to collects other members.

3.4. Departure Time Modelling

Departure times during evacuation scenarios are affected by a number of factors [29]. Our departure time model applies the evacuation triggers and spacial behaviour groups to estimate departure times for each vehicle in the simulation. When an evacuation trigger is received by a group, a departure time is calculated for those members that are responsive to the specific trigger. We model the departure time of these evacuees as a sum of two components: decision time delay and preparation time. The decision time delay represents the interval between an occurrence of an evacuation trigger (e.g., warning, fire visible) and the collaborative decision of the group to evacuate. This delay is modelled as a constant specific to the event type that triggered the group to evacuate, where a higher urgency evacuation trigger leads to a lower decision time delay.

The preparation time component is modelled as a random variable following the Rayleigh distribution. This distribution has been found to closely match data on the typical evacuation preparation time provided by subject matter experts [15]. The Rayleigh cumulative distribution function with a mode of σ can be expressed as:

$$F(x) = 1 - \exp(-x^2/2\sigma^2), \quad x \in [0, \infty). \tag{3}$$

The parameters of the decision time delay and preparation time for each of the evacuation triggers used in our evaluation are provided in Section 6.3. The location-dependent departure times per vehicle are then used by the traffic simulation to generate the origin-destination pairs and vehicle start times.

3.5. Destination Selection

In this study we assign destinations to evacuees based on proximity. We define $b_i \in M$ as the destination of evacuee i. If C is a set of destinations (outside the threatened areas), then a destination c is chosen for person i with the minimum distance between c and the initial position p_{i0} (note that 'arg min' evaluates to the argument that minimises the objective term):

$$b_i = \arg\min_{c \in C} d(p_{i0}, c). \tag{4}$$

We acknowledge the limitations of this basic destination selection model; however, it is sufficient for answering the research question we are investigating in this study.

3.6. Traffic Simulation

An agent-based traffic simulator was used for the prediction of vehicle (and thus, people) movements for each scenario. The particular simulator we use, SUMO (Simulation of Urban Mobility) [23], falls into the *microscopic* category. In microscopic traffic simulation, the dynamics of each individual vehicle are modelled, and results are derived from the interactions of each agent/vehicle with road conditions and other vehicles. This contrasts with the *macroscopic* model where traffic can be modelled on a road-by-road basis [24]. Microscopic traffic simulation has been applied to evacuation simulation at the neighbourhood scale in the past [8, 19]. SUMO was chosen due to the granularity of its output, which includes, for example, the exact coordinates of each vehicle at any given time during the simulation. The path of each vehicle is computed using Dijkstra's shortest path algorithm.

For our analysis we are interested in the set of vehicle trajectories. If v_{jt} is the position of vehicle $j \in V$ at time t, then the position p_{it} of person i is $v_{\psi(i),t}$. People who do not evacuate are assumed to remain at home ($p_t = p_0, \forall t \in T$).

3.7. Risk Analytics

This component computes the risk metrics as described in the next section and pre-processes the simulation results to be used in visualisation.

4. Risk Metrics

With the detailed results produced by the simulators and models described in Section 3, it is possible to derive more granular risk predictions. Specifically, we approximate the danger to a person by considering their proximity to the threat. We introduce here the person-threat distance and the related exposure count for an area or population.

4.1. Clearance time

A common metric used in estimating risk for an area is the *clearance time* [5, 8, 13, 19]. For the purpose of this investigation we define the clearance time relative to the start of the scenario t_0. That is, the clearance time c_k for an area A_k is the earliest time when there are no people left within A_k. This includes both people originating within A_k and those passing through. Recalling that P is the total population in a scenario,

$$c_k = \inf \{t : A_k \cap U_t = \varnothing\}, \quad \text{where} \quad U_t = \bigcup_{i \in P} p_{it}. \tag{5}$$

The infimum, 'inf', is the largest quantity that is less than or equal to each of a given set or subset of quantities.

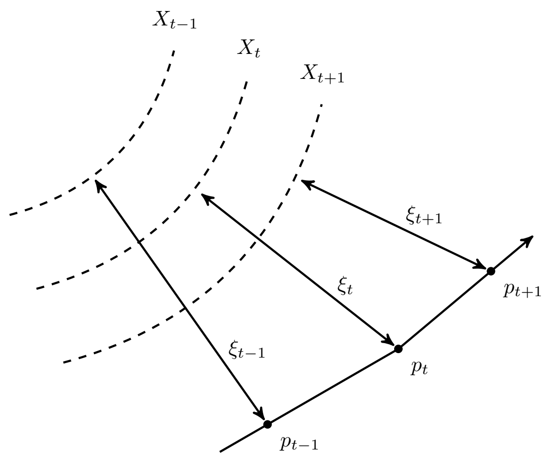


Figure 3: Person-threat distance

4.2. Exposure count

Han et al. [18, 30] advocate for measures of evacuation effectiveness that account for risk that varies in both space and time. We here describe how such a measure can be derived from our simulations. Our modelling approach yields estimates of the position of people over the course of a scenario, as well as the progression of the fire. People near or within fire-affected areas may suffer injury or loss of life. It is therefore useful to count how many of these *exposures* occur in our simulated scenarios.

For the purpose of this investigation we are concerned with the people who leave; the modelling of those who remain at home does not change between the *static* and *dynamic* cases. A future extension might consider how estimates of the resiliency of shelter-in-place options can be used to calculate an adjusted exposure count that includes people who do not evacuate.

