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On Evacuation Planning Optimization Problems from Transit-based Perspective

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Abstract: Increasing number of complex traffic networks and disasters today has brought difficulty in managing the rush hours traffic as well as the large events in urban areas. The optimal use of the vehicles and their assignments to the appropriate shelters from the disastrous zones are highly complicated in emergency situations. The maximum efficiency and effectiveness of the evacuation planning can be achieved by the appropriate and significant assignment of the transit dependent vehicles during pre and post-disaster operations.

This paper presents a comprehensive overview of the evacuation planning optimization techniques developed over the years, emphasizing the importance of their formulation and the solution strategies on disaster management from the transit-based perspective. Each technique is briefly described and presented lucidly with some of its known applications, significances, and solution strategies expecting that it should be able to guide much more interest into this important and growing area of research.
Keyword — Disaster management; evacuation planning; transportation network; vehicle assignment.

1. INTRODUCTION

Evacuation planning is an important aspect of disaster management. Emergency evacuation is the immediate and urgent movement of people away from threat, from the danger zone to the safety zone. According to (DHS, 2004) an evacuation is "organized, phased, and supervised withdrawal, dispersal, or removal of civilians from dangerous or potentially dangerous areas, and their reception, and care in safe areas." It concentrates mainly to find the optimal use of vehicles and the routes as effectively as possible with utmost reliability. The most fundamental necessity of human beings is saving lives which should be the core objective of the planning. But the life of a human being is always in danger and under the threat because of natural or man-made disasters. Most of the disasters cannot be predicted and are unavoidable, and the damages caused by them are severe. The increasing rate of such disasters demands the comprehensive analysis and planning for the evacuation management. Past evacuation experiences on different situations are to take account of planning and mitigation strategies which are followed by the response and recovery to normalize the situation. Disaster operations can be performed before or after the disasters as pre-and post-disaster operations. Short-notice evacuations, facility location, and stock pre-positioning are carried out as the main pre-disaster operations whereas the relief distribution, logistic support services, and the casualty transportations are the main aspect of post-disaster operations (Caunhye et al., 2012; Dhamala et al., 2018). In evacuation planning, auto-based and transit-based evacuees can be categorized like high and low-mobility populations, respectively. The former are supposed to withdraw the hazardous area by using their own vehicles whereas the latter need to be sent to the transit hubs for further evacuation. In large cities of developing countries, many people fall into low-mobility population and are to be given a special attention due to their ages, language inefficiencies, different health problems, or other physical disabilities. The great loss of people on Hurricane Katrina was due to the lack of proper planning for the transit-based evacuees (Litman, 2006).

The traditional vehicle routine problem (VRP), deals for the distribution of goods from different depots to customers to design the least cost delivery is the main root of transit dependent evacuation planning. It has several variations depending on different contexts, among them relief distribution, logistic support and management, and evacuee transportation are of great importance on emergencies. Among its different extensions, the Split Delivery Multi Depot Vehicle Routing Problem with Inter-depot Routes is relatively similar and applicable form of VRP in evacuation scenarios for transit dependent vehicles. For an overview of VRP variants and their different applications, we refer to (Kumar and Panneerselvam, 2012; Laporte, 2007).

Basically, evacuation models can be classified into two broad categories, microscopic and macroscopic. The

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former emphasizes individual parameters like walking speed, physical ability, reaction time, and the interaction of each evacuee with other evacuees during the movement and are based mainly on simulation (Dhamala, 2015). But in later the occupants are treated as a homogeneous group and are taken account of their common characteristics only and are able to produce mainly the lower bounds (Hamacher and Tjandra, 2002). These two aforementioned models can also be combined in an interactive solution process as in (Hamacher et al., 2011), where the output of one is used as input to other so that the output of both remains stable and is named as sandwich method. The effectiveness of transit-based evacuation highly depends on the location of pick-up facilities, allocation of the resources and evacuation management system. Different mathematical models were developed to address such transit-based evacuation under both predictable and unpredictable disasters and are integrated to the location-allocation design with the routing, assignment and scheduling of the buses on evacuation network. In a real scenario, the evacuee walking time to various pick-ups, their waiting and loading time at pick-ups, service delays on the system etc. are also to take account which is rarely been considered in existing literature. Comparatively, a reliable location model has been developed in (Shi et al., 2013) which integrate the pre-and post-emergency operations in an exponential number of facility disruption scenarios including their interconnection to pick-up location, service facility and the vehicle assignment to determine the optimal evacuation, however, the assumptions like constant rescue demand with identical and independent facility disruptions may not always be realistic. Moreover, not only the evacuation network, pick-up facilities might also be disrupted in real practice. Hence, during designing of the evacuation system, the care should be taken not only on the efficiency but also on the reliability and efficacy.

Evacuation problems were combined with location analysis to reduce the evacuation time by facility location approach in (Hamacher et al., 2013). In a modeling by (Chen and Zhan, 2008) on three different types of road networks like a grid network, a ring road structure, and a real road network the overall benefit of the chosen bus stops located within the evacuation area has been maximized by dividing the area into smaller sub-sections, zones can be grouped together, and a minimum number of bus stops can be set for the sub-section of evacuation bus stops where the total benefit will increase as the total number of optimum bus stops increased. Assuming that a complete evacuation is not possible, authors in (Sayyady and Eksioglu, 2010) used to maximize the number of evacuees served, which incorporates traffic flow dynamics from the simulation package with a logistic function to estimate the number of evacuees at each pickup location, likewise for solving the problem of refuge location through facilitating buildings to provide shelter to the victims with the quality service after a disaster has also been highlighted in (Pèrez-Galarce et al., 2017). Dealing with the household behavior under the emergency evacuation scenarios, authors in (Murray-Tuite and Mahmassani, 2003) have provided two formulations to determine the meeting location for household members and their sequence pick-up. Vehicles are distributed according to the location of the drivers and are taken heterogeneous depending upon their capacity which is more convenient in an emergency.

Evacuation planning strategies, models, methods, and their operations may vary due to their applicable geographical scales, total affected population size and density, behavioral and organizational situations, modes of transportation, traffic capacity, evacuation objectives, and the time spans. An emergency situation caused by different factors like fire, nuclear reactor accident, terrorist attack, hurricanes, earthquakes, floods or landslides are all different in nature. Evacuation scheduling, traffic route guidance, destination optimization, optimal route choice, and other various approaches have significantly contributed to accelerate the evacuation process, even then the integrated optimal plan to have a single comprehensive solution to the problem is lacking for real case scenarios. Different models and strategies have been developed so that the solution methods can be applied effectively to the realistic networks of reasonable size and also with possible extension of further improvements on different parameters to enhance the performance of evacuation process. Significant contributions have been made by many researchers in the scientific field of evacuation planning utilizing the highly prominent transit like in (Abdelgawad and Abdulhai, 2012; Chiu et al., 2007; Hobeika and Kim, 1998; Shayti and Mahmassani, 2006). An overview of the mathematical modeling and algorithms of evacuation problems has been presented in (Bretschneider, 2012; Hamacher and Tjandra, 2002) whereas, different surveys of discrete dynamic network flows are in (Aronson, 1989; Dhamala, 2015).

