# Towards a Better Management of Emergency Evacuation using Pareto Min Cost Max Flow Approach

by

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- Keywords: Emergency Evacuation, Intelligent Transportation, Pareto Solutions, Min-Cost Max Flow Algorithm, Traffic Theory, Modeling and Simulation, Cooperative Driving and Traffic Management.
- Abstract: Events during an emergency unfold in an unpredictable fashion which makes management of traffic during emergencies pretty challenging. Furthermore, some vehicles would need to be evacuated faster than others e.g., emergency vehicles or large vehicles carrying a lot more people. The Prioritized Routing Assistant for Flow of Traffic (PRAFT) enables prioritized routing during emergencies. However, the PRAFT solution does not compute multiple plans that can help handle better dynamic nature of emergencies. PRAFT maps the prioritized routing problem to the Minimum-Cost Maximum-Flow (MCMF) problem, hence its solution can accommodate maximum flow while routing vehicles based on priority (maps higher priority vehicles to better quality routes (i.e., ones with minimum cost)). We build upon the PRAFT solution to make the following contributions: (a) Develop a Pareto Minimum-Cost Maximum-Flow (Pareto-MCMF) algorithm which can compute all the possible MCMF solutions. (b) Through a series of experiments performed using the well known traffic simulator SUMO, we could show that all the solutions generated by Pareto-MCMF indeed have properties similar to a MCMF solution thus providing multiple high quality options for traffic police to pick from depending on the situation.

# 1 Introduction

Governments across the world need to be prepared to handle evacuation of traffic during emergencies independent of whether it is a frequent or rare occurrence or whether it is an anticipated or unanticipated situation. Planning for such emergency situations needs to consider a different set of factors than regular traffic management (Pel et al., 2012)(Kwon and Pitt, 2005). As mentioned in literature (Quarantelli, 1988)(Chen et al., 2008), during emergency events it is reasonable to assume that traffic police will perform a centralized control of traffic as they tend to have a better idea of the situation. Prior work has shown different ways to plan for such emergency evacuation (Yamada, 1996)(Hobeika and Kim, 1998). However, emergency evacuation is usually dynamic in nature since the intensity and effects of the emergency can change with time (Turoff et al., 2004). Furthermore, traffic behavior can be unpredictable during emergencies that can add to the need for handling dynamic situations (Sorensen et al., 1987) e.g., panic, convergence (road blocks), failure to respond to evacuation warning etc. Considering all these factors, it becomes important to plan for alternate evacuation strategies or plans beforehand.

During a typical evacuation, some vehicles would need to be evacuated faster than others e.g., emergency vehicles or large vehicles carrying a lot more people (Jotshi et al., 2009), (Larson et al., 2006). We therefore build upon the Prioritized Routing Assistant for Flow of Traffic (PRAFT) solution (Gupta et al., 2018) which accounts for prioritized routing during emergencies. PRAFT maps the prioritized routing problem to the minimum-cost maximum-flow (MCMF) problem, a standard problem formulation in network flow theory, where priority refers to priority of routes or priority of vehicles. Since the PRAFT solution does not compute multiple plans we develop a **Pareto Minimum-Cost Maximum-Flow (Pareto-MCMF)** solution which can suggest multiple MCMF solutions to the traffic police, each of which retains characteristics of a MCMF solution i.e., can accommodate maximum flow while routing vehicles based on priority measured using a cost function.

For illustration purposes, we assume that there are 6 paths between point A and B (path is a combination of roads and intersections as described later). Suppose that the solution computed by MCMF includes paths 2 and 5 expressed as  $\{2, 5\}$  with min cost of x units. By using Pareto-MCMF, if we were able to find 3 additional solutions:  $\{1, 2, 4\}, \{4, 6\}$  and  $\{3, 4, 5\}$  each with cost x units (we skip details of the number of vehicles in each path), we then have 4 solutions in total. Traffic police can use different solutions for emergency evacuation based on the current situation in different regions. Thus Pareto-MCMF can (a) Suggest different evacuation plans beforehand while (b) Enabling the traffic police to maximize the traffic flow while allowing for prioritized routing within the min cost paths. Traffic simulators are a popular way to evaluate infrastructure and policy

changes before actually implementing them in realworld (Paruchuri et al., 2002)(Balmer et al., 2006). We evaluated our algorithm using Simulation of Urban Mobility (SUMO)(Behrisch et al., 2011)(Krajzewicz et al., 2012), a free and popular microscopic traffic simulator. We let SUMO handle all the low level dynamics of vehicles i.e., we do not make any changes to the dynamics apart from prescribing the route a vehicle should take.