Depending on the intensity of a fire and various environmental factors, the area that constitutes a direct threat to personal safety may extend beyond the fire front. For this reason we would like to include in our exposure count metric the ability to specify a distance threshold. By adjusting this distance dynamically, the fire intensity can be taken into account when calculating the exposure count. In this paper, however, we assume that the fire intensity and environmental conditions are static.

We can calculate the minimum distance between a point $p \in M$ and the points under threat X_t as $d(p, X_t) \equiv \inf\{d(p,a) : a \in X_t\}$. Both the threat and the position of each person will vary over time, as is seen in Figure 3. We then define the *person-threat distance* at time t as:

$$\xi_{it} = d(p_{it}, X_t), \quad \forall i \in Q, \tag{6}$$

where Q is a set of people. We also obtain a minimum person-threat distance as:

$$z_i = \min_t \xi_{it}, \quad t \in T. \tag{7}$$

We define the *exposure count* for a population Q in a given scenario as the total number of people who were within some distance δ of the threat at some point in time, then we can compute it as follows:

$$E_Q = \sum_{i \in Q} H(\delta - z_i), \quad \text{where} \quad H(x) = \begin{cases} 0, & x < 0, \\ 1, & x \geq 0. \end{cases} \tag{8}$$

5. System Design and Implementation

Simulating evacuation response as a result of a dynamic fire threat requires the integration and robust interaction of number of different modelling and simulation components. The approach discussed in this paper is integrated into the

IBM Evacuation Planner, which is a solution offered to customers (evacuation planners, analysts, etc.) as a SaaS. The solution presents users with a web interface through which they can run evacuation simulations based on a number of different environmental variables such as the location and starting time of fire(s), the placement and capacity of shelters, and the velocity of wind. This allows experts to better understand some of the conditions that exacerbate the risk to a population, as well as investigate possible solutions. For instance, experts can explore the following questions. What is the effect of a fire starting at a certain area, during a hot dry day under high winds (i.e., what is the average clearance time of the region, how many people would be exposed to the oncoming fire, what is the vehicle departure time profile for each region)? Which road segments cause the most congestion during an evacuation? How would evacuations improve if the behaviour profile of a population in a region were to change (e.g., if people were more alert, prepared and cautious)?

The architecture of the system follows a Service Oriented Architecture (SOA) approach with multiple independent services for the various modelling and simulation components, as shown in Figure 4. This separation into multiple bounded web-services improves the ease and efficiency of development, testing, deployment, maintenance and scalability of the system. In addition, the architecture of the system enables easy composition of new capabilities (as services) into the platform as well as the replaceability of any module by a functionally equivalent alternative service (e.g., a different behaviour modeller or wildfire simulator) with minimal impact to dependent services. This is achieved through the loose coupling of services and the standardisation of the Application Programming Interfaces (APIs) for all services. Loose coupling is achieved by using the data requirements and outputs of modules as a point of dependency rather than specific APIs. Additionally, all modelling, simulation and analytics services are exposed through a standardized REST API designed around the abstract concept of a Job. A common service framework to handle job management, request processing, data input and output validation, as well as cross-cutting concerns has been implemented and used across all services.

Four services, a wildfire simulator, behaviour modeller, traffic simulator, and analytics engine, collectively compose the system's core capabilities as shown in Figure 4. The four modelling and simulation services shown in the diagram map to the model composition flow diagram in Figure 2 discussed in Section 3 as follows: the wildfire simulator and traffic simulator components directly map to the wildfire simulation and traffic simulation steps in Figure 2. The behaviour modelling service is responsible for the evacuation trigger modelling, departure time modelling, behaviour categorisation, and destination modelling aspects. Finally, the analytics engine is responsible for computing risk analytics.

In addition to the core services, ancillary services: a workflow manager, an orchestrator, and a data service, drive the computation and data flow of these systems. The workflow manager service, specifically, is responsible for reactively driving the sequence of computations that are outlined in Figure 2. The orchestrator service is responsible for managing a registry of services and data event notifications (data inputs and outputs of modules) across modules. Finally, the data service component is responsible for both storing and serving the simulation outputs as they are generated by individual modelling components.

6. Evaluation

To quantify the impact of dynamic factors on wildfire evacuation simulation, we investigate two modelling approaches. The first approach, which we will refer to as the *static* model, links the wildfire to the behaviour through a single impact time for the region. Evacuee departure times are sampled from a global probability distribution designed to capture the variation of behaviours among all evacuees.

The second approach, which we will call the *dynamic* model, implements the procedures described in Section 3. The dynamic model captures the time-dependent interactions between the fire front evolution, evacuation triggers, and behavioural characteristics.

We have conducted our experiments for a region called The Dandenong Ranges, which is a wildfire-prone part of Victoria, Australia. Figure 5 presents the features of the region subdivided into 28 areas following the Statistical Areas Level 1 (SA1) classification as defined by the Australian Bureau of Statistics (ABS)[3]. These areas are designed to contain an average population of approximately 400 people. There are around fifty-five thousand such areas covering

