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EMERGENCY EGRESS PATHWAY PREDICTION USING VENTILATION MODELS

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ABSTRACT

Mine ventilation models are now an accepted component of most mine management systems. However, modern ventilation models also represent a highly structured spatial data source, defining underground pathways and connections across a mine. This creates opportunities to extend the use of network models beyond ventilation design, by using critical path algorithms to find pathways such as minimum distance or minimum time.

This paper explores the use of ventilation network models to automatically analyse and calculate potential emergency escape routes. A variation of Dijkstra's algorithm is used to predict complex pathways between any two points across a model, representing an escape route from an emergency area (such as a fire) to a safe location (such as the surface or a refuge station). Weighting can be assigned to paths to represent potential travel speed, obstructions or preferred routes. Finally, emergency considerations such as smoke or gas in some parts of the mine can then incorporated into the pathways to force the algorithm to avoid dangerous routes and specify safer pathways. Ventsim is used to visually show example results.

Emergency egress pathway prediction using ventilation network models can provide an efficient way to quickly predict the quickest or most efficient escape routes for emergencies or planning purposes.

Keywords: Emergency egress, ventilation models, Ventsim

INTRODUCTION

In China, around 86,000 deaths in coal mining accidents between 1991 and 2001 occurred (Yan and Feng, 2013), many related to fire and entrapment of miners. Mine fires and explosions impact on the effectiveness of established escape routes, when smoke, gas, visibility and physical restriction impact access to normal pathways, and alternative pathways may be difficult to quickly analyse and review in an emergency.

Mine ventilation flow and pressure modelling typically uses a process called 'network analysis' to solve airflow and pressure through complex interconnected pathways. Although originally described as an algorithm to be used for hand calculation, Professor Hardy Cross's seminal paper in 1936 "Analysis of flow in networks of conduits or conductors" (Cross, 1936) paved a path forward to implement digital computers to solve complex network problems.

The name network analysis is derived from the study of interconnected nature of nodes (junctions) and branches (airways) that represent a mine ventilation system. Initial studies by Hardy Cross focused on the flow of water and the resulting pressure changes from resistances within the circuits. As computers became available in the 1950's and grew more powerful in the following decades (Tien, 1997), analysis was broadened to include flow of airflow, heat and humidity, gases, natural ventilation changes and other more exotic features such as Radon decay and diesel fumes (McPherson, 1986).

More recently, the rapid escalation in the use of remote sensor technology has resulted in the ability for real time information about heat and gases to be fed directly into a network model for distribution and prediction in downstream areas.(Stewart, Aminossadati and Kizil, 2015). Network models therefore have most of the essential environmental information required to assist in mine emergency planning and escape route analysis.

Graph Theory in Ventilation Networks

Modern mine ventilation models are generally created using a strict mathematical configuration of defined airways and junctions. This can be represented and analysed by a field of mathematics called 'graph theory'. Graphs are mathematical structures used to model relations between vertices or nodes, connected by edges, arcs or lines. The concept was introduced by Euler in 1736 (Alexanderson, 2006) who created a formula relating the number of edges, vertices and faces of a convex polyhedron. Many of the techniques for solving the distribution and flow or air and pressure in a model require the application of graph mathematics such as the formation of minimum resistance loops by spanning trees used in the Hardy Cross analysis.

A commonly used application of graph theory is Dijkstra's algorithm (Dijkstra, 1959). Dijkstra demonstrated a method of finding the shortest path between nodes or vertices in a graph structure. Variations of this algorithm are used in many types of modern problems such as finding the quickest route on navigation device maps. The original Dijkstra algorithm has been improved using Fibonacci heap priority queues (Fredman and Tarjan, 1987) to ensure searches are prioritised in the quickest directions, and a variation called the 'A*' algorithm, which uses heuristics to direct the graph search towards a destination (Hart, Nilsson and Raphael, 1972).

In mining applications, variations of Dijkstra's algorithm have been used to predict shortest haul path routes (Choi and Nieto, 2011), robotic entry into mines (Shuai, 2008), and planning communications layouts with minimum cabling (Pei *et al*, 2009). In recent times, the poor record of safety in Chinese mines has prompted studies using Dijkstra's and other algorithms to calculate escape paths and avoidance routes in coal mines (Yan and Feng, 2013).

