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An integrated solution approach for the time minimization evacuation planning problem

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Abstract: Traffic route guidance, destination optimization, and optimal route choice are some of the approaches to accelerate the evacuation planning process. Their effectiveness depends upon the evacuee arrival patterns at the pickup locations and their appropriate assignment to transit-vehicles in the network. Here, the integrated evacuation network topology is composed of two constituent sub-networks, namely, the primary and the secondary sub-networks. We are focused on the collection of evacuees at the pickup locations of the primary sub-network from the danger zone in the earliest arrival flow pattern, and then their assignment to the transit-vehicles in the secondary sub-network.
Transit-vehicles are provided from the bus depot in the secondary sub-network. Pickup locations are taken as the sources for the subsequent process to minimize the overall network clearance time from the danger zone to safety. In this paper, we have proposed an integrated optimization approach in such an integrated network to achieve the minimum clearance time. The earliest arrival pattern respects the partial lane reversal strategy, whereas the better assignments are based on the dominance relations concerning the evacuation duration.
Keyword — Integrated network, arrival pattern, vehicle assignment, clearance time, partial lane reversals, dominance relations.

1. INTRODUCTION

The massive loss of human life and the socio-economic damage caused by different disasters draw increasing attention from society and also researchers towards disaster management. Effective evacuation planning helps to save the life of people from such disasters. In most of the large cities, many people depend on transit-vehicles. The great loss of people in disasters is due to a lack of proper planning for transit people and vehicles rather than the disaster itself.

Mostly, evacuation planning solutions are based on network flow models. A network consists of nodes and edges. Each node corresponds to the intersection of streets, and each edge, connecting a pair of nodes, corresponds to a road or street segment in the region. Commodities flow between nodes, transported by edges having a capacity constraint, which restricts the amount it can transverse and compromises the balance and flow of the process. The locations where evacuees are situated initially are the source nodes and the safe locations where the evacuees are to be transported to are sink nodes. The transit time is the amount of time it takes for the flow to travel through the edges. Network flows have many applications on transportation modeling. For example, the evacuation planning problems deal with shifting the maximum number of evacuees from disastrous areas or potential danger zones to safe destinations as quickly as possible with utmost reliability. For dynamic network flow problems, not only the amount of flow transmitted but also the time needed for the flow plays an important role. The flow may be auto-based, transit-based or the pedestrian movements, and the time may be discrete or continuous. Such problems arise in many applications of the evacuation planning problems. There has been a fair amount of work in this area, as referred by Dhamala and Adhikari (2018); Dhamala, Pyakurel, and Dempe (2018).

The pioneering work of Ford and Fulkerson (1962) opened a wide horizon for the flow over time problems, which seek the optimal maximum flows over time in the given time horizon T. The quickest flow problem minimizes the time to transfer a given amount of flow value from an initial position to the destination Chen and Chin (1990). The earliest arrival flow maximizes the amount of flow units reached a sink at each point in time simultaneously. Such a flow may not necessarily exist in every network, though it exists for a single-source single-sink Gale (1959).

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A prominent bus-based evacuation planning problem BEPP is proposed by Bish in Bish (2011) to minimize the time of evacuation in case of a short notice using a given number of homogeneous buses satisfying all evacuee demands, without violating both the sink and vehicle capacity constraints. In this, the number of evacuees at the demand node might be greater than the capacity of a bus, and it demands the split delivery within the pickup locations. But if the number of evacuees at every source is known in terms of the integral multiples of the busloads, then it does not demand the split Goerigk, Grün, and Heßler (2013). The majority of the evacuation planning problems in the literature had used the homogeneous fleet of vehicles though some of them like Baou, Koutras, Zeimpekis, and Minis (2018) have used the heterogeneous fleet of vehicles.

Pyakurel, Goerigk, Dhamala, and Hamacher (2015) explored a broad horizon to the research related to the transit-dependent evacuation planning problem. Kathmandu, one of the densely populated city, has been considered as the disaster region for their case study and have drawn different findings on evacuation planning problem. In such a problem, evacuees were supposed to gather themselves from their residents, depending on the disasters scenario, to the nearby pickup locations. The excess exterior points of the endangered region were taken as the pickup locations and the available open spaces as the sinks. Evacuees were supposed to be brought at such sinks from the pickup locations by using the homogeneous buses having the uniform capacity for the evacuees' pickup.

A deterministic and a stochastic formulation are proposed by Goerigk and Grün (2014), where the exact number of evacuees is not known in advance, although a set of possible scenarios is provided. However, after some reckoning time, such uncertainty is removed with exact figures. The problem is to decide for each bus, whether it is better to move right now on such uncertainties as a here-and-now bus, or to wait till the uncertainties are removed as a wait-and-see bus. Their approach aims to minimize the total network clearance time, that is, the time needed until the last evacuee is brought to safety.