[3]Australian Bureau of Statistics. `http://abs.gov.au/`

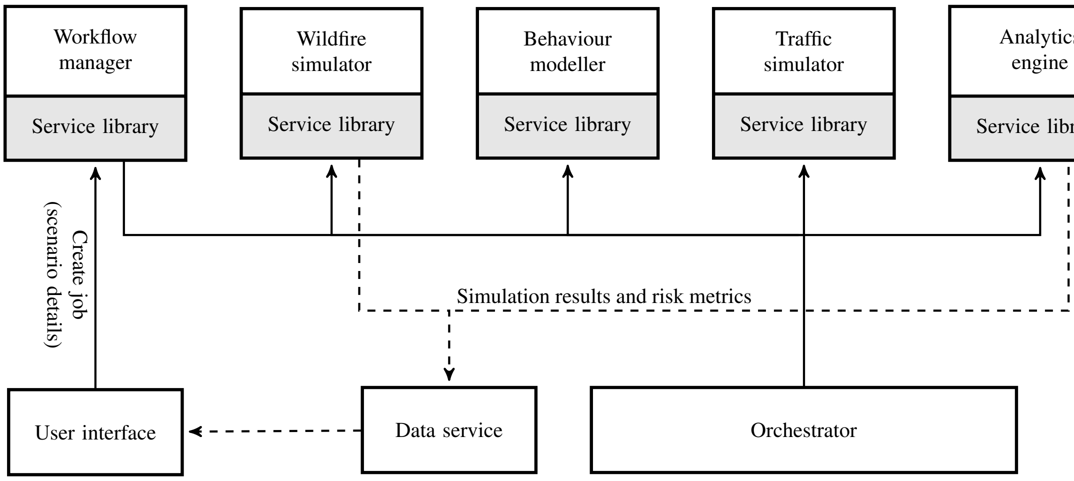
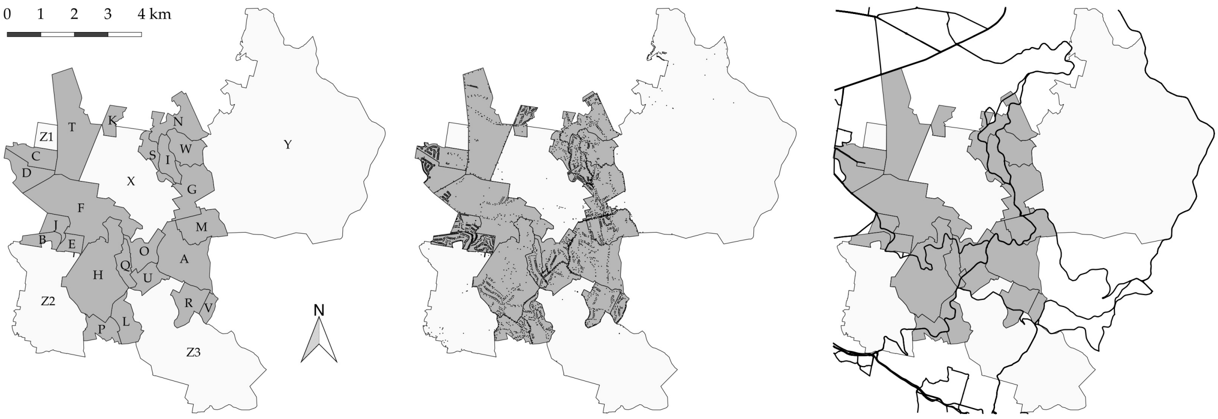


Figure 4: System architecture



(a) Regional subdivisions (b) Addresses (c) Major roads

Figure 5: The Dandenong Ranges

Australia. In particular, Figure 5a shows the areas we use in our experiments labelled $A, \ldots, Z3$ ordered by decreasing population size. Areas $Z1, Z2$ and $Z3$ have no registered residential population. Figure 5b shows the location of all the addresses within the areas considered, where each dot represents one or more registered addresses. Finally, Figure 5c highlights the major roads in and around the region. The detailed data on the region and population are provided in Appendix A.

Both the static and dynamic modelling approaches are applied to three independent evacuation scenarios defined by wildfire simulation with different ignition points and environmental conditions within The Dandenong Ranges as discussed in the next section.

6.1. Ignition Points and Environmental Conditions

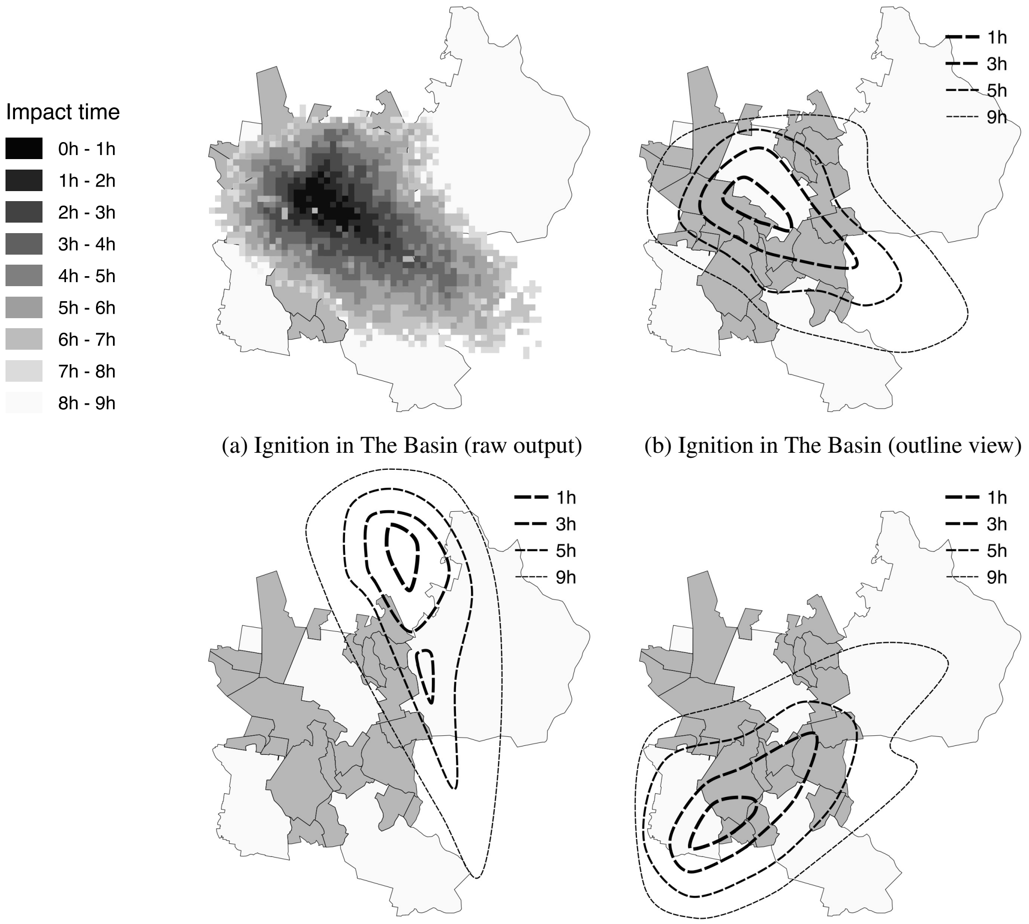
We have selected three wildfire scenarios typical for The Dandenong Ranges based on historical records and discussions with local experts. We refer to these scenarios by the names of suburbs where the ignition points are located: The Basin, Montrose, and Tremont. The environmental conditions corresponding to each of the simulated ignition points are shown in Table 1.