Contraflow has gained a considerable attention in evacuation literature because by finding the ideal direction of lanes of a road network, the flow can be increased and evacuation time can be reduced as compared to the evacuation in the existing road reconfiguration and is applicable to reduce congestion, eliminates the crossing at intersections and traffic jams during the day-to-day rush hours.Depending upon the objectives, different contraflow variants on the evacuation models like maximum dynamic contraflow, lexicographic contraflow, the earliest arrival contraflow and many more have been studied by the authors in (Dhamala and Pyakurel, 2013; Pyakurel et al., 2015; Pyakurel, 2016; Pyakurel and Dhamala, 2014; Pyakurel and Dhamala, 2015).

A critical review on the evacuation planning of network design problem has been presented in (Abdelgawad and Abdulhai, 2009) which has reviewed and compiled the main evacuation strategies, network design problem formulation, traffic simulation and the optimization tools. Depending upon the nature and circumstances of the disasters a survey in (Xiongfeil et al., 2010) has suggested for the improvements of models with more reasonable and realistic assumptions including travel behaviors. There are many uncertain factors in disasters like evacuee's route choice behavior, departure time, road capacity and so on, which demands the stochasticity and robustness.

In this paper, we present a comprehensive overview of the most important transit dependent evacuation approaches focused on disaster management that were not covered widely in an organized form in the literature. Section 2 presents the transit-based evacuation model from different perspectives. Different solution strategies will be discussed in section 3 whereas the applications in section 4 with the conclusions in section 5.

2. TRANSIT-BASED EVACUATION MODEL

Transit has a unique role in evacuating the car-less, elderly, and the needy populations with different disabilities. Even when transit evacuation is planned carefully, communications and logistics issues are taken care of, the behavior, knowledge, attitude and nature of the evacuees still play a major role in effective emergency evacuations. Moreover, the knowledge, ages, readiness, and/or the willingness of people to evacuate may be different, it also demands behavioral analysis. Furthermore, the lack of coordination between the transit agencies and the traffic operators may highly affect the system. In a survey of about high-risk area of hurricane as in (Blendon et al., 2005) have noticed that about 54 % of households, the traffic congestion was the main reason for not evacuating on such high-risk hurricane strikes and has noticed that more fatalities were caused by evacuation than the hurricane. Whereas, in a survey (Litman, 2006) it was noticed that, 71 % of those who died in Hurricane Katrina in New Orleans were age of 60 and 47 % over of 75. This also demands the need of transit vehicles for effective evacuation.

To cope the situations, a prominent bus-based evacuation problem (BEP) model, as a unique variant of VRP is proposed by (Bish, 2011), with the objective to minimize the time of evacuation in case of a short notice using given number of homogeneous buses. It is formulated as a mixed integer linear program in which the decision variables determine the assignment of routes to buses and assignment of buses to the evacuees so that the evacuation time of the last evacuee to reach the safe destination is minimized for the given number of evacuees at the sources. For the formulation of BEP network, let N be the set of nodes and A be the set of arcs in the networks $\left(N, A\right)$, where N is composed of three subsets Y, P and S where Y stands for the set of yards at which buses are initially located and dispatched from; P, as a set of demand nodes representing pickup locations requiring the evacuation services; and S, as a set of shelters (sinks) where the evacuees are to be transported. Let V be the available vehicles (say buses) each having a capacity Q is subdivided into the subsets V_i for $i \in Y$, and the bus $j \in V_i$ is initially located at yard i. Let the demand node j has a demand $D_j, j \in P$ and shelter i has a capacity $C_i, i \in S$. Then the arc $\left(i, j\right)$ has a non-negative travel cost of τ_{ij} for $\left(i, j\right) \in A$. In fact, the travel cost is proportional to the travel time and distance. All costs in the network are taken symmetric and are supposed to satisfy the triangle inequality for all arcs.

Decision variable

x_{ij}^{mt} : 1, if trip t for bus m transverse arc $\left(i, j\right)$, else 0, $\forall \left(i, j\right) \in A, m \in V, t = 1,2,..,\theta$.

b_j^{mt} : No. of evacuees assigned to bus m after trip t (or, released from, if j is a shelter),

$\forall j \in N, m \in V, t = 1,2,\ldots,\theta.$

Γ_{evac} : duration of evacuation

BEP formulation

$$minimize \quad \Gamma_{evac} \tag{1}$$

$$such\ that \quad \Gamma_{evac} \geq \sum_{\left(i,j\right)\in A} \sum_{t=1}^{\theta} \tau_{ij} x_{ij}^{bt}, \forall m \in V \tag{2}$$

$$\sum_{i:\left(i,j\right)\in A} x_{ij}^{mt} = \sum_{K:\left(i,j\right)\in A} x_{jk}^{m\left(t+1\right)}, \forall j \in P, m \in V, t = 1,2,\ldots,\theta-1 \tag{3}$$

$$\sum_{i:\left(i,j\right)\in A} x_{ij}^{mt} \geq \sum_{K:\left(j,k\right)\in A} x_{jk}^{m\left(t+1\right)}, \forall j \in S, m \in V, t = 1,2,\ldots,\theta-1 \tag{4}$$

$$\sum_{\left(i,j\right)\in A} x_{ij}^{mt} \leq 1, \forall j \in P, m \in V, t = 1,2,\ldots,\theta-1 \tag{5}$$

$$x_{ij}^{m1} = 1, \forall j : (i,j) \in A, m \in V_i \tag{6}$$

$$x_{ij}^{mt} = 0, \forall j : (i,j) \in A, m \in V, t = 2,\ldots,\theta \tag{7}$$

$$x_{ij}^{m\theta} = 1, \forall j \in P, (i,j) \in A, m \in V \tag{8}$$

$$b_j^{mt} \leq \sum_{(i,j)\in A} Q x_{ij}^{mt}, \forall j \in N, m \in V, t = 1,\ldots,\theta \tag{9}$$

$$0 \leq \sum_{j\in P}\sum_{l=1}^{t} b_j^{mt} - \sum_{k\in S}\sum_{l=1}^{t} x_k^{ml} \leq Q, m \in V, t = 1,\ldots,\theta \tag{10}$$

$$\sum_{m\in V}\sum_{t=1}^{\theta} b_j^{mt} \leq C_j, \forall j \in S \tag{11}$$

$$\sum_{m\in V}\sum_{t=1}^{\theta} b_j^{mt} \leq D_j, \forall j \in P \tag{12}$$

$$\sum_{j\in P}\sum_{t=1}^{\theta} b_j^{mt} = \sum_{k\in S}\sum_{t=1}^{\theta} b_k^{mt}, \forall m \in V \tag{13}$$

$$x_{ij}^{mt} \in \{0,1\}. \forall (i,j) \in A, m \in V, t = 1,2,\ldots,\theta \tag{14}$$

$$b_j^{mt} \geq 0. \forall (i,j) \in A, m \in V, t = 1,2,\ldots,\theta \tag{15}$$

Constraint (2) needsthe evacuation duration be greater than or equal to the maximum cost incurred by the bus with the highest travel cost and is to be minimized by (1) as the "min–max" objective. Constraint (3) ensures that a bus traveling to demand node j on trip t leaves node j on trip $t+1$, the flow-balance constraint for the demand nodes. Constraint (4) ensures that the last trip of the bus may end at a shelter, the flow-balance constraint for the shelters. Constraint (5) allows a bus to make at most one trip at a time; constraint (6) tells that the first trip of each bus starts from its yard; constraint (7) tells that the buses do not leave the yard for later trips; and constraint (8) does not allow the last trip a bus can make to end at a demand node. Constraint (9) signifies that a bus can only pick up evacuees from node j ,if it is traveling to that node where constraint (10) and constraint (11) are the bus capacity and the shelter capacity constraints respectively. Where, constraint (12) and constraint (13) signify that all evacuees are picked up and are delivered to a shelter, respectively. Moreover, constraints (14) and (15) are the logical binary and non-negativity restrictions on the x and b variables, respectively.