# 2 Related Work

#### 2.1 Emergency Evacuation

There are many emergency evacuation strategies that have been studied such as contraflow, traffic signal optimization, ramp metering, crossing elimination among others. (Wang et al., 2012) uses contraflow with focus on traffic setup time in the case of roadblocks and repairs. (Dong and Xue, 1997) and (Kim et al., 2008) propose different contraflow approaches which are considered a potential remedy to solve congestion during evacuations in the context of homeland security and natural disasters. However, these solutions are complex and do not account for vehicle priorities. Traffic signal optimization evacuation methods like (Chen et al., 2007) do not consider priority and events such as congestion or roadblocks. Methods like ramp metering(Daganzo and So, 2011) and cross elimination(Yuan et al., 2018) are good for evacuation during emergencies but priority of vehicles is difficult to adopt into them. (Jahangiri et al., 2011) present an optimal signal timing method to increase the outbound capacity of the network during an emergency evacuation. (Vitetta et al., 2008) propose two different approaches namely k shortest path and genetic algorithm for vehicle routing problem during evacuation. (Yueming and Deyun, 2008) employ evacuation route construction and traffic flow assignment algorithms at each junction to route traffic in evacuation area to a safe region rapidly and safely. However, these works do not focus on the dynamic aspects of evacuation while considering the priority of vehicles.

#### 2.2 Pareto optimality

Pareto optimality is a state of allocation of resources from which it is not possible to reallocate to make any one individual agent or preference criterion better off without making atleast one more agent or criterion worse off. A pareto solution set is a set of all such pareto optimal solutions (Nisan et al., 2007). We use pareto optimal solutions and pareto solutions interchangeably through the paper. For purposes of this paper, a Pareto-MCMF refers to the fact that given a min-cost max flow solution we cannot decrease the cost of the solution or increase flow on one route without decreasing flow on atleast one other route. Hence for *n* possible MCMF solutions  $MIN(c_1) = MIN(c_2) = ... = MIN(c_n)$  and  $MIN(f_1) = MIN(f_2) = ... = MIN(f_n)$ , where  $MIN(c_i)$  and  $MAX(f_i)$  represent the minimum cost and maximum flow in the *i*<sup>th</sup> solution.

# 2.3 Min Cost Max Flow (MCMF) Problem

The Ford-Fulkerson Algorithm (FFA) (Ford Jr and Fulkerson, 2015), (Ford and Fulkerson, 1956) is a popular algorithm to compute maximum flow in a flow network be it water flow, liquid flow or flow of traffic. The minimum-cost flow problem (MCFP) (Goldberg, 1997) is an optimization and decision problem to find the cheapest possible way of sending a certain amount of flow through a flow network. Multiple solutions exist in literature to solve this problem (Edmonds and Karp, 1972), (Galil and Tardos, 1988). The Minimum-cost Maximum-flow (MCMF) problem is an extension to the Min cost flow problem where we need to find the minimum cost to send the maximum flow through the network (i.e., given flow value is equal to the max flow). There are different solutions developed such as the Cycle Cancelling Algorithm (Goldberg and Tarjan, 1989), Hungarian Algorithm (Kuhn, 2005) and others to solve the MCMF problem. (Yamada, 1996) uses MCMF for shortest evacuation plan in the city, but doesn't consider priority. (Gupta et al., 2018) present PRAFT, which accounts for prioritized routing during emergencies using a MCMF based approach. However, PRAFT generates one plan assuming the world remains static during emergencies.

### **3** Illustrative Example

Figure 1 shows a road network (directed graph) with 4 vertices (or intersections)  $\{0, 1, 2, 3\}$  and 5 edges (or roads)  $0 \rightarrow 1, 0 \rightarrow 2, 1 \rightarrow 2, 1 \rightarrow 3, 2 \rightarrow 3$ . The source vertex is 0 and the destination vertex is 3. There are two values associated with each edge/road. The first value marked on an edge represents the number of lanes in that edge i.e., capacity of the edge. The second marked value represents the priority of that edge.