Previous studies have mainly focused on using specially built networks to describe and model the graphs required for an effective shortest path algorithm, a cumbersome process that requires continual updating to ensure currency. As computers and software have become more powerful, modern mine ventilation networks created by engineers are now typically highly detailed and frequently updated, laying out nearly every pathway within a mine plan. Ventilation modelling software arranges these pathways into a network, which can be made to conform to the definition of a graph as described in graph theory. This allows algorithms such as Dijkstra's to be adapted for finding paths in ventilation models with only some simple modifications.

Dijkstra's algorithm searches for optimum path ways within a system by an iterative method that expansively searches for the shortest travel distance from the starting location to each adjacent node. As each new adjacent node is encountered, the combined previous node distance plus the edge distance to the new node is assigned to the new node. The algorithm keeps searching outwards until the target node is reached, and non-minimum nodes distances are removed. The resulting minimised assigned nodes distances can then be used to define a path of edges to the destination node.

Yan and Feng (2013) proposed using an alternative 'ant algorithm' citing the inability of the Dijkstra algorithm to produce rapid results with flexibility and alternative route prediction, however these concerns are largely resolved in this study by using sequential path refactoring, and implementing high speed optimisations such as minimum priority queues and heuristic directional optimisation to create the necessary speed to analyse large ventilation models very quickly.

Least path selection in Ventilation Networks

Dijkstra's algorithm works on the concept of 'weight' or distance being assigned to an edge or pathway between two vertices within a graph. The weight can be (for example) the length, travel time or perhaps resistance of a pathway, and the algorithm will find the path with the lowest possible summation of weights. For example, minimum resistance pathways can be used to show the presence of an unrestricted airway between two points, or can be used for example to define a minimum resistance mesh loop around a high resistance airway.

Another use proposed by this paper is to analyse emergency escape routes in a mine system, either to a surface exit, or to a safe location such as a refuge station within a mine. While a good mine emergency plan may typically have escape routes well planned and usually signposted in advance, situations may occur in an emergency which may limit access through these pre-planned escape ways. Some examples of unexpected variations may include;

- Mine fires or explosions where some escape ways or parts thereof may be inundated with fire or poisonous gases.
- Blockage of an escape way through mine collapse or flooding.
- Some parts of a mine may not have planned or established fully escape ways into all regions of the mine.

In large complex modern mines, there may be many alternative escape path options available even if not planned. Access to a quick, reliable and safe escape route is a critical factor in any mine emergency, both for potential victims of the emergency, as well as emergency services who may be required to access the emergency area. If regular routes become unavailable or unreliable, analysing alternative routes manually is time consuming and potentially inaccurate in terms of optimum distance and travel time and therefore an automated least path algorithm may offer significant advantages.

PRACTICAL APPLICATION TO VENTILATION MODELS

To adapt Dijkstra's algorithm to this problem, the ventilation model must be converted to a graph, and consideration must be given as to how to weight the edges or pathways within a ventilation model to ensure the safest and fastest pathway solutions are offered. Ventilation models are normally defined by an array or matrix of either connected nodes and airways and can be transformed into connected graph structures with little effort.

The weighting of the connections between nodes (called 'edges' in graphs) needs be estimated. Relevant considerations for graph weighting include

- The speed and safety of escaping personnel include the walking slope or angle of the pathway
- Can the path can be driven, walked or climbed (with a ladderway)?
- The presence of blockages or non-thoroughfare controls like inaccessible regulators or walls
- The presence of smoke, gas, fire or impassable water within a pathway.
- What about if the roadway is intake or return?
- The presence of mask stations or rescue chambers in those roadways?

The weighting of potential pathways should be such that undesirable paths such as gas or smoke filled tunnels are not considered, or are considered as a last resort. It should be noted that the weighting of pathways, particularly from smoke and gas is highly subjective and little data or scientific information is available to recommend factors. In general travel way through smoke is highly discouraged in emergency response. Thus, the recommended weightings suggested below should be critically assessed and changed if considered necessary.