Example 1: *In this instance as in Figure 1 with one yard, three demand nodes and three sinks, it is assumed that the number of evacuees at the demand nodes be as same as the vehicle capacity or its integral multiples where the demands be* $l_i = (3,3,1)$*, capacities at sinks be* $u_j = (3,4,3)$ *with buses available be* 3*. The distance of the demands from the yard be* $d = (4,3,6)$ *with the distances between* P *to* S *as*

$$\tau = \begin{bmatrix} 4 & 7 & 9 \\ 10 & 7 & 5 \\ 7 & 6 & 9 \end{bmatrix}$$

In general, BEP is formulated so as to choose the minimum of the evacuation times of all possibilities where the critical path of the plan is for B3 or bus B1 as in Table 1, which shows the feasible solution of BEP with the evacuation duration of 25.

Table 1. Table of feasible solution of BEP

Trip	1	2	3	Tour plan	Time
B1	(1,3)	(2,1)	-	$\tau_1 + \tau_{13} + \tau_{33} + \tau_{31}$	25
B2	(2,1)	(2,3)	-	$\tau_2 + \tau_{21} + \tau_{21} + \tau_{23}$	21
B3	(1,1)	(1,2)	(2,3)	$\tau_1 + \tau_{11} + \tau_{11} + \tau_{12} + \tau_{22} + \tau_{23}$	25

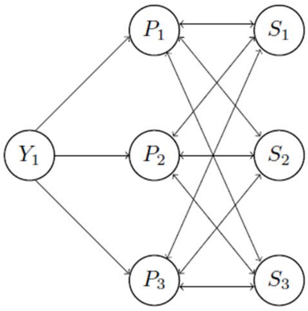

Figure 1: A simple BEP

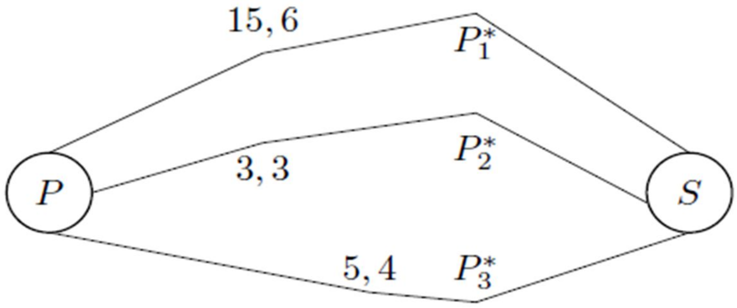

Figure 2: A simple evacuation network

Authors in (Goerigk and Grün, 2014) have presented lucidly the robust bus evacuation problem (RBEP), in which the exact numbers of evacuees are not known in advance though a set of likely scenarios is known and after sometime such uncertainty will be removed. In such instance, it is to decide whether the buses are better to send right now as the *here-and-now* bus under such uncertainty or to wait as *wait-and-see* bus until the exact scenario becomes known.

Considering both the transit time and capacity on each path, the concept of combined evacuation time (CET) and the quickest paths has been introduced by (Min and Neupane, 2011). For T be the travel time of the path (the sum of travel time of edges in the path), C be the capacity of path (the minimum capacity of the edges in the path), and x be the number of evacuees at the source P, the evacuation time (ET) is given by,

$$ET = T + \left\lceil \frac{x}{C} \right\rceil - 1. \tag{16}$$

The path P_1^* is said to be the quickest path if and only if,

$ET = T + \left\lceil \frac{x}{C_i} \right\rceil - 1 \leq ET = T + \left\lceil \frac{x}{C_j} \right\rceil - 1, \forall j \in \{1,2,\ldots,k\} \setminus \{i\}$. Let $P_1^*, P_2^*, \ldots P_k^*$ be edge-disjoint paths from source P to sink S with C_i and T_i be the capacity and transit times of paths P_i^* and x be the number of evacuees at P then the combined evacuation time is given by

$$CET\left(P_1^*, P_2^*, \ldots P_k^*\right) = \left\lceil \frac{x + \sum_{i=0}^{n} C_i T_i}{\sum_{i=0}^{n} C_i} \right\rceil - 1. \tag{17}$$

Example 2: *Consider three possible paths P_1^*, P_2^*, P_3^* in between demand node P and the sink S with their respective travel time T and capacity C as in Figure 2. Suppose the evacuees at demand node be 52 then the ET through these paths can be calculated by using equation (16) be 23, 20 and 17 respectively among them $ET\left(P_3^*\right)$ be chosen as the quickest path. But if the next path P_1^* be added on the evacuation route then the CET as in equation (17) becomes $CET\left(P_3^*, P_1^*\right) = 16$ which is shorter than the current evacuation time. Moreover, by adding the next path P_2^* also on the route CET becomes $CET\left(P_1^*, P_2^*, P_3^*\right) = 13$ further improved, which is smaller even than the route P_1^*, with longest travel time. Hence, we can remove the route P_1^* with longer travel time from the evacuation route, since $CET\left(P_2^*, P_3^*\right) = 11 < CET$ and the evacuation time be reduced even more by 2. Note that, the purpose of adding paths into the evacuation route is to reduce the ET by distributing the evacuees in multiple paths and will be terminated when the CET by the current quickest path becomes greater than the previous CET. Running time is determined by the number of iteration which is bounded by the total number of paths in and does not depend much on the number of evacuees.*

2.1 Dominant Vehicle Assignment on Transit Routes.

Among all feasible routes on the evacuation network, a route p is said to dominate another route p' and is named as the dominant route, if it does not have longer evacuation duration, it does not have the more cost for the demand nodes considered and every unreachable demand nodes on route p is also unreachable for p'. If different routes lead to the same shelter and neither of them is better than the others over all criteria, then neither of the routes is dominating. There are different factors affecting for the selection of such dominant routes and mainly depends upon nature of the available network. The problem is not only on the selection of a route and the selection of a shelter for each route but also on the route-to-vehicle assignment and vice versa, which is more complex in practice. Furthermore, the network adds complexity to the solution and impacts on the problem. It needs the modification and extension on the model to make it more realistic and applicable.

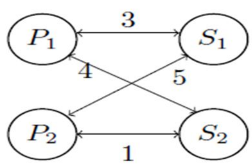

Figure 3: A simple network

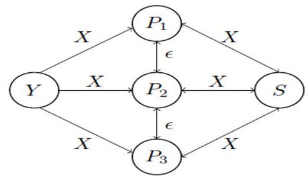

Figure 4: A split delivery network

In general, it seems that sending each vehicle to its closest shelter to last pickup node is the appropriate route to be assigned for the optimal routing. Likewise, one may assume that the split delivery network will improve the evacuation duration. But, it is not always (Dror, 1990).

Example 3: *In this simple network as in Figure 3, let a bus which has picked up a full load of evacuees at* P_1 *can still pick up a full load at* P_2 *with uncapacitated shelters* S_1 *and* S_2. *Then, if the shelter closest to its last pickup node is assigned, then the bus would be on* $P_1 - S_1 - P_2 - S_2$ *and will have the cost of 9, whereas the optimal solution would be on the route* $P_1 - S_2 - P_2 - S_2$ *with cost of 6.*

Example 4: *Consider a simple split delivery network as in Figure 4 where Y and S are yard and sink respectively, with* P_1, P_2 *and* P_3 *be three different demand nodes. The evacuation durations with and without split delivery and their respective bounds are shown as in Table 2, where the vehicles were scheduled simultaneously. This signifies that the split delivery network will not always improve the evacuation duration.*

Table 2: Table showing the observations.