#### 4 Algorithm for MCMF

We now present a brief recap of the MCMF algorithm presented as Algorithm 2 in (Gupta et al., 2018). The algorithm as presented, has two different matrices for the same network: (a) Capacity Matrix (for number of lanes, i.e., width of the road) and (b) Cost matrix. Both the matrices are of same dimension since they are for the same graph. The algorithm uses Uniform Cost Search (UCS) to guide its search for solution. In particular, at every step of UCS the next node which is expanded is the one whose cost g(n) is the lowest, where g(n) is the sum of edge costs from the root to the node n. However, the algorithm finds only one MCMF solution. We therefore build upon this work to develop the Pareto-MCMF, which can identify all the possible max-flow solutions which can route the flow for the (same) lowest cost.

Working of MCMF: For the graph in Figure 1, there are 3 paths identified by UCS step:

• Path I:  $0 \rightarrow 1 \rightarrow$ 3, Path II:  $0 \rightarrow$  $2 \rightarrow 3$  and Path III:  $0 \rightarrow 1 \rightarrow$  $2 \rightarrow 3$ 

with costs of 4, 5,

Figure 1: Example road network

4 for the paths I, II and III respectively. Since UCS picks paths based on the edge cost, path I, path III and then path II are picked. Since paths I and III have the same path cost, path I is picked first as it is inserted first into the queue. 3 units of flow is allowed in path I since the minimum edge capacity in Path I is 3, which is then subtracted from the residual graph. Residual graph with edges on Path I now have 0 capacity. Path III is considered next since it has the minimum cost among the rest of paths. However, no flow is allocated since 0 flow is allowed through edge  $0 \rightarrow 1$ . Path II is then considered where 2 units of flow can be sent [as edge  $0 \rightarrow 2$  has (lowest) capacity of 2]. Paths I (3 units) and Path II (2 units) sum up to 5 units of flow which is the maximum allowed flow in the network. The cost of this allocation  $\{3, 2, 0\}$ for paths I, II and III is 22 units (flow on Path I \* cost of Path I + flow on Path II \* cost of Path II + flow of Path III \* cost of Path III = 3\*4 + 2\*5 + 0\*4), which is the minimum cost of all the maximum flow solutions possible.

		Table 1:	Notation	table for	Pareto-MCM	F algorithm
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Notation	Description		
G(V,E)	Graph with V vertices		
	and E edges		
$G_f(V,E)$	Residual Graph with V		
-	vertices and E edges		
c(U,V)	Capacity of the edge		
	from U to V		
$c_f(U,V)$	Capacity of the edge		
	from U to V in the resid-		
	ual graph		
f(U,V)	Flow of edge from U to		
	V		
S	Source node		
t	Sink node		
pf	priority function(cost of		
	edges)		
mf(u, v)	Max flow value from u to		
	V		
mc(u, v)	Min cost to send max		
	flow from u to v		
tp(u, v)	Set of total paths from u		
	to v		
cp	Set of total cost of all		
	paths from u to v		
partition <sub>i</sub>	Array representing in-		
	leger partition of $m_f$		
n amoutation	A more representing per		
permutation <sub>j</sub>	mutation of values in		
	nutation of values in		
cost parmutation.	$paration_i$		
cosi_permutationj	corresponding flow dis		
	tribution in permutation		
nermutation [n]	Flow value for the path n		
perminanonj[p]	in permutation:		

#### **5** Pareto-MCMF Algorithm

Pareto Min Cost Maximum Flow (Pareto-MCMF) algorithm works on a directed graph and aims to find all the possible MCMF solutions i.e., find all the solutions that allow the maximum number of vehicles to flow (i.e., max flow) from a source to a sink that have minimum cost among all the possible solutions. We define cost of the solution as follows, where  $a_{ij}$  represents the weight/priority of edge between the *i*th and *j*th vertex while  $f_{ij}$  is the flow through the same edge.