Pre-conditioned Weights

The pre-conditioned weight is the time taken to travel a path between each node and is based on the physical state of pathways. It considers the accessibility or otherwise of tunnel and ventilation controls and inaccessible paths must be flagged if no pedestrian or vehicle access can be permitted. For this study, only pedestrian walking and climbing speeds were considered for analysis. Yan and Feng (2013) also considered other factors in escape paths such as wind resistance and crowding factors however for modern mines these are considered relatively insignificant.

Parameters such as the effect of slope can be weighted by the application of simple rules such as Naismith's rule (Rees, 2004) , a mountaineer who in 1892 suggested that walking a route will take one (1) hour for every five kilometres forward plus one (1) hour for every 600m ascension. Brake (1999a) suggested a flat ground walking pace of around 4.5 km/h while considered a 40% factor for walking up ramps (2.9 km/h), which is considerably faster up ramps than Naismith's rule, but may reflect the urgency of an escape situation. Rees (2004) suggested a more sophisticated model based on metabolic cost can also be used.

A compromise based on Naismith's method is suggested based on a horizontal walking pace of 4.5 km/h with an inclined penalty of an extra hour travel per 1000 m vertical distance. Due to reduced visibility a further walking speed penalty of 40% is recommended (Brake, 1999b) for travelling in adverse conditions such as smoke or gas. Using Equation 1 a 1:8 inclined ramp (for example), this calculates to around 2.9 km/h.

$$\textit{Travel Speed} = TD/(TD/4.5+H)\ (1-E)\ \ km/h \qquad (1)$$

$$\textit{Travel Time} = (\textit{Travel Speed})/L\ \ hours \qquad (2)$$

Where *TD* = Total Distance (km)
L = Length Pathway (km)
H = Vertical Height (km) up only
E = Environmental Penalty Factor, 0% = Clear, 40% = Smoke

Ladderways often form alternative escape ways within a mine, but usually at a heavy travel time and metabolic cost due to physical exertions, confined space and limited access space for multiple personnel. An estimate of travel time up a ladderway for an average fitness person in the authors mine rescue experience is approximately 300 m – 400 m vertically per hour, including rests. In fact, Brake suggested that modern mine workers may struggle to travel even this distance due to sedentary job roles and limited fitness (Brake, 1999a). For the study assumptions, a vertical climbing speed of 350 m/h was assumed.

Post-conditioned Weight Factors

Post-conditioned factors do not affect travel speed, but are additional multiplied weighted factors applied to the graph to force it to consider alternative paths. Factors include smoke spread and dangerous gases from fires or explosions, and blocking of tunnels due to tunnel fire, collapse or flooding.

These factors can be introduced into a ventilation model in several ways:

1. Manual entry of data directly into the ventilation model airway parameters.
2. Simulated entry of data, such as using the results of a fire simulation at a particular time to condition the weight of an airway with fire products like carbon monoxide and smoke.
3. Providing real time sensor data into a transient simulation to condition the mine tunnels with real data, both at the sensor location, and downstream from the sensors into the simulated zones.

The use of the above techniques (particularly options 2 and 3) provide a powerful method of applying the best possible data to the selection of potential escape paths. This paper will focus on perhaps the two most important factors for fire emergencies; Carbon Monoxide (CO) gas, and smoke effecting visibility.

Weighting of CO should consider the Total Weighted Average (TWA) and Short Term Exposure Level (STEL) levels of CO to dictate the safe accessibility of an escape way. NIOSH (1988) guidelines suggest an 8-hour TWA of 35 ppm and a STEL of 200 ppm. Safework Australia (2012) recommends a TWA of 30ppm with STEL listed in **Table 1**.

A weighting factor for pathways with CO can be considered by applying a progressive factor starting at the TWA value, and increasing to the maximum STEL of 400 ppm. For levels above the peak STEL, a much higher weighting factor should be applied to discourage consideration of these paths (which could normally only be safely traversed using self-rescuers or breathing apparatus). Proposed weighting of gas factors is shown in **Table 2**.