No. of Vs.	With SD	Without SD	Bound	Remarks
1	4X+ϵ	6X	1.5	Improved
2	2X+ϵ	4X	2	Improved
3	2X	2X	1	Not improved

Moreover, in Figure 4, the evacuation cost is 6X for 3 vehicles without split delivery where the cost becomes approximately the same, i.e., $6\mathrm{X} + \varepsilon$, only for 1 vehicle. Which signifies that 1 vehicle covering all the routes will have approximately the same cost as multiple vehicles covering the same routes in such simple evacuation network.

2.2 Location Allocations of Transit Vehicles

Authors in (Zhang and Chang, 2014) have proposed a model to determine the pick-up locations within several clusters of demand zones for the routing and scheduling of transit vehicles based on vehicle availability and the time-dependent evacuee demand pattern. By suggesting the equilibrium of the evacuee arrival process and the functioning pick-up facility, authors in (An et al., 2013) have presented the optimal resource allocation strategy to balance the trade-off between evacuees' risks and the operation costs, and about its dynamic nature in (He and Peeta, 2014) addressing of when, for how long, and where to assign to improve the evacuation efficiency.

Let $\left|P_i\right|$ be the number of evacuees in pick-up location who need to be transported one of the shelters; $A = \left|f_{ij} : 1 \le i \le n, 1 \le j \le m\right|$ be the allocation of fleet; f_{ij} be the amount of fleet assigned to transferring the evacuees from P_i to S_i with τ_{ij} be the time for round trip between them including the boarding and alighting time. Define $\eta_{ij} = \frac{f_{ij}}{\tau_{ij}}$ be the number of evacuees transferred per unit time from P_i to S_i and $\tau_i = \sum_{j=1}^{m} \eta_{ij} = \sum_{j=1}^{m} \frac{f_{ij}}{\tau_{ij}}$ the rate at which evacuees are transferred from P_i to any of the shelters. Then maximum evacuation rate resource allocation is to maximize the number of evacuees who reach safety by any given deadline after the evacuation, under some capacity constraints, and is given by,

$$maximum \quad s\left(\Gamma\right) = \Gamma \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{f_{ij}}{\tau_{ij}} \tag{18}$$

For S^* be the optimal solution of (18) as in (Aalami and Kattan, 2017), the minimum network clearance time resource allocation is to evacuate the whole endangered population to shelters in the shortest possible time, i.e.

$$minimum \quad \left\{ S^*\left(\Gamma\right) \ge \sum_{i=1}^{n} \left|P_i\right| \right\} \tag{19}$$

Theorem 1. (Aalami and Kattan, 2017), Let $\kappa_i = \frac{\left|P_i\right|}{\tau}$ denote the clearance time of P_i. Then in the minimum clearance time resource allocation, $k_i = k_j \forall i, j \in \left\{1, 2, \ldots, n\right\}$.

Proof: Let $K_x = \left\{ i : k_i = \max_j k_j \right\}$ and $K_y = \left\{ i : k_i = \min_j k_j \right\}$ be the set of indices of the pick-up locations with largest and smallest clearance time respectively. K_x and K_y both are non-empty. Assume the contrary, $K_x \cap K_y = \varnothing$. If not, then, $x_j k_j = \min_i k_i$, proof becomes obvious. So for, $K_x \cap K_y = \varnothing$ the network clearance time can be reduced by taking a small portion of the resonance from the pick-up locations with indices in K_x and allowing them to pick-up locations with indices in K_y which contradicts the assumption. Hence, $K_x \cap K_y = K_x = K_y$. ■

However, in general, minimizing the evacuation time for all pick up locations is desired during evacuation, but if a city is threatened by wildfire then the neighborhoods close to the wildfire are supposed to be evacuated before the ones faraway where the minimum network clearance time resource allocation is not the right choice.

2.3 Lane-based Vehicle Assignment for Transit Vehicles during Congestion

Most of the traffic delays and the potential accidents are due to the merging and crossing conflicts at the intersection. To address this, comparatively a smart traffic routing without crossing and merging conflicts has been proposed by (Cova and Johnson, 2003) and is further improved by many others like (Bretschneider, 2012; Bretschneider and Kimms, 2011; Xie and Turnquist, 2011), following the assumption that, vehicles have to order in the appropriate lanes that correspond to their subsequent turn before they enter the intersection and the restructuring of traffic routing with regard to a safe evacuation process to minimize the evacuation time. Likewise, the effectiveness of lane based system even in the damage traffic sensors and interrupted communication system has been presented by (Ardekani and Hobeika, 1988). Different heuristic approaches have been suggested in (kimms and Massen, 2011; Kim et al., 2007) to solve the problem of minimization of evacuation egress time with time-dependent node and arc capacity by lane reversal approach. The demand management strategies of staging and routing have been presented in (Bish et al., 2013) incorporating to some extent for the evacuee behavior aspects subjected to route the vehicles to their closest evacuation zone exit and to minimize the number of intersection merging-conflicts, which also satisfy the shortest evacuation plan criterion given by (Yamada, 1996).

Lane-based reversal design and routing with intersection crossing conflicts elimination for the evacuation has been integrated in a bi-level model in (Zhao et al., 2016) by applying a tabu search algorithm to find an optimal lane reversal plan in upper-level and the simulated annealing algorithm on the lower level consisting of single arc and multiple arcs approaches on lane based route plans with intersection crossing conflict elimination to minimize the total evacuation time on the network. Such network optimization model with the bi-level scheme has been formulated in (Liu and Luo, 2012) with the upper level determining the best sets of signalized and uninterrupted flow intersections and the lower-level handling routing assignment of evacuation traffic demand. The upper level describes the behavior of the policy makers or planners for minimizing the total evacuation cost whereas, the lower-level problem captures the behavior of evacuees in choosing the evacuation routes under the budget constraints. In fact, such information is critical for emergency managers to allocate the limited resources to the most appropriate location and the mass transit VRP can been solved iteratively between two levels of problems as the transit problem and the passenger problem as in (Pages et al., 2006), where the transit problem has been taken as the initial problem and its initial solution is used to improve by assigning the passengers on the routes. The transit signal priority method in (Lin and Gong, 2016) has given the priority on (i) transit vehicle arrival time estimation, (ii) queuing vehicle dissipation time estimation, (iii) traffic signal status estimation, (iv)transit signal optimization, and (v) arterial traffic signal coordination for transit vehicle in evacuation route. In a survey, with some demographical analysis of the Upstate New York city, the authors in (Hess and Gotham, 2007) have suggested to the planners, transit providers, emergency management officials and even to the researchers for the development of multi-modal mass evacuation plans with the incorporation of more high-capacity vehicles for the comprehensive and effective emergency management plan for the large scale evacuation.