Cost of solution = 
$$\sum_{i,j} a_{ij} * f_{ij}$$

The Pareto-MCMF algorithm starts with computing the maximum flow and minimum cost possible through the network using the MCMF algorithm mentioned earlier and stores it in the variables mf and mc respectively (as shown in line 2 of Algorithm (1)). In line 3, we use Breadth First Search (BFS) (Zhou and Hansen, 2006) to compute all the possible paths from source to sink and store the set of paths in tp(total paths) along with storing the cost of each corresponding path in cp(cost of paths). Cost of the path is the sum of edge costs of each edge/road along the way from source to sink, where cp[i] is set to the cost of *ith* path stored in tp. Let's assume we identified n such paths i.e., *cardinality*(tp) = n. A valid flow solution uses these n paths such that: (a) The flow through a path is conserved i.e., for every path, flow input at the source is the same as the flow through all its constituent edges and finally received at the sink and (b) If an edge (u, v) is part of k paths, then the sum of the flow through all k paths should be less than or equal to the capacity of the edge c(u, v).

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	Algorithm 1: Algorithm for Pareto Minimum-					
_	cost Maximum Flow					
1	Pareto-MCMF algorithm;					
	<b>Input</b> : Given a network $G(V, E)$ with flow					
	capacity c, weight of edge w, with					
	source node s and sink node t.					
	<b>Output:</b> Compute all possible ways in which					
	vehicles can be sent from s to t to get					
	the maximum flow with minimum					
	cost.					
2	mf, mc = MCMF(G, s, t)					
3	tp(s,t), cp(s,t) = BFS(G,s,t)					
4	solutions $\leftarrow \emptyset$					
5	For each <i>partition</i> <sub><i>i</i></sub> $\in$ partitions( <i>mf</i> , <i>tp</i> ):					
6	For each <i>permutation</i> <sub>j</sub> $\in$					
	permutations( <i>partition</i> <sub>i</sub> ):					
7	$G_f(V,E) \leftarrow G(V,E)$					
8	$cost_permutation_j = 0$					
9	For each path <i>p</i> from <i>s</i> to $t \in tp(s,t)$ :					
10	$cost_permutation_j = cost_permutation_j +$					
	$cp[p]^*$ permutation <sub>j</sub> [p]					
11	For each edge $(u, v) \in p$ :					
12	$c_f(u,v) \leftarrow c_f(u,v)$ - permutation <sub>j</sub> [p]					
13	If $c_f(u,v) < 0$					
14	break					
15	If <i>permutation</i> $_j \notin$ <i>solutions</i> and					
	$cost_permutation_j == mc:$					
16	solutions.append(permutation <sub>j</sub> )					
17	return solutions.					

Using the flow value stored in mf, a partition generator generates distributions of the flow across all npaths. In number theory and combinatorics, a partition of a positive integer n also called an integer partition, is a way of writing n as a sum of positive integers. Two sums that differ only in the order of their summands are considered the same partition (?). Generating partitions can be compared to distributing mf objects into n identical boxes, where every box has a minimum capacity of 0 and a pre-decided maximum capacity of  $c_i$ . For instance, we can partition a flow of 3 among 2 paths as: (0+3) stored as  $\{0,$ 3} and (1+2) as  $\{1, 2\}$ . Note that  $\{1, 2\}$ , implies a flow of 1 through the first path and 2 through the second. Every permutation of such a partition could be a possible maximum flow solution. We therefore permute these partitions so we consider all the possibilities e.g.,  $\{3, 0\}$  along with  $\{0, 3\}$  and  $\{2, 1\}$  along with  $\{1, 2\}$ . Thus, in lines 5 to 6, the maximum flow is partitioned across *n* paths as *partition<sub>i</sub>* and every permutation *permutation*; of *partition*; is validated. This is done by iterating through each path and ensuring that for each edge (u, v), its maximum capacity c(u, v) is not exceeded by the flow solution or its residual capacity  $c_f(u, v)$  remains  $\geq 0$  (shown in lines 11 to 14). We also track cost of the solution in line 10 i.e., cost of the permutation  $(cost_permutation_i)$  obtained by summing up the product of flow value and cost of the path in the permutation. In line 16, we append the newly verified flow solution to the output set if not already present in the set and the cost of the solution equals the minimum cost calculated in line 2. The set of flow solutions are represented as an array of n values, where the  $i^{th}$  value represents the flow through the  $i^{th}$  path from source to destination. Hence using Pareto-MCMF, we can obtain the set of all solutions that guarantee the maximum flow from source to destination at the least cost. Note that this is offline planning with a one-time computation involved for the entire network. Once identified, different solutions can be used for emergency evacuation based on the different conditions like traffic, roadblocks, congestion etc., thus enhancing the ability to save lives.