An alternative weighting factor due to smoke is based on an assumed visibility range calculated from opacity derived from smoke soot particle assumptions (a product of fire) (Kang, 2007). Kang suggests that visibility of more than thirty metres is required if signage is to be able to be read without hindrance and higher smoke levels may progressively hinder progress and travel speed. In addition, entry into smoke is discouraged by most mine emergency plan guidelines, and therefore any level of smoke needs to be heavily factored to discourage path selection through these zones. In this study, smoke visibility below 25 m is factored as shown in **Table 2**.

Post-conditioned factors are applied as multipliers to the pre-conditioned weights. Thus, a post-condition factor of ten (10) for example would increase the graph weighted travel time of an airway to ten times the original travel time, thereby discouraging Dijkstra's algorithm from selecting this path, at least until other pathways were considered.

Multiple Pathway Options

A weakness of Dijkstra's algorithm is that it chooses only one path. To encourage the algorithm to consider alternative paths, the Graph must be re-weighted each iteration, with existing pathways applied with a further weighting factor representing a previously travelled path. This forces the algorithm to avoid previous paths (unless no other option is available) and thus progressively choose less optimum paths for consideration. To prevent trivial changes of pathways, a 'new' path is recommended to have at least a 10% variation on previous paths to be considered as a new option.

Combining with Dynamic Models

Dynamic or transient simulation in ventilation models has demonstrated significant benefits in predicting the spread of fire contaminants (Greuer, Chang and Laage, 1995) (Brake, 2013) or gas information from real time sensors (Stewart, Aminossadati and Kizil, 2015). Dynamic modelling allows the simulation to spread contaminants and alter ventilation behaviour over time, thus creating a more realistic likely spread of gases and smoke. When combined with the proposed Dijkstra's algorithm approach, this information provides a powerful tool to analyse safe pathways to escape or refuge locations at any time during the emergency. Indeed, safe pathways early in the emergency may change and become unsafe later, and the use of dynamic simulation data will allow this change to be predicted by running the escape path algorithms at different times.

Example – Escape Path to Safe Locations

A portion of a bord and pillar coal ventilation design is presented in **Figure 2** to demonstrate the behaviour of the algorithm in the presence of existing pathways with smoke or gas. Many mines which utilise refuge stations locate them within a defined maximum distance from working areas, typically within 700 m (Brake, 1999a) or at a distance defined by the likely time and range of a miner wearing a self-rescuer.

A safe location could be defined as the presence of a refuge bay, a surface exit or a location with guaranteed fresh air such as the base of an intake ventilation shaft. Under normal and clear conditions, the algorithm would normally select the shortest / quickest pathway to the nearest safe location (Refuge Bay 2 as shown in **Figure 2**), however the presence of a simulated fire in this example inundates some of the pathways with gas and smoke to this location.

The algorithm avoids smoke filled pathways to find the next closest refuge bay in a clear location. Note that because fire simulation or real-time sensor modelling distributes gases progressively through the model, the algorithm may produce different results at different times.

The algorithm can target single or multiple destinations and both methods were trialled. The multiple destination option tended to limit potentially viable pathways to more distant safe locations, as the pathways to them were often weighted from previous visits to closer locations. Therefore, the best results were gained using a sequential method that considered only one destination at a time, and the pathway results of each destination added to a common list and sorted by best and safest travel time.

Example – Escape Pathways Connected to the Surface

A sample ventilation model was chosen, representing a sublevel stope design with decline access, and a mock truck fire was assumed in the mine. The algorithm was incorporated into Ventsim to utilise the fire simulation features to generate gas regions, and then graphically show the pathway options to the surface.

A truck fire was assumed in the lower half of the mine, and trapped persons were assumed below the fire in the ramp. Carbon Monoxide is shown as a coloured concentration in the lower ramp. The ventilation system directs smoke and gas downstream of the ramp from the fire, subjecting personnel to potentially life threatening conditions. Using the algorithm, pathways to the surface were analysed using both decline ramps and escape ladderways, and the algorithm calculated around 15 pathway options, ranked in order of quickest time and least hazard.

Two escape pathways were graphically selected (highlighted in WHITE) and shown in **Figure 3**. The left figure shows the preferred pathway in terms of minimum travel time and least exposure to smoke. Essentially the route chosen is up an escape ladderway to near the surface, and then on to the main ramp for the remaining distance, a total walking / climbing travel time of about two (2) hours.