2.4 Cost Objective and Min-max Objective on Transit Vehicle Assignment

(Bish, 2011) illustrates the impact to the optimality of the solution on the min-max objective given by (1) and the cost objective, where the cost objective is taken as,

$$minimize \quad \sum_{(i,j)\in A} \sum_{m\in V} \sum_{i=1}^{\theta} \tau_{ij} x_{ij}^{mt} \tag{20}$$

Both the min-max and the cost objective can have multiple optimal solutions, some of which are better than others and become the dominating solutions. In case of multiple optimal solutions, there might be some bottle-neck vehicles where some of the solutions may include the undesirable or unnecessary routes and may increase the costs and trips on evacuation process. An alternative lexicographic min-max objective with the lexicographic constant L has been introduced as,

$$minimize \quad \Gamma_{evac} + \frac{1}{L} \sum_{(i,j)\in A} \sum_{m\in V} \sum_{i=1}^{\theta} \tau_{ij} x_{ij}^{mt} \tag{21}$$

The first term denotes the evacuation duration and it lexicographically dominates the second term denoting the total evacuation cost on cost objective. (Sherali, 1982) has considered the lexicographic constant, $L = \sum_{m\in V} \sum_{t=1}^{\theta} \max\left\{\tau_{ij} : \left(i,j\right) \in A\right\}$ as the maximum possible value of the second term such that the first term will lexicographically dominates the second term. As a dual, the cost and duration can be minimized lexicographically as,

$$minimize \sum_{(i,j)\in A}\sum_{m\in V}\sum_{i=1}^{\theta}\tau_{ij}x_{ij}^{mt}+\frac{1}{L}\Gamma_{evac} \quad (22)$$

By various approaches including some empirical evidences (Bish, 2011) has concluded some useful results on BEP regarding the fleet size and different objectives:

- *For a single vehicle as the fleet size, the min-max and cost objectives have equivalent optimal solutions.*
- *For the min-max objective there is an optimal threshold fleet size. Increasing the fleet size beyond this threshold does not impact optimality.*
- *For the min-max objective, the evacuation duration does not always decrease in a convex manner with the number of vehicles.*

In another approach, the authors in (Campbell et al., 2008) concentrate on the min-max objective to minimize the time until the last delivery is made for the relief supplies in a disaster. In general, when the cost objective is taken, it becomes the route selection problem and if min-max objective, then it becomes the route selection as well as the route-to-vehicle assignment, and is obviously more complex.

As already mentioned above, the VRP objective minimizes the total routing cost for the entire vehicle considered where the minimization of the duration of evacuation, i.e., the min-max objective for the routing cost is concerned on BEP. Basically on evacuation, minimizing the cost should not be the primary concern as the most common objective is to minimize the time till the last delivery, including the safety of drivers and evacuees. Besides this common mini-max objective on BEP, authors in (Sayyady and Eksioglu, 2010) have addressed to identify the number of public transit vehicles needed to evacuate all transit-dependent citizens during no-notice evacuation. Not only this, the model is concentrated to identify paths for vehicles to have the minimum the number of casualties; to minimize the total evacuation time; and to maximize the vehicle utilization on the system. Moreover, their model maximizes the number of evacuees served assuming that a complete evacuation is not possible and thus the objective function is quite different from the common min-max objective.

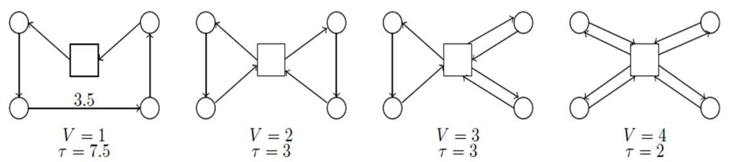

Figure 5: Different scenarios of vehicle assignment

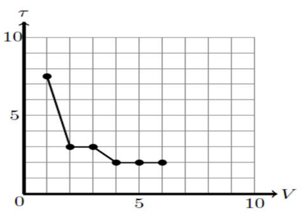

Figure 6: Relation between τ & V

Example 5: *Consider a simple scenario with four different assignments with one, two, three and four vehicles as in Figure 5 where vehicles start from the depot* S *denoted by square and assigned to the demands* P_i *denoted by circles and finally return to the depot again. Let all the unmark arcs are with length unity, the relation between the number of vehicles* V, *and the respective maximum route length* τ *is shown in the Figure 6.*

2.5 Integrated Contraflow Approach of the Vehicle Assignment on Transit-based Evacuation

Authors in (Kim et al., 2007), study the microscopic model for the reconfiguration of transportation network and provide a pair of heuristic approaches as the *greedy* and *bottleneck relief* for the high quality solution with significant performance and for the large scale evacuation, respectively and they improve the evacuation egress time by about 40 percent or above in different experimental results. In a recent work, different analytical solutions of continuous time contraflow problems has been presented in (Pyakurel et al., 2017), with an extension of dynamic contraflow to more general setting where the given network is replaced by a two terminal abstract contraflow network with each element having symmetric capacity and established a remarkable theorem with its analytical proof, on the flow value.

Theorem 2.(Pyakurel et al., 2017) If the minimum d*ynamic abstract cut capacities are symmetric for a two terminal abstract contraflow network, the flow value can be increased up to double with contraflow reconfiguration.*

An integrated contraflow strategy has been presented by (Hua et al., 2014)containing non-contraflow to shorten the strategy set up time, full-lane contraflow to maximize the evacuation network capacity and bus contraflow to realize the transit cycle operation. Here, the routing problem of the transit-based evacuation has been considered as the minimum cost flow problem with multiple origin nodes and single super destination node. This is a mixed integer linear programming problem which can be solved in a very efficient way using the branch and bound method. The auto-based evacuation method has a bi-level structure and is usually solved by using heuristic algorithms as in (Miandoabchi and Farahani, 2011). The evacuation model has been formulated with the objective to route the transit vehicles to their closest evacuation destination as follows:

$$minimize \quad Z_D = \sum_{(i,j)\in A_R} x_{ij}^{*} l_{ij} \tag{23}$$

$$subject\ to \quad \sum_{j\in\Gamma_i} x_{ij}^{*} - \sum_{j\in\Gamma_i'} x_{ki}^{*} = 0, \forall i \in N_A \cup N_I \tag{24}$$

$$\sum_{j\in\Gamma_i} x_{hi}^{*} = d_h^{*}, \forall h \in N_S \tag{25}$$

$$x_{ij}^{*} \le c_{ij}^{*} z_{ij}, \forall (i,j) \in A_R \tag{26}$$

$$0 \le x_{ij}^{*}, \forall (i,j) \in A_R \tag{27}$$

Constraints (24) and (25) describe the equality of inflow and outflow volume i.e., the flow conservation. Constraint (26) ensures the proper amount of flow on each link (i,j) i.e., if $z_{ij} = 1$ then the bus contraflow configuration is applied on the link, otherwise the link is not served on evacuation for N and A be the set of nodes and links, as usual for $N = N_S \cup N_A \cup N_I \cup N_D$ as different nodes like super origin, access, intersection and destination nodes. The lower bounds on all transit-based flow variables are provided by constraint (27).

A multi-modal optimization evacuation framework has been proposed by (Abdelgawad et al., 2010) to optimize simultaneously the minimizing of in-vehicle travel time, minimizing of the at-origin waiting time and minimizing fleet cost for mass transit evacuation. By the comparative analysis of different evacuation scenarios they claimed that considering only the travel time underestimates the waiting time of the evacuees in no-notice evacuation. In another hand, minimizing of the evacuee waiting time implies evacuating all the population instantly and will ultimately demand their simultaneous evacuation, which may lead to longer travel times in the system and the longer evacuation time with congestion on the transportation network. Furthermore, minimizing travel time causes the delaying of the evacuees at the origin and will ultimately increases the waiting time. A good compromise and their proper trade-off is always challenging as these two objectives might be conflicting to each other.