**Approximate Pareto-MCMF:** If the number of Pareto-MCMF solutions happen to be less than the number of options, we may relax the minimum cost (*mc*) condition used in Pareto-MCMF as below. The goal here is to allow solutions to be accepted as part of Pareto set even if the max flow solution is not of lowest cost but within some bounds (where  $\varepsilon$  is tolerance allowed) i.e.,  $mc \leq cost\_permutation_i \leq mc + \varepsilon$ 

#### 6 Pareto-MCMF on example setup

We now show trace of Pareto-MCMF solution for the same graph in Figure 1. In line 2, Pareto-MCMF identifies the maximum flow(mf) to be 5 and the minimum cost(mc) to be 22 (determined using MCMF). In line 3, it then identifies following three paths from source to destination:

• Path I:  $0 \rightarrow 1 \rightarrow 3$ , Path II:  $0 \rightarrow 2 \rightarrow 3$ , Path III:  $0 \rightarrow 1 \rightarrow 2 \rightarrow 3$ 

Line 5 of Pareto-MCMF algorithm calculates the partitions of mf (= 5) as  $\{0, 0, 5\}, \{0, 1, 4\}, \{0, 2, 3\}$ and  $\{1, 2, 2\}$ . Here  $\{0, 1, 4\}$  represents that 0 units of traffic(vehicles) is flowing on Path I, 1 unit on path II and 4 units on path III. Line 6 then permutes  $\{0,$ (0, 5) into 3 unique permutations i.e.,  $\{0, 0, 5\}$ ,  $\{0, 5, ..., 0, 5\}$ 0 and  $\{5, 0, 0\}$ , however all these permutations are invalidated by lines 11 to 14 as they violate the maximum flow conditions. Likewise  $\{0, 1, 4\}$  has 6 unique permutations i.e., { {0, 1, 4}, {0, 4, 1}, {1, 0, 4}, {1,  $\{4, 0\}, \{4, 0, 1\} \text{ and } \{4, 1, 0\} \}$ . Four of these  $\{1, 2, 1, 0\}$ 0}, {1, 0, 2}, {2, 0, 1} and {0, 2, 1} are invalidated by lines 11 to 14 similarly as they violate the maximum capacity constraints of the constituent edges.  $\{0, 2,$ 3} have 6 permutations out of which only  $\{3, 2, 0\}$ is valid. Finally  $\{1, 2, 2\}$  have 3 permutations out of which  $\{1, 2, 2\}$  and  $\{2, 2, 1\}$  give the min cost of 22. We now have 3 ways to distribute the flow of 5 across the three paths with min cost of 22 which gives us the solution set. Finally {3, 2, 0}, {1, 2, 2} and {2, 2, 1} are the Pareto-MCMF solutions. This contrasts with MCMF algorithm that provides only one solution ( $\{3,$ 2, 0 as seen in section 4).

Dispatching Strategy: As mentioned earlier, vehicles will be released in waves and each wave will have vehicles less than or equal to the maximum flow (5 in our example). In wave 1, assume that we have 5 vehicles v1, v2, v3, v4, v5 generated with priority 5, 4, 2, 3, 1 [Higher number implies higher priority]. From the example, we have three pareto-MCMF solutions i.e., {3, 2, 0}, {1, 2, 2} and {2, 2, 1}. Pareto-MCMF maps priority of vehicles to priority of paths in descending order i.e., we assign vehicles in the order of routes identified (Path I, Path III and then Path II). For the first solution  $\{3, 2, 0\}$ , vehicles v1, v2, v4 will be assigned to Path 1 and v3, v5 to Path II. In the case of second solution  $\{1, 2, 2\}$ , v1 is assigned to Path I, v2, v4 to path III and v3, v5 to Path II respectively. Compared to a general max flow solution, all the solutions of pareto-MCMF will result in either lower travel time or lower fuel consumption (depending on the metric we model), taking all the vehicles into consideration.