Figure 6a shows the raw output of the wildfire simulator for the wildfire ignited in The Basin, where darker cells represent the earlier fire impact time. Figure 6b shows the corresponding simplified outline-based representation of

Ignition	FFDI	Wind direction	Wind speed (km/h)
The Basin	80	SE	60
Montrose	80	SSE	60
Tremont	75	NNE	40

Table 1: Fire ignition points and environmental conditions

the wildfire evolution, which we use in further visualisations for the sake of clarity. The outline-based simulation outputs of the Montrose and Tremont wildfires are shown in Figures 6c and 6d respectively. These particular wildfire scenarios were selected to represent a range of patterns in which a wildfire may impact the region.



(a) Ignition in The Basin (raw output)

(b) Ignition in The Basin (outline view)

(c) Ignition in Montrose

(d) Ignition in Tremont

Figure 6: Wildfire simulation output for the ignition points and environmental conditions shown in Table 1

6.2. Behaviour Categorisation Parameters

As discussed in Section 3.3, groups of evacuees make collaborative decisions on whether to respond to an evacuation trigger. In our experiments, the behaviour is assigned to groups according to participation rates listed in Table 2. The total participation rate over the complete set of evacuation triggers is 85%, which means 15% of evacuee groups are assumed to stay at home (shelter in place / defend).

Evacuation trigger	Participation rate	Decision time delay (min)	Preparation time mode (min)
Fire visible	40%	0	10
2-h warning	30%	10	20
6-h warning	10%	20	30
24-h warning	5%	30	60

Table 2: Evacuee behaviour parameters for each evacuation trigger

6.3. Departure Time Distributions

The departure time parameters (i.e., decision time delay and preparation time mode) used in the dynamic model are presented in Table 2. Since in the static model evacuees leave according to a global departure time distribution, in order to obtain an accurate estimate of distribution we have taken an approach of first conducting a simulation of the corresponding dynamic case and then estimating the distribution from the sample of the simulated departure times. Based on a biased estimator of the Rayleigh scale parameter, Siddiqui [25] derived an unbiased estimator:

$$\sigma = \hat{\sigma}\frac{\Gamma(N)\sqrt{N}}{\Gamma(N+1/2)}, \quad \text{where} \quad \hat{\sigma} \approx \sqrt{\frac{1}{2N}\sum_{i=1}^{N} x_i^2}. \tag{9}$$

We used this estimator to estimate the parameters of the departure time distributions for each of the static cases—The Basin ($\sigma = 148$), Montrose ($\sigma = 204$) and Tremont ($\sigma = 160$). Figures 7a, 7c, and 7e show the departure times obtained from the dynamic scenario simulations. These figures also show the probability density functions of the corresponding Rayleigh distributions estimated from the samples using (9). Figures 7b, 7d, and 7f show departure times sampled from the estimated Rayleigh distributions for each of the corresponding static cases. The relative frequency in the diagrams corresponds to the probability that a vehicle leaves at the given time after the fire ignition event. The time distributions for the dynamic case exhibit a more wave-like pattern when compared to the static case. This is more realistic for people responding to staged warnings and fire visible events such as the evacuation triggers shown in table 2.