However, because of concerns about the ability for personnel to climb 800 m of ladderway, a second option was highlighted by the user which minimises most of the ladderways, only using them to skirt the fire and smoke region of the ramp. This highlights the flexibility of the Dijkstra algorithm to choose multiple potential pathways.

The list shown in **Table 3** summarises each of the potential pathways, listing not only estimated travel time, but also the time exposed to CO (as a TWA 8-hour exposure level, and time spent above TWA and STEL limits). This provides valuable feedback to rescuers on both the potential and risk to personnel utilising these pathways, as well as the potential exposure to mine rescue personnel should they enter the mine and try to travel to the location.

A discussion is warranted on whether any entry into smoke or gas should be considered; however, in this example the trapped miner's location was already in smoke and there was no choice. Brake (1999) for example suggests that travel through smoke, while not desirable, should be considered when taken in context of the early potentially lower toxicity conditions of the fire, and the more serious later outcomes which may be present if the personnel wait for rescue.

CONCLUSIONS

This paper presents a further use for ventilation models beyond simply modelling ventilation conditions. Modern, detailed ventilation networks offer the potential to use this structured data for emergency response planning and action purposes. The Dykstra algorithm when applied to graphs generated by ventilation models efficiently predicts a variety of potential optimum pathways which, where possible can be made to avoid dangerous conditions while providing the quickest pathway of egress from the mine.

When a ventilation model is coupled with live sensor readings or simulated fire results which can be modelled with gases or smoke, it offers a powerful tool to assist in Mine Emergency Response decision making during an actual or planned fire exercise. The result of the modelling can then be used to assist both extraction of trapped personnel, or to send mine rescue resources to the required locations, with the assurance that travel time and risk can be minimised.

Further testing and optimisation of the technique is required, particularly regarding the weighting of pathways in the model to encourage the algorithm to avoid hazardous conditions. As with all simulation tools, the results are only as good as the quality of the model and assumptions, therefore caution should be observed when considering any results. Tools such as the method proposed in this paper cannot replace planning and preparation for emergencies. All mines should undertake emergency preparedness reviews and develop procedures for emergency situations, providing signage and training to personnel on regular escape routes.