# 7 Experimental Setup

**Road Network:** For experimentation purposes, we consider a point close to the area of emergency as the source point (or starting point) of evacuation and a safe point i.e., a place from where vehicles can safely exit the system as sink point. While we model a single



Figure 2: Road map and its corresponding graph

sink problem, prior work has shown how to abstract a multi-source multi-sink problem into a single-source single-sink problem (Megiddo, 1974). The road map is represented as a graph where intersections are modeled as nodes and roads are modeled as edges of the graph. Every edge is associated with two values: the first value is the weight of the edge which is the number of lanes in the road while the second value indicates the cost/priority to traverse the edge (modeled as distance/speed limit). For evacuation purposes, we consider only the roads that fall within a certain radius of the source node and lead to destination within reasonable distances. An example road map we use for our experiments is provided in Fig. 2 along with its modeling as a graph. As shown in the figure, there are 6 intersections numbered 0 to 5 and directed edges between the intersections showing the direction of flow of traffic. The number on each edge represents the weight of the edge which for purposes of this paper is modeled as the number of lanes in the road corresponding to that edge. Priority/cost is modeled as the time taken to traverse an edge (i.e., the distance between the nodes of an edge/max speed of the road). The max flow for this network comes out to be 22 and number of Pareto-MCMF solutions found is 3.

The start/source vertex of our simulation is 0 and the destination vertex is 5. We assume that no vehicle starts between nodes 0 and 5. The police agent would then provide routes for each vehicle, that enables maximum flow in the network. We let SUMO handle all the vehicle dynamics (e.g., speed, acceleration, interaction with other vehicles like overtaking etc.). Each wave of vehicles is released every (flow\_wave\_time) set to 5 seconds in our simulation, so we give enough time for vehicles to cover a safe

Table 2: Vehicle characteristic and its value in simulation

Characteristic of vehicle	Value
Maximum speed	180 kph
Maximum Acceleration	2.9 meters/ $s^2$
Maximum Deceleration	7.5 meters/ $s^2$
Minimum gap between vehicles	2.5 meters
Length of the vehicle	4.3 meters

distance before the next wave enters. Note that a route here specifies only the path to take from source to sink node but does not identify the specific lane to take, speed to travel and other dynamics that SUMO specifies. We borrowed this setup from prior work on emergency evacuation (Gupta and Paruchuri, 2016).

#### 7.1 Sumo Parameters

We assume traffic at the start of experimentation to be negligible and traffic lights are not being used in the simulation since it is an emergency situation and we assume that police would have control over the situation. The characteristics of each vehicle shown in Table 2, are the default values defined by SUMO (SUMO contributors, 2018). All the vehicles in our experiments follow these parameters unless specified otherwise. A total of 6600 vehicles were modeled in each of our experiments.

Vehicle Modeling in SUMO: For each vehicle routed through the network, SUMO assigns an identifier (i.e., name), type id, route id, time step of depart, departLane, departPos, departSpeed and similar for arrival related data i.e., arrivalLane, arrivalPos and arrivalSpeed. SUMO has provision to add more details for each vehicle such as the departure and arrival properties, lane to use, velocity or position of the vehicle. There are different vehicle classes in SUMO such as bus, car and others. Each class has associated shape, dimensions, minimum gap, maximum acceleration  $(a_max)$ , maximum deceleration (b), length of the vehicle(l), maximum speed ( $v_max$ ) and emission class. All the vehicle characteristic values used in this paper (as presented in Table 2) are default values defined by SUMO (SUMO contributors, 2018).

#### 8 Experiments

We perform a variety of experiments as showcased below. All our results are obtained as an average over 30 runs (unless specified otherwise).