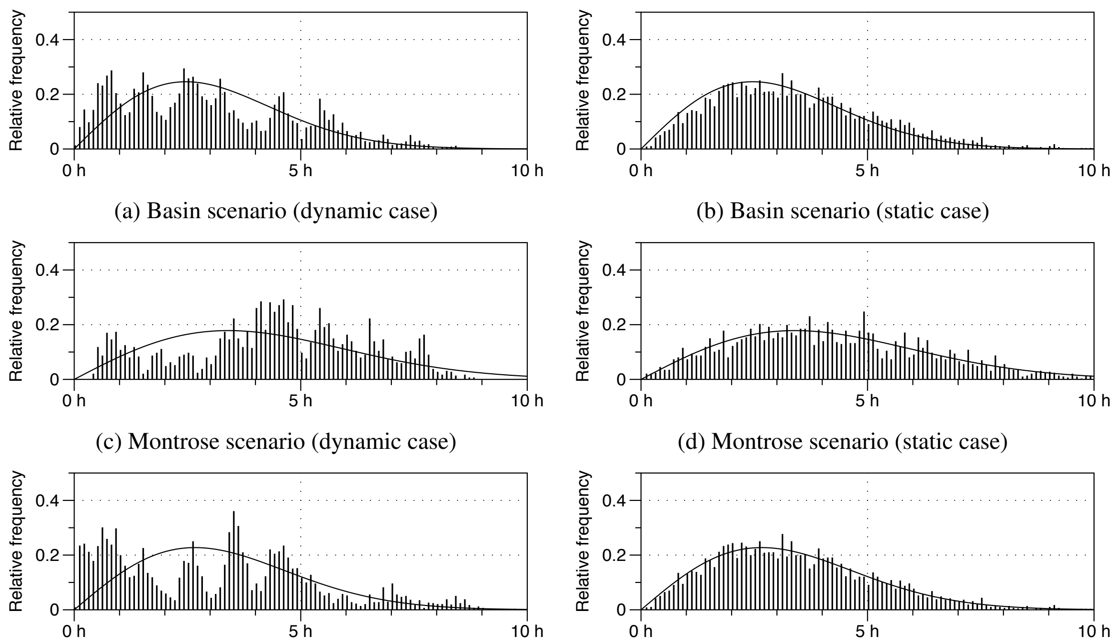
6.4. Data Sources

Our experiments make use of several public data sources along with input from subject matter experts. In particular, the road network model used in this study takes input from the OpenStreetMap (OSM) project[4]. The project creates and distributes free and open geographic data, licensed under the Open Data Commons Open Database License (ODbL)[5]. The study in this paper utilises the OSM road network data current for April 2013.

Demographic data were obtained from the ABS. In particular, a subset of the data collected during the Census of Population and Housing conducted by the ABS on 9 August 2011, which was Australia's sixteenth national Census[6]. We make use of addresses and population data sets for the areas shown in Figure 5. The provided data sets are of the highest quality available on the demographics of Australia. Prior to being released, the data pass through a confidentiality process, which results in small introduced errors; however, the information value of the data set as a whole is not affected.

Through the Victorian Government Data Directory[7], elevation[8] and vegetation[9] data sets have been obtained to use as inputs to the wildfire simulator. Transformation of these data sets was carried out using PostgreSQL with the PostGIS extension to obtain regular gridded data as required by the wildfire simulator.

[4]OpenStreetMap. `http://openstreetmap.org/`
[5]OpenStreetMap: Copyright and License. `http://openstreetmap.org/copyright`
[6]Australian Census of Population and Housing. `http://abs.gov.au/websitedbs/censushome.nsf/home/census`
[7]Victorian Government Data Directory. `https://www.data.vic.gov.au`
[8]Elevation data set. `https://www.data.vic.gov.au/data/dataset/vicmap-elevation-1-5-contours-relief`
[9]Vegetation data set. `https://www.data.vic.gov.au/data/dataset/vicmap-vegetation--25-000`



(a) Basin scenario (dynamic case) (b) Basin scenario (static case)

(c) Montrose scenario (dynamic case) (d) Montrose scenario (static case)

(e) Tremont scenario (dynamic case) (f) Tremont scenario (static case)

Figure 7: Departure time distributions

6.5. Population Assignment

The publicly available data sets described in Section 6.4 contain data on the locations of addresses and population counts per area. Since the modelling requires input data on the initial locations of people within the area, an additional step of assigning population to address locations is required. Taking into account performance and scalability, the following procedure has been adopted. Let n be the population size that needs to be assigned to m addresses. First, each address is assigned $\lfloor n/m \rfloor$ people, then an address subset of size $n - \lfloor n/m \rfloor$ is randomly selected and assigned one extra person each (assuming $n \leq 2m$). This procedure can be efficiently implemented using PostgreSQL.