3. SOLUTION STRATEGIES

Mathematical models seldom represent all the existing characteristics of real-life situations as on their formulation, one has to idealize the real-life problem by making some simplifying hypotheses (Lancaster, 1976). So, one has to be careful using the solutions of such models as they tend to be large and exhibit an exponential complexity with the problem size. Its performance and efficiency depends upon the nature of road network, population density, the behavior of the population and on many other factors.

So far as the BEP is concerned, the objective is to minimize the duration of evacuation by routing and scheduling a fleet of homogeneous and capacitated buses which were initially located at one or more yards. Most often, the number of evacuees at each pickup location can exceed the capacity of a single bus, which signifies the necessity of split delivery service. Moreover, the number of available buses is insufficient to transport all the evacuees without multiple trips and each shelter has a capacity that limits the number of evacuees it can serve. Such situations also demand the split delivery service. In such situations, the author in (Bish, 2011) has proposed and analyzed two alternative models for the multi-depot, multi-trip, bus-based evacuation problem, at which the first simultaneously identifies optimal route construction and assignment of the vehicle where the next identifies the optimal route assignment from a set of feasible routes. Unlike to this, a multi-items, multi-vehicles, multi-periods, soft time windows with a split delivery strategy has been formulated in (Lin and Luo, 2011) as a multi-objective integer programming model and is solved heuristically by the genetic algorithm (GA) followed by decomposition of the original problems. Whereas, (Goerigk et al., 2013) have developed a simplified version of BEP model for the evacuation of a region from a set of collection points to a set of capacitated shelters with the help of buses in minimum time assuming that the bus pick-ups exactly the number of people that equals its capacity when visiting a source and hence, no need of split delivery services. By assuming that the number of evacuees is not known exactly, the BEP is extended to RBEP in (Goerigk and Grün, 2014) as mentioned above.

The development of large scale simulation-optimization approach as a decision support tool optimizing network performance and logistics during emergencies has been presented in (Cavusoglu et al., 2013) for the evacuation of car-less populations via different transits. Considering the preferences of the evacuees for their departure times, routes, and destinations, authors in (Huibregtse et al., 2011) have developed an iterative solution technique where the objective function and the simulation model can be chosen by the analyst, and can be applied to an arbitrary region and hazard. However, the output depends upon the choice of the objective function. Simulation models also enable transportation planners and practitioners to develop and compare different evacuation plans for different hypothetical situations to predict traffic conditions and the evacuation duration. Such techniques has also been used to investigate how different evacuation scenarios like alternatives exits, number of vehicles changed, and other traffic control plans would affect the evacuation duration. Such models have been presented systematically in (Naghawi and Wolshon, 2010) to simulate the transit based evacuation strategies where the average travel time and total evacuation time were used to compare the results of different evacuation time periods. They also proposed comparatively the effective scenario of transit based evacuation routing plan with reduction in overall travel time as well as the total evacuation time with respect to the peak hour general evacuation scenarios. Simulations are the powerful tools to evaluate traffic scenarios though it misses the optimization potential. Fluid models and the models based on differential equations capture very well the dynamic behavior of traffic as the continuous quality but comparatively inefficient to handle the large network. The authors in (Xie and Turnquist, 2011) have presented comparatively the effective way to use existing network capacity by identifying the candidate emergency vehicle routes and then the reconfiguration of the network for evacuees to satisfy the multiple objectives for emergency management.

An intelligent algorithm, by embedding the GAhas been developed in (Deai et al., 2011) to solve the optimization model of a real evacuation network having 19 pickups and 4 shelters. A hybrid type of GA has been formulated in (Song et al., 2009) for the solution of a location routing problem to get its optimal transit routing in the system. Various constraints have been satisfied in its initialization and reproduction process. The proposed hybrid GA has also been tested in a small evacuation network and found to be better than the traditional GA. An alternative evacuation route plan strategy is suggested by (Lim et al., 2016) with mixed integer nonlinear programming formulation for real time evacuation where the traffic network are affected partially or totally for short or long periods of time. Though in a minor incident, one can wait until the incident is cleared to follow the pre-planned route but in a severe incident it is better to have an alternative path to evacuate the outbound flows due to over congestion and minimize the evacuation clearance time. Unlike to this the authors in (Sayyady and Eksioglu, 2010) have considered the case of minimum casualties within minimum time with maximum use of vehicles.

As the exact methods tend to perform poorly on large size instances and demands the heuristics. Two heuristic algorithms have been used to solve BEP in (Bish, 2011), the first is to produce quickly the feasible solution and is also to improve the solution by route swapping and assignment based on a simple search technique whereas the next based on mathematical programming formulation. Authors in (Goerigk et al., 2013) have presented branch and bound algorithms for various computational results to find lower and upper bounds with several node pruning techniques and branching rules. Four greedy algorithms are also presented to construct the feasible solutions and three algorithms to find lower bounds, though the greedy algorithms cannot give always the optimal solution. These bounds have been integrated into the branch and bound framework to obtain the near optimal solution.

Authors in (Pereira and Bish, 2014) have presented a spatial-temporal synchronization of vehicles with customer-oriented objective function to mitigate the evacuation risk for maximum service level with the routing and scheduling having a constant evacuee arrival rate, BEP-CA. They signify the dynamic relationship between the maximum service level and the fleet size for the development of more efficient transit based regional evacuation plan. Assuming the evacuation to begin in zero time the objective is taken as to minimize the total exposure,

$$\sum_{j\in P}\frac{D_j}{2}\sum_{J=1}^{F}(q_j^f)2 \tag{28}$$

Here, D_j is the CA rate of the evacuee at pickup node and $q_j^f = p_j^f - p_j^{f-1}$ be the time intervals between pickups. For a given parameter F the minimum exposure schedule, is the pickup schedule to minimize (28), i.e. where the total exposure is dominated by the largest interval between pick-ups and is given as,

$$minimize \quad \sum_{j\in P}\frac{D_j}{2}\sum_{J=1}^{F}(q_j^f)2 \tag{29}$$

$$subject\ to\ \sum_{J=1}^{F}\left(q_j^f\right) = L_j, \forall j \in P, \tag{30}$$

$$\sum_{J=1}^{F}\left(q_j^1\right) \geq t_{oj}, \forall j \in P, \tag{31}$$

$$q_j^f \geq 0, \forall j \in P, f \in 1,2,\ldots,F. \tag{32}$$

Unlike to such constant arrival rate, the arrival pattern of the evacuees at a pick-up locations have been represented as a mobilization curve in (Jamei,1984) by

$$\xi_t = \frac{1}{1+\exp\left[-LR\left(t'-h\right)\right]} \tag{33}$$

where ξ_t is the cumulative percentage of evacuees loaded in the network by time t', LR is the loading rate of the evacuees to disaster and is referred as the slope of (33) and h be the half loading time. With reference to different LR, there are different evacuation scenarios, as the low LRs is during the early stage of evacuations for the no notice evacuation scenarios and the high LRs during short notice evacuation scenarios.

A simplified version of one of the earliest algorithms, Capacity Constrained Route Planer (CCRP) algorithm is also presented in (Mishra et al., 2015) and is claimed better than most of the heuristic algorithms.

Algorithm 3.1: Simplified CCRP Algorithm
1. P is added to the priority queue.
2. The nodes in priority queue are ordered based on its distance from P
3. While the evacuees are in P, find a path P* having minimum destination arrival from P to S taking the capacity of nodes and edges into consideration.
4. Find the capacity of P* and reserve capacity along the path for a group size equal to minimum capacity.
5. If evacuees left at P, go to step 3.