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TABLES AND FIGURES

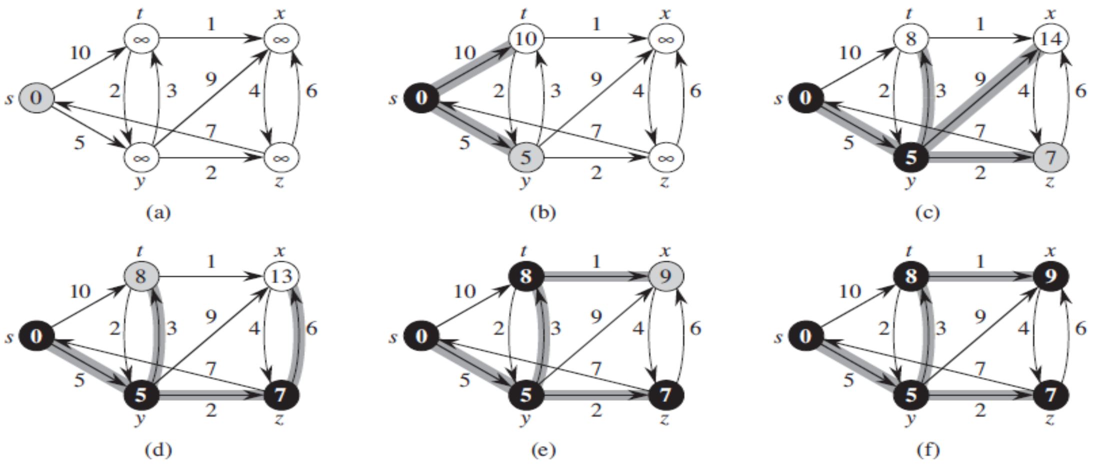

Figure 1: Example of Dijkstra Optimum Path Search

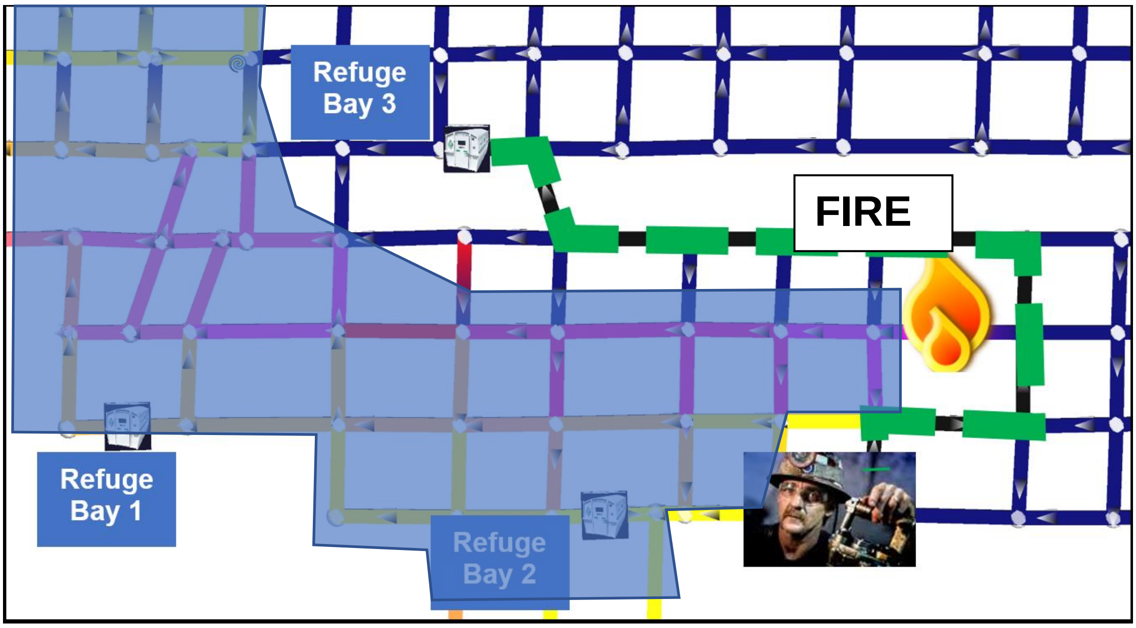

Figure 2: Recommended escape path to safe Refuge 3 (green dash line) avoiding fire combustion gases (shaded area)