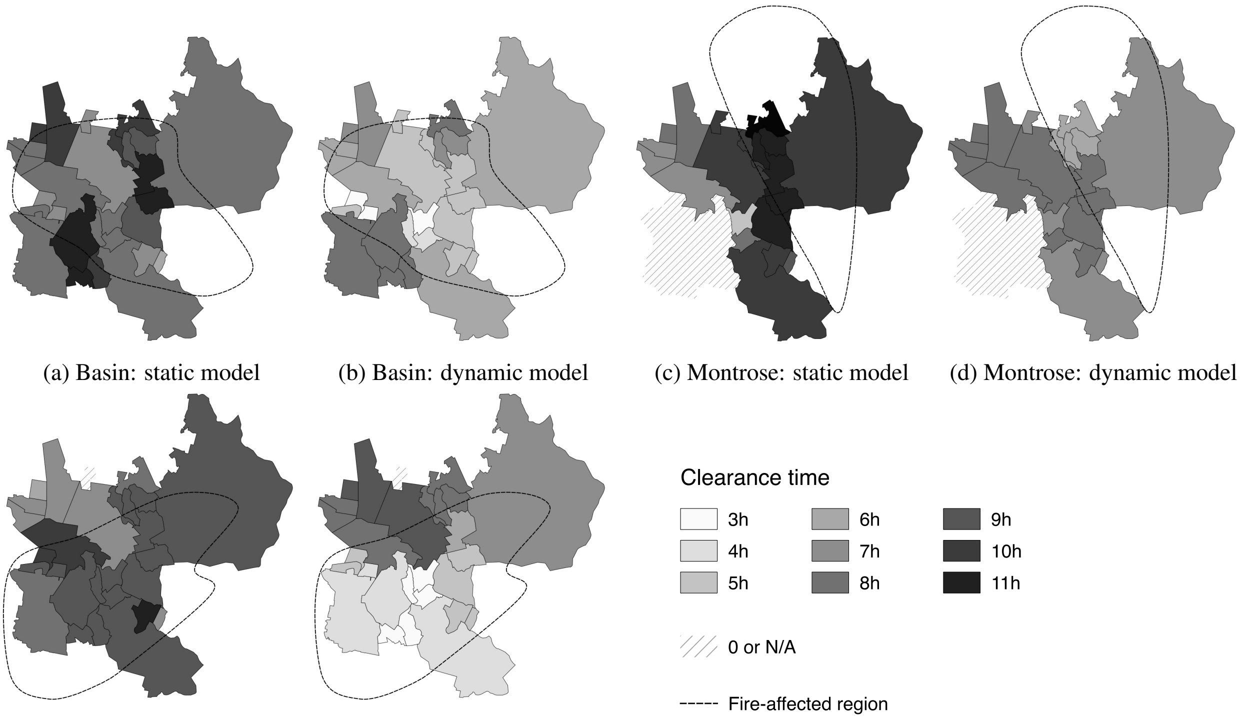
6.6. Assumptions

The scenarios presented are not necessarily representative of all possible scenarios and care should be taken when attempting to generalise from any findings. Furthermore, the following assumptions need to be taken into account when interpreting the results:

- Vehicle numbers are derived from residential data and do not depend on the time of day. However, in reality, the number of people in an area may vary with time. For example, during the week many people leave the region during the day because their workplace is located elsewhere. Conversely, on weekends the number of people in the area can significantly increase as the area is a population tourist destination.
- Route selection is static; drivers do not change their route even when encountering significant delays.
- People drive to their nearest exit, and obey the speed limits.
- Residents all receive warnings when they are sent. We assume authorities will use a variety of channels (SMS, radio, television, social media, etc.) to communicate with the public and that this provides sufficient coverage to reach all the relevant people.
- Weather conditions are constant throughout the scenario, i.e., FFDI, wind velocity. Fire intensity is also assumption constant in our exposure risk metric.

6.7. *Results*

Our stated objective is to assess the impact of dynamic factors on wildfire evacuation simulation. And we are particularly interested in the implications this might have for quantifying risk in regions subject to wildfires. To this end, we simulated scenarios using the static model and the dynamic model for each of the three fire ignition points: The Basin, Montrose, and Tremont.



(a) Basin: static model (b) Basin: dynamic model (c) Montrose: static model (d) Montrose: dynamic model

(e) Tremont: static model (f) Tremont: dynamic model

Figure 8: Clearance times

The clearance times computed for each scenario are shown in Figure 8. Through visual inspection it is apparent that there is a significant difference in how the evacuation progressed when comparing the static models with the corresponding dynamic model. In particular, in the dynamic model the clearance time of the areas closer to the fire ignition point are lower and increase towards the boundary of the final fire shape. This is explained by the fact that areas closer to the fire ignition point get triggered earlier allowing the evacuees to leave while the roads are not yet congested. The clearance times increase in the farther areas as more vehicles appear on the roads following the fire progression. By contrast, in the static models the clearance times do not follow such a pattern due to the single global departure time distribution which does not account for the spatial distribution of people in relation to the dynamic evolution of the wildfire.

We can confirm these observations through statistical tests on the clearance times. One appropriate technique is the paired t-test, where the pairs are naturally formed by the clearance times of the same region computed from the static and dynamic models respectively for each of the fire ignition points. This results in the total of 84 value pairs, that is, 28 areas for each of the 3 fire ignition points. To meet the assumptions of the paired t-test, the differences between the values of each pair are required to be normally distributed. The Shapiro-Wilk normality test [26] on the differences results in a p-value of 0.237, which means we accept the null hypothesis of the differences coming from a normal distribution. A paired t-test on the pairs of the corresponding clearance times results in a p-value < 0.001, which means there is a statistically significant difference between the clearance times from the static and dynamic models.

Another risk metric we use to compare the two modelling approaches is the exposure count introduced in Section 4. Figure 9 visualises the exposure counts for each scenario. As with the clearance times, it is clear that the