Authors in (Min and Neupane, 2011) have presented the simple version of Quickest Path Evacuation Routine (QPER) algorithm for R be the set of paths in the evacuation routes with $RC\left(e\right), CP\left(e\right)$ and $TT\left(e\right)$ be the reserved capacity, original capacity and the travel time respectively of the edge e then the capacity and travel time of the paths for $p^* \in P$ becomes $CP\left(p^*\right) = \min_{e\in p^*}\left(CP\left(e\right) - RC\left(e\right)\right)$ and $TT\left(p^*\right) = \min_{e\in p^*}\left(TT\left(e\right)\right)$. Then based on above mentioned equation (16), the combined evacuation time by the route R becomes

$$CET\left(R\right) = \left|\frac{x + \sum_{p^*\in R} CP\left(p^*\right)TT\left(p^*\right)}{\sum_{p^*\in R} CP\left(p^*\right)}\right| - 1. \tag{34}$$

Algorithm 3.2:QPER Algorithm
●Initialization
1. Set $R = \varnothing$ and $RC\left(e\right) = 0, \forall e \in E$.
2. Set $CET = \infty, p^*CET = \infty$.
● Iteration
3. Repeat the following while $CET \leq \mathrm{p}^*CET$:
(i). Find the quickest path p^* with the minimum combined evacuation time $T = CET\left(R \cup \left\{p^*\right\}\right)$.
(ii). If $T = p^*CET$ do the following:

(a). Set $R = \left(R \cup \left\{p^*\right\}\right), p^*CET = C$ and $CET = T$.

(b). For each edge e on p^* set $RC\left(e\right) = RC\left(e\right) + CP\left(p^*\right)$.

● Path removal

4. Repeat the following while there is a path $p^* \in R\ s.t.\ TT\left(p^*\right) > CET\left(R\right)$.

(i). Set $R = R \setminus \left\{p^*\right\}$.

The running time of QPER algorithm is determined by the number of iterations and is bounded above mainly by total number of paths rather than the number of evacuees and makes it suitable for large scale networks. A slightly modified and simple version of this algorithm has been presented and applied for the single source single sink evacuation (SSEP) problem in (Mishra et al, 2015) for k edge-disjoint paths $P_1^*, P_2^*, \ldots, P_k^*$ from P to S in ascending order of their transit times with $T_1 \le T_2 \le \ldots \le T_k$. For $S_i = P_1^*, P_2^*, \ldots, P_k^*$ paths to the set of routes R are added as a simple SSRP algorithm as in Algorithm 3.3.

Algorithm 3.3: SSEP Algorithm

(i). $R = \left\{P_1^*\right\}$.

(ii). $CET = CET\left(S_1\right)$.

(iii). Start with $i = 1$. Execute step (iv) and (v) till $i \le k$ and $T_{i+1} \le CET$.

(iv). Add path P_{i+1} to R.

(v). $CET = CET\left(S_{i+1}\right)$ and $i \leftarrow i + 1$.

(vi). Return R.

For such edge disjoint paths $\{P_1^*, P_2^*, \ldots, P_i^*\}, i \le 1,$ the next path P_{i+1}^* is discovered in residual graph if and only if $T_{i+1} \le CET\left(S_i\right)$. As the saturated nodes and edges in each iterations are deleted in maximum $m + n$ iterations are carried out but not more than x as each path can evacuate at least an evacuee. So, at most $\min\left(m + n, x\right)$ paths are disconnected. For $m = O\left(n\right)$, its time complexity is at most $O\left(xn \log n\right)$. For such single source single sink problem the SSEP algorithm has been developed to the evacuation route planner algorithm.

Algorithm 3.4: Evacuation Route Planner Algorithm for $\boldsymbol{P - S}$.

●**Input:** A network $G\left(V, E\right)$ with designated $P, S \in V$. Every node $v \in V$ has an occupancy and maximum capacity. Every edge $e \in E$ has a maximum capacity and transit time. Initially, all evacuees are in P.
●**Output:** Evacuation route plan for each evacuee.

```
begin
    Initialize R = ∅ and CET = ∞.
    Initialize i ← 0.
    While S is reachable from P and number of discovered paths p* − 1 do
        Find the shortest path p*_{i+1} from P to S for T_{i+1}, C_{i+1} be its transit time and capacity.
        if T_{i+1} ≤ CET then
            R = R ∪ {p*_{i+1}}
            CET = CET(S_{i+1})
            Reduce the capacity of each node and each edge of P_{i+1} by C_{i+1}.
            V = V \ {v : v is a saturated node of P_{i+1}}.
            E = E \ {e : e is a saturated edge of P_{i+1}}.
```

```
            end
            else
                break
            end
      end
      Let R = {p_1^*, p_2^*, ..., p_k^*}.
      Send x_i evacuees via p_i^* for 1 ≤ i ≤ k, where T_i + ⌈x_i / C_i⌉ − 1 = CET.
end
```

The idea of CET in (Min and Neupane, 2011) is extended to the probabilistic behavior of the evacuees in (Mishra et al, 2015) assuming that the evacuees do not follow the path suggested as in Algorithm 3.1. For this, let α and $1-\alpha$ be the probabilities that for suggested and the next (those, who will try to reach their nearest exit), then the total number of evacuees following p_1 and p_i becomes $x_i + \sum_{i=2}^{k}\left(1-\alpha\right)x_i$ and αx_i, $i \neq 1$ respectively with the expected time at which the last person arrive at the destination through such paths be $T_1 + \frac{x_i + \sum_{i=2}^{k}\left(1-\alpha\right)x_i}{C_1} - 1$ and $T_i + \frac{\alpha x_i}{C_i} - 1, i \neq 1$ respectively. Thus the expected evacuation time in this scenario becomes,

$$E\left[T\right] = \left(T_1 + \frac{\left(1-\alpha\right)n}{C_1} - 1, \max_{2\le i\le k}\left(T_i + \frac{\alpha x_i - 1}{C_i}\right)\right) \tag{35}$$

It has the lower bound as $T_1 + \frac{\left(1-\alpha\right)n}{C_1} - 1$.

Emergency evacuation strategies based on the spatial and temporal information of the evacuees has been formulated in (Zheng, 2014) where the buses run continuously on the basis of the where-and-when information and according to the needs of the evacuee, rather than the fixed routing in order to minimize the exposed casualty time rather than the operating cost. For the solution, a Lagrangian-relaxation-based algorithm was proposed where the model was formulated as usual as a mixed-integer linear programming formulation.

4. APPLICATIONS

Two instances of (i) finding a bomb within city center of Keiserslautern Germany and (ii) an earthquake with a subsequent flood in the area of Nice, France were taken in (Goerigk and Grün, 2014) to test the applicability of their modeling of a comprehensive evacuation planning using genetic solution algorithm. Four notable applications of lane-evacuation routing were effectively conducted in a similar manner in Salt Lake City, Utah as in (Cova and Johnson, 2003) for different situations by creating pedestrian and vehicle evacuation zone. The evacuation of Yokosuka City by (Yamada, 1996) and the evacuation of Knox County, as a county-wide evacuation scenario for Tennessee in (Han et al., 2006) were carried out using a maximum cost flow network model. An application of BEP is presented by (Pyakurel et al., 2015) in a hypothetical case study of the evacuation planning of transit dependent people of Kathmandu valley to evacuate the population of around 25,672 within the area of 1.45 km2 using branch-and-bound and tabu search algorithms. The best results obtained for an instance are; evacuation time of 29 minutes with 6 or 5 sources and 5 sinks for evacuation of 50 percent population using 140 buses having 90 evacuees per bus capacity and 15 km/hr speed.