# 8.1 Individual Characteristics of Pareto-MCMF solutions

In this experiment, we examine the effect of modeling priorities on routing of vehicles. In particular, we modeled 4 priority classes/categories for vehicles. We then find all the possible solutions/routes using the Pareto-MCMF algorithm, with priority modeled as the estimated time needed to traverse the route (i.e., distance/speed limit). Table 3 shows the priority type and count of vehicles present in the simulation with

Table 3: Count of Vehicles for each type of priority

Priority	Type 1	Type 2	Type 3	Type 4
Count	1200	1500	1800	2000

that priority. The Pareto-MCMF identified 3 different MCMF solutions for this experiment. We then operationalize each of the solutions in the simulation as follows: Pareto-MCMF maps a descending priority of vehicles to routes with descending priority i.e., the highest priority vehicles (Type 1) are first assigned to the highest priority routes (i.e., routes with lowest estimated travel time), Type 2 vehicles with next highest priority are considered next and so on and they are mapped to routes in descending order of priority.

For each of the Pareto-MCMF solutions, we compare the individual vehicle behaviors during the entire simulation. We first compute the time needed to evacuate each individual vehicle in seconds for all the Pareto-MCMF solutions. We also have different colors for vehicles with different priorities. For example, we use red for Type 1 (highest priority) vehicles, blue for Type 2 and so on as indicated in the figures.

Figure 3 shows three scatter plots with simulation time on x-axis from 0 to 1500 seconds and time taken by each vehicle to exit the simulation in seconds on y-axis. A total of 6600 points are represented in each of the plots in the figure, one point per vehicle. Given that 22 vehicles are released per wave (i.e., every 5 seconds), we have (6600/22) \* 5 = 1500 seconds for all the vehicles to be released. The plots show that each of the Pareto-MCMF solutions results in a scatter plot which is neatly distributed in terms of priorities. The reason here is that higher priority vehicles are explicitly assigned higher priority routes i.e., routes with shorter time to finish evacuation while the vehicles with lower priority are assigned routes which take longer to evacuate. Hence the reason we see a clear distribution where Type 1 vehicles need shortest time to exit the simulation, Type 2 next and so on. To conclude, each Pareto-MCMF solution not only assigns a faster route for high priority vehicles but also has a predictable trend in the evacuation time for vehicles of each priority category and each of the pareto solutions can be used with similar effectiveness during emergency evacuation.

# 8.2 Diversity of Parameter Values for Vehicle Types

In this experiment, we use a different set of parameters for the different vehicle types as presented in Table 4 to model real-life scenarios better. In particular, we assign higher priority to slower moving vehicles



(b) Second Pareto-MCMF solution (c) Third Pareto-MCMF solution Figure 3: Scatter Plots for Pareto-MCMF solutions

Table 4: Parameter values for different vehicles (B = Bus, T = Truck, C = Car, M = Motorcycle)

Vehicle	B	T	C	М
Туре				
Acceleration	1.5	3	5	6
$(\operatorname{in} m/s^2)$				
Deceleration	4	4	7.5	10
$(\operatorname{in} m/s^2)$				
Max speed	85	130	180	200
(in km/hr)				

Table 5: Average evacuation time for different solutions for different vehicle types (B = Bus, T = Truck, C = Car, M = Motorcycle, Soln. = Solution)

Vehicle	В	Т	C	M
Туре				
Soln. 1	95.09	103.95	108.35	131.53
Soln. 2	95.12	103.10	108.34	133.34
Soln. 3	95.13	103.15	118.38	134.86

and compute the average time taken by each vehicle type using all the Pareto-MCMF solutions shown in Table 5. From the table, we observe that the average evacuation time in seconds (i.e., average time needed to traverse from source to sink) for an individual vehicle type is comparably similar across the different pareto solutions. Pareto-MCMF would therefore be pretty useful to traffic police and/or policy makers since they can pick and use among the pareto solutions depending on the situation while the solution properties remain similar.

# 9 Conclusions

In this paper, we develop Pareto-MCMF algorithm which identifies the set of all MCMF solutions. Since emergencies are typically dynamic in nature, having multiple plans beforehand would make it easier to tackle them. As evidenced in our experimental results, the different Pareto-MCMF solutions have properties similar to a MCMF solution which can make them useful in practice. As part of future work, we plan to study further the nature of events that can happen during an emergency and check if it is possible to create an ordering or specification of suitability among the pareto optimal solutions. At this point the different solutions are deemed equivalent till the traffic police identify changes in ground situation that can make some solutions better suited over the others.

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