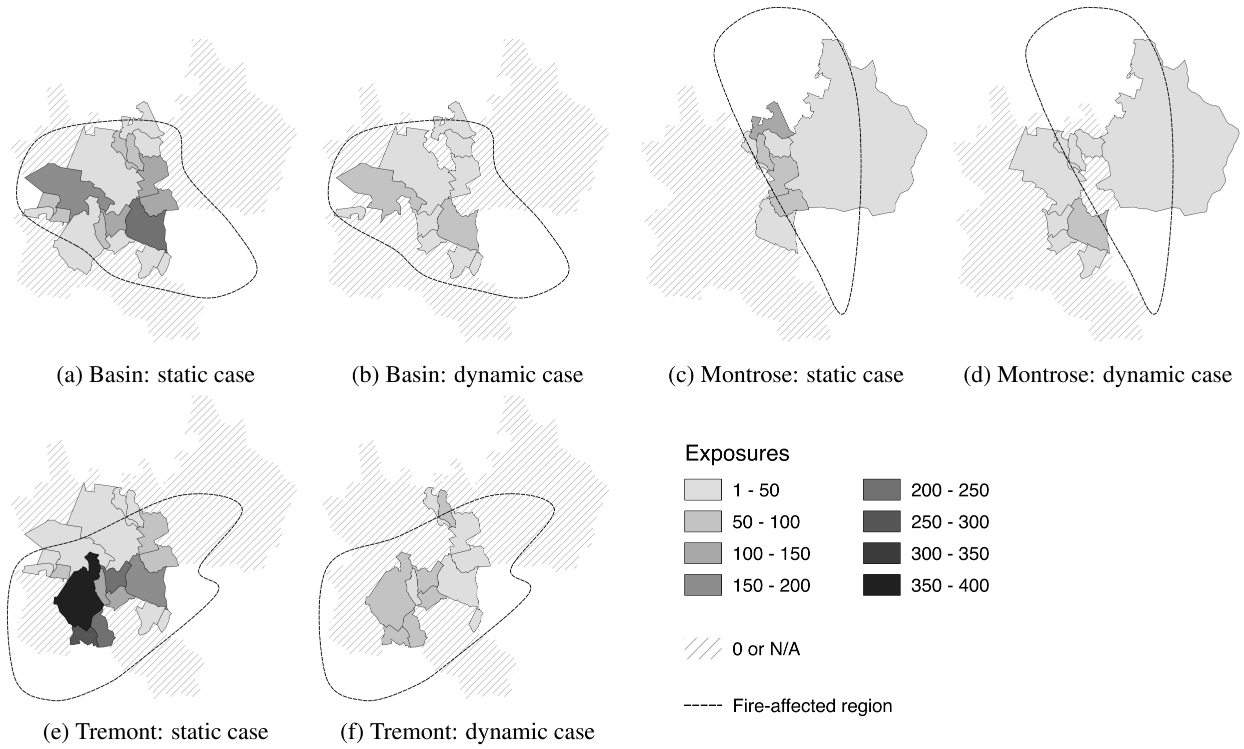


Figure 9: Exposure counts (δ = 0)

exposure counts differ significantly between the static and dynamic models. In particular, the exposures in the scenarios employing the static model are higher. This can be attributed to the fact that the evacuees leave their homes based on a global departure time distributions rather than responding to evacuation triggers as in the dynamic cases.

We can confirm these observations using statistical tests. Applying the Shapiro-Wilk normality test on the differences between the pairs of exposure counts predicted by the corresponding static and dynamic scenarios yields a p-value of 0.01, which means the null hypothesis of the differences being normally distributed must be rejected. This also means that the assumptions of the paired t-test are not satisfied. Therefore, we resort to a non-parametric Wilcoxon signed-rank test [27] for comparing two related samples. This test results in a p-value < 0.001, which means that the difference between the two samples is statistically significant. The detailed scenario results are presented in Appendix B.

7. Discussion

As was shown in Section 6.7, incorporating dynamic factors into our modelling approach creates a statistically significant difference, when compared with the static modelling approach. This also means that the static modelling approach is not able to capture the dynamics of a complex wildfire evacuation scenario involving dynamic threat evolution and multiple evacuation triggers, which happen in reality.

It is not, in general, surprising to see models with greater representational capacity producing more realistic predictions of complex phenomena. And the model we have presented is by no means the most sophisticated model conceivable. But developing models of arbitrary complexity should not be our aim. We are primarily concerned with the suitability of a model for some purpose, and this should take into account other factors such as data requirements, ease-of-use and computational complexity. The assumptions and simplifications we have made were chosen for these reasons.

The model presented here is typically solved in under five minutes on a cluster of mid-tier Virtual Machines (VMs). For our experiments, the instances provisioned were mostly dual-core Linux machines with 4GB of RAM. The only exceptions were the VMs hosting our database (quad-core, 16GB) and traffic-simulator (8-core, 8GB), owing to their more advanced computational requirements. It should also be noted that the architecture we have designed is suited to concurrent execution of scenarios and can scale horizontally by adding more VMs.

The initial data required as inputs (e.g., road networks, vegetation, population statistics) are readily available for most parts of the world, and again, this is where the modularity of our approach eases the task of integrating variable sources of data. There would, of course, be some work required to correctly apply streams of data into the system. However, this is neither an onerous nor complex task. Moreover, the modelling and general approach we employ can be understood by non-experts, which is an important feature for some real-world applications.

For an area the size of the one we have studied (68 km^2) there is a significant difference in the timing of the events considered, as experienced by the people distributed throughout. For larger areas this will also be the case, but for smaller areas this may be less critical. Thus the importance of the dynamic factors we have studied here is expected to increase with the size of the region being studied. One should also consider the distribution of people in the region. These factors can be accounted for in the subdivision of the population. The manner in which we group people was influenced by our model of how warnings are delivered. More complex models of the information flowing to people might need to consider alternatives to the geographic categorisation strategy, e.g., social groups.

The exposure count metric, which we have introduced here, provides a more direct estimate of the severity of a scenario. By comparison, the clearance time can mask anything between inconvenient traffic congestion and a multi-fatality tragedy. Clearance times are also sensitive to small changes in vehicle trajectories. For this reason we believe the exposure count is a more useful metric.

An extension to the exposure count metric which may better account for the dynamics of these scenarios would be to look not only at the minimum person-threat distance, but at some aggregate of their threat proximity over the duration of the scenario. For example, one can define a function f that quantifies the person-wise instantaneous level of threat in terms of distance and integrate this with respect to time: $\int f(d(p(t), X(t)))\, dt$. The application of this measure is the focus of ongoing work.

8. Conclusions

In this paper we presented a new model for predicting the outcome of wildfire evacuation scenarios. The model extends existing approaches by including dynamic evacuation triggers as determined by an evolving wildfire simulation. The actions of evacuees are dependent on their location relative to the threat. Thus, dynamic triggers enable us to model departure times with greater location sensitivity. In addition, the combination of a microscopic traffic simulator with a dynamic fire spread simulator has enabled the use of a new metric, the exposure count, which provides a more direct estimate of the threat to a population in an evacuation scenario.