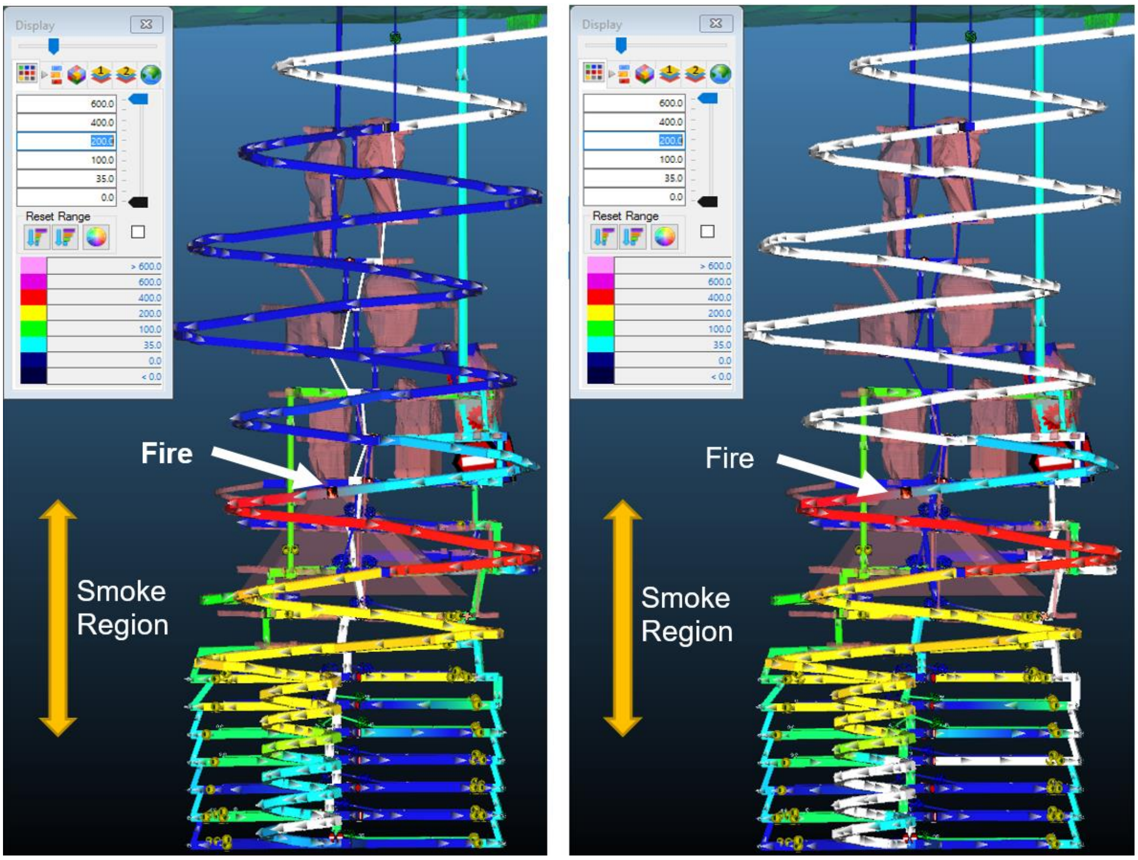

Figure 3 Examples of Escapeway Routes (left) showing ladderway option and (right) showing ramp escape route (Ventsim Software)

Table 1: Short Term Exposure Levels Carbon Monoxide (Worksafe Australia, 2012)

Total Exposure Time	Allowable Concentration
15 minutes	200 ppm
30 minutes	100 ppm
60 minutes	60 ppm
Peak exposure limit	400 ppm

Table 2: Weighting of environmental factors

Smoke Visibility	Carbon Monoxide	Graph Weighting Factor
>= 25 m	<35 ppm	1 X
>= 10 m and < 25 m	>35 ppm and <=200 ppm	2 X
>= 1 m and < 10 m	>200 ppm and <=400 ppm	10 X
< 1 m	> 400 ppm	100 X

Table 3: Summary of escape pathway options (pathways increasingly affected by gas shown in colour)

Path Finder (0s), Length Beeline 1,608.2 m, Difference in Position (X= -148.5 m ; Y= -134.7 m ; Z= 716.3 m)

Select	Path	Estimated Time	Total Distance	CO (Max) ppm	Time above STEL	Time above TWA	TWA (8hrs) ppm	Visiblity (Min) m
☐	Path 1	02:03:46.1420000	1,608.2	127.3	0s	31m:20s	3.2	10.4
☐	Path 2	02:06:19.9260000	1,754.4	127.3	0s	31m:20s	3.1	10.4
☐	Path 3	02:11:30.1510000	2,061.7	127.3	0s	34m:53s	2.6	10.4
☐	Path 4	02:31:23.5750000	3,590.1	191.2	0s	41m:21s	3.2	10.3
☑	Path 5	02:44:37.0640000	4,395.5	135.6	0s	59m:07s	4.4	9.8
☐	Path 6	02:48:50.5190000	4,427.4	173.4	0s	52m:47s	4.0	7.7
☐	Path 7	03:17:05.3890000	5,824.9	365.1	24s	1h:08m:27s	5.0	3.6
☐	Path 8	02:49:57.1220000	4,466.5	365.1	4m:44s	1h:14m:46s	8.1	3.6
☐	Path 9	02:53:42.0160000	4,479.5	365.1	5m:49s	1h:15m:47s	7.9	3.6
☐	Path 10	02:53:36.9750000	4,476.9	365.1	5m:49s	1h:16m:00s	7.8	3.6
☐	Path 11	02:53:57.9350000	4,962.5	389.1	26m:35s	1h:25m:18s	12.6	3.4
☐	Path 12	02:51:49.8980000	4,934.2	389.1	35m:47s	1h:23m:10s	14.3	3.4
☐	Path 13	03:05:15.5220000	6,024.6	636.6	59m:30s	1h:25m:19s	19.1	2.1
☐	Path 14	03:12:49.2900000	6,348.2	636.6	55m:11s	2h:32m:53s	18.0	2.1