By using an optimal spatio-temporal evacuation (OSTE) model, authors in (Abdelgawad et al., 2010) have investigated, analyzed and purposed the multiple time-structure model for the transit vehicle routing and scheduling from a multi-objective perspective with real-life constraints and also suggested for the need of other modes like cycling and walking. For large-scale multi-modal emergency evacuation, authors in (Abdelgawad and Abdulhai, 2010) have also used it to optimize the routing and scheduling of mass-transit vehicles on the city Toronto by using only 1320 transit shuttle buses and 4 rapid transit lines to evacuate efficiently the transit-dependent population of about 1.34 million within 2 hours.

Among others, authors in (Zhang et al., 2010) have applied the numerous optimization and simulation approaches to model the trip route assignment to maximize the flow of evacuees from the risk area to safety or to minimize the travel time based on Dijkstra algorithm on time-space network. For this, firstly all residents or other evacuees are evacuated safely to temporary safe stop by foot and secondly they are picked up by public transit which also signifies the importance of public transit-dependent emergency evacuation in developing countries, like Nepal. Moreover, a transit based evacuation model for metropolitan areas was tested significantly on the city of Baltimore's downtown road network in a study by (Zhang and Chang, 2014) assuming an incident of sudden terrorist attack. There were about 40 pedestrian demand points, 2 transit depots, and 10 safe destinations. The applicability of the proposed model and its advantages compared with the available models in the literature was found significant.

The effective and imperative study on the emergency evacuation planning model for the specific need populations addressing the optimal location of bus stops has been presented by (Kaisar et al., 2012) and was applied to a real-life to evacuate the effects of location, number, and distribution of optimal evacuation bus stops. By selecting 20, 40, and 60 bus stop scenarios; they experienced that 20-bus-stop scenario has a high delay because of the congestion of the buses; 40-bus-stop scenario yields the highest delay, travel, and stop times since the bus stop locations still requires a large number of evacuation trips whereas the 60-bus-stop scenario produced the most efficient evacuation time. Its delay, travel, and stop times were all the lowest compared to the others. The proposed methodology was applied to the real-life case of the downtown Washington, D.C. to select the most suitable location and number of bus stops. It suggests not only for the need of different evacuation routes, headways and frequencies in which the buses depart or pick up, but also to explore the new, possible and appropriate evacuation bus stop locations within the network. Restructuring of evacuation planning approach has been implemented in (Lim et al., 2016) including a network preprocessing algorithm and a network flow optimization approach and was developed to find a set of alternative paths and their corresponding flow rates. This approach was tested successfully further on the actual evacuation network of the Greater Houston area.

To test the integrated contraflow strategy for the multi-modal evacuation, authors in (Hua et al., 2014) have considered the evacuation network of Ningbo city, located on the east coast of the Pacific Ocean where there are on an average of 3.1 typhoons per year. They present a plan to evacuate 350,000 people with 69,000 auto vehicles each vehicle with an average capacity of 2.9 and buses with each 35 seats. An arterial sub-network, as the road segment without direct connection to the origin nodes and the local roads which are connected to the origin nodes as the access to arterials are considered on the network aggregation for the two-stage evacuation process. They have presented the separate evacuation models for the transit-based and auto-based evacuees where the transit-based evacuation problem is solved with a minimum cost flow model in first priority and then only the auto-based evacuation problem is addressed with a bi-level network flow model. The approximate optimal evacuation plan of the evacuation network has been obtained at the top level, where the traffic volumes and travel times in streets were derived from equilibrium traffic assignment in the bottom level. However, it is almost impossible to optimize an evacuation network containing all the arterials and local roads, simultaneously. But, the network aggregation method has maintained the balance between the accuracy and efficiency though the management of arterial-arterial intersections and the transit priority at the intersections are not considered which may further improve the transit-based evacuation. To evacuate the area surrounding a nuclear power point, (Campos et al., 2000) have successfully applied the k-shortest path method. For such disasters situations, like nuclear accidents, hurricanes, and floods etc. different approaches of simulation tools has also been applied. For the mass evacuation of the areas surrounding the sites of nuclear power points (Sheffi et al., 1982) have used the macroscopic traffic simulation model to simulate the traffic patterns to have minimum clearance time.

The most prominent applications of the transit vehicles with their optimal routing and scheduling has been applied in (Abdelgawad and Abdulhai, 2012) to evacuate the entire city of Toronto, Canada with a population of about 2.37 million. The model generates optimal scheduling and timetable for each train on the subway lines and the big shuttle buses on the transportation network. The results show that the Toronto Transit Commission fleet is capable of evacuating the transit-dependent population of about 1.34 million within 2 hours on average. The four subway lines of the city of Toronto carry approximately 0.62 million people and can evacuate these people in less than 3 hours of average whereas, 1320 shuttle buses of the Toronto Transit Commission can evacuate the remainder of the transit dependent population of about 0.72 million in approximately 1.5 hours on average.

5. CONCLUSIONS

This paper has attempted to provide a comprehensive review of the fundamental and prominent transit-based approach of evacuation planning optimization problems. With some highlights on various types of the evacuation models on different basis, we are concentrated mainly on the bus-based evacuation. At the meantime, different mathematical models and algorithms which were developed over the years to address such transit-based evacuation under both predictable and unpredictable disasters with the location-allocation design, pick-up locations, their routing, assignments and scheduling on the evacuation network are also addressed. The determination of optimal fleet size, their assignment for optimal routing, and the appropriate network structure and their impact to the optimality of the solution on the mini-max objective and the cost objective are also addressed with some highlights on the traffic control delays at the intersections, the lane reversal and crossing elimination strategies including their different characteristics. Additionally, some representative real-world applications of each approach have also been presented so far, expecting that it should be able to guide much more interest into this important and growing area of research and some of the extensions might be as follows:

●Therouting modification, management of arterial sub-networks, and transit priority at the intersections can be considered for the further improvements of the lane reversal and crossing elimination strategies.

●In practice, people may be of limiting resources during the evacuation planning. So, different resource-constraint version of the problem can also be expected.

●Most of the problems have been tackled with various heuristics. In the networks of practical size, alternative solution methodologies, such as problem decomposition and use of meta-heuristics and different other relevant algorithms can be performed to improve and adjust the solutions.

●Most of the evacuation models are with several assumptions like symmetric networks, constant evacuation demand, constant evacuee rate, and homogeneous distributions of evacuees, identical and independent facility disruptions and many more; which are not always realistic.

●Various simulation approaches are developed on various situations with different parameters for different objectives and constraints and might be the better choice for further modifications.

●The location planning of the collection points, selection of the optimal pick up locations, appropriate shelters, planning of logistic surroundings and the provisioning and medical shelters can also be considered moderately for the better evacuation planning in practice.

●Public transit shuttle buses, rapid transit vehicles and different automobiles are used on evacuation planning in a single platform demands the multi-modal evacuation and can also be integrated with walking, cycling etc. The coordination between transit modes, route choice and the evacuees' behavior and some specific needs are still lacking. It demands the further investigation.

●Furthermore, more theoretical and analytical studies, relevant lower bounds, algorithms with performance guarantee and their dominance, complexity results, etc. are still lacking and insufficient.

●Many of the parameters are not known and mostly non-linear with full of uncertainties. So, various limitations may exist on the findings and always expecting for the further improvements.

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