Through our experiments we have shown that the dynamic modelling approach produces a statistically significant difference in the predicted outcome of evacuation scenarios compared with the static model. Specifically with respect to the area-wise clearance times and exposure counts. Finally, the approach we propose was enabled by the model composition architecture we discussed. This architecture supports the seamless integration of modelling and simulation components in a way that is both efficient and scalable.

The work we have described is part of the IBM Evacuation Planner, which is a decision support system for emergency service personnel. The system is applicable to staged evacuation planning, where the sequence and timing of evacuating groups can be studied in terms of the predicted exposure count. The definition of staging strategies can be achieved through the warning system model and the related response of residents to these warnings. According to Chen et al. [5] staging strategies are difficult to generalise, and thus tools that enable scenario-specific investigations are required. Another use case for our system follows from recent work by Li et al. [10], where household-level staging is considered. The multi-model agent-based approach we employ is well suited to studying such granular strategies and will be useful for further research in this area.

An interesting aspect of future work is investigating the sensitivity of simulation results to various behavioural factors, such as the number of people per vehicle, timing of warnings and responses, granularity and area size of evacuation triggers. A comparative study on these and other factors could provide insights on the robustness of the model also in relation to the dynamics of fire fronts. In addition, more realistic vehicle routing could take into account the behavioural preferences of drivers, such as their use of major roads or the tendency to choose gathering points, such as shopping centres, as their evacuation destinations. Vehicle re-routing due to blocked roads and fire or smoke visibility can further enhance the applicability of the model to real-world scenarios. Another direction mentioned earlier is taking into account the resiliency of shelter-in-place options to calculate an adjusted exposure count that includes people who do not evacuate and remain in a fire-affected area.

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Appendix A. Region and Population Data

Area	Population	Addresses	SA1 ID
A	575	273	2128220
B	547	250	2125214
C	540	176	2126311
D	539	201	2125202
E	529	225	2125213
F	498	187	2125250
G	498	358	2128223
H	492	282	2128232
I	485	219	2128222
J	467	207	2125215
K	459	149	2128013
L	431	185	2128218
M	396	222	2128219
N	347	199	2128216

Area	Population	Addresses	SA1 ID
O	347	187	2128224
P	322	153	2128228
Q	285	123	2128202
R	265	134	2128210
S	230	113	2128226
T	229	125	2127711
U	228	105	2128225
V	214	102	2128206
W	181	107	2128221
X	18	35	2128217
Y	10	103	2128230
Z1	0	1	2126328
Z2	0	45	2128227
Z3	0	67	2128231

Appendix B. Detailed Scenario Results

Area	The Basin				Montrose				Tremont			
	Clearance		Exposures		Clearance		Exposures		Clearance		Exposures	
	Stat.	Dyn.	Stat.	Dyn.	Stat.	Dyn.	Stat.	Dyn.	Stat.	Dyn.	Stat.	Dyn.
A	9:51	5:28	241	54	11:25	8:53	30	78	9:59	5:18	175	24
B	8:06	5:58	25	11	–	–	–	–	9:21	5:04	44	0
C	8:59	6:52	–	–	7:14	8:40	–	–	7:43	8:47	–	–
D	8:24	6:51	–	–	7:15	8:41	–	–	7:42	8:45	–	–
E	7:18	3:20	69	0	–	–	–	–	9:08	4:47	58	0
F	8:44	6:50	182	78	7:16	8:43	–	–	10:15	8:45	5	0
G	11:39	5:13	121	2	11:11	8:16	87	1	9:10	6:17	79	38
H	11:04	8:54	31	1	–	–	–	–	9:50	4:33	356	89
I	9:31	7:52	70	0	11:16	6:17	73	20	9:16	8:45	16	74
J	7:32	3:30	67	0	–	–	–	–	10:16	5:31	17	0
K	7:59	5:06	–	–	10:05	7:35	–	–	–	–	–	–
L	10:56	8:52	0	0	–	–	–	–	9:54	2:41	236	59
M	11:40	5:15	103	0	11:25	8:51	72	1	9:59	5:36	92	10
N	10:37	8:16	5	35	12:53	6:01	141	0	8:32	8:57	0	0
O	8:35	3:28	149	2	5:15	7:55	0	33	9:55	3:02	204	75
P	11:05	8:54	0	0	–	–	–	–	9:48	2:23	262	88
Q	8:15	4:37	58	0	–	–	–	–	9:50	2:39	150	33
R	7:11	5:51	15	2	10:06	8:05	0	2	11:02	5:24	46	0
S	10:37	5:21	53	0	10:13	6:15	41	23	9:10	8:57	4	8
T	10:14	7:59	–	–	8:06	8:43	–	–	7:50	9:58	–	–
U	8:36	4:37	48	16	8:31	8:47	0	8	9:49	2:52	126	56
V	6:09	5:33	12	21	9:32	7:29	0	0	7:20	5:18	26	2
W	9:31	7:52	3	2	11:45	6:17	48	2	9:16	8:44	0	0
X	7:59	5:17	9	2	10:07	8:48	0	9	7:40	9:45	2	1
Y	8:31	6:02	0	0	10:41	7:38	5	7	9:11	7:22	0	0
Z1	10:14	7:59	–	–	8:06	8:40	–	–	6:31	9:57	–	–
Z2	8:36	8:26	–	–	–	–	–	–	8:28	4:27	–	–
Z3	8:15	6:04	–	–	10:05	7:56	–	–	9:51	4:55	–	–