Hua, Ren, Cheng, and Ran (2014) had presented an integrated contraflow strategy for multimodal evacuation. Their strategy contains non-contraflow to shorten the strategic set-up time, full-lane contraflow to maximize the evacuation network capacity and bus contraflow to realize the transit cycle operation. Pyakurel and Dhamala (2015) had investigated the lexicographically maximum dynamic contraflow problem in which the flow is maximized in a given priority ordering. By introducing the continuous network contraflow approach, they have addressed different analytical and theoretical aspects for evacuation planning problems at arbitrary and zero transit times, Pyakurel and Dhamala (2017a). The quickest continuous contraflow problem on single-source-single-sink arbitrary networks and the continuous earliest arrival contraflow problem on single-source-single-sink series-parallel networks with undefined supply and demand have been solved in Pyakurel and Dhamala (2016). Pyakurel, Dhamala, and Dempe (2017) have considered the value approximate earliest arrival transshipment contraflow approach for the arbitrary and zero transit in arcs. Recently, the authors in Pyakurel, Nath, Dempe, and Dhamala (2019) have introduced the partial contraflow model and addressed different issues on it with constant transit times and inflow-dependent transit times.

Here, in the integrated evacuation approach, the network topology is composed of two constituent sub-networks, namely, the primary and the secondary sub-networks. Evacuees are collected at the pickup locations of the primary sub-network in the earliest arrival flow pattern, and then they are assigned to the transit-vehicles, in the secondary sub-network. It is more general than the network for the earliest arrival flow and the transit-based network, separately. It is an integrated approach to solve for the time minimization evacuation planning problem.

The rest of this paper is organized as follows. Section 2 gives few preliminary concepts with the network topology for the integrated evacuation planning problem. Section 3 presents an integrated evacuation scenario in three different subsections. Firstly, we introduce the earliest arrival evacuee problem in a network of a single source and multiple pickup locations. Considering the flow model with zero transit time, we present a polynomial-time algorithm following the principle of temporally repeated flows to transship given flow value from the source to the pickup locations by saving all unused arc capacities of arcs in Subsection 3.1. We study the BEPP, and prove the dominance relation of different heuristics with respect to the evacuation duration in Subsection 3.2. Then combining these two approaches, we present an integrated evacuation model in Subsection 3.3. The solution approach in an integrated evacuation network is presented in Section 4. Finally, Section 5 concludes the paper.

2. PRELIMINARIES

We consider a network $\mathcal{N}$, obtained by combining two of its components $\mathcal{N}_1$ and $\mathcal{N}_2$ representing a primary and a secondary sub-network, respectively. The first part $\mathcal{N}_1$ contains directed two-way road segments and the partial arc reversals is applicable. The second part $\mathcal{N}_2$ contains directed one-way road segments, connecting the bus depot to the pickup locations, and undirected edges connecting such pickup locations to the sinks for the bus routing. The network topology of such an embedded network, $\mathcal{N} = \mathcal{N}_1 \cup \mathcal{N}_2$ is illustrated in Figure 1.

The primary sub-network is denoted as $\mathcal{N}_1 = (s, V, A, u_a, \tau_a, Y)$ with a single source s, set of auxiliary nodes $V = \{v_1, v_2, \dots, v_n\}$, set of pickup locations $Y = \{y_1, y_2, \dots, y_n\}$, set of arcs $A = \{a \mid a = (s, v) \vee (v, y)$ where $v \in V,\ y \in Y\}$, capacity u_a and transit time τ_a for each $a \in A$. Here, Y is also considered as a set of multiple sinks. The capacity $u_a : A \to \mathbb{Z}_{\geq}0$ restricts the amount of flow on the arc and the transit time $\tau_a : A \to \mathbb{Z}_{\geq}0$ represents the amount of time to transverse the respective arc. As we consider τ_a to be constant for all $a \in A$, it is assumed to be zero.

Also, secondary sub-network is denoted as $\mathcal{N}_2 = (d, Y, E, \tau_e, Z)$, where d is the bus depot at which a set of transit-buses $B = \{b_1, b_2, \ldots, b_n\}$ having the homogeneous bus capacity are located initially and are assigned as required during the evacuation process. This node d does not play significant roles further on the solution procedure as the buses do not return to it even after the completion of the evacuation plan because of risks under threat. The set of nodes Y with respect to $\mathcal{N}_1$ is considered as the set of sources for $\mathcal{N}_2$. The set of sinks is denoted by $Z = \{z_1, z_2, \ldots, z_n\}$. In this mixed sub-network, the set E consists of the one-way arcs $e = (d, y)$ with $y \in Y$ and the undirected edges $e = [y, z]$ with $y \in Y, z \in Z$. Transit times of the respective arcs and edges are denoted by $\tau_e \in \mathbb{Z}_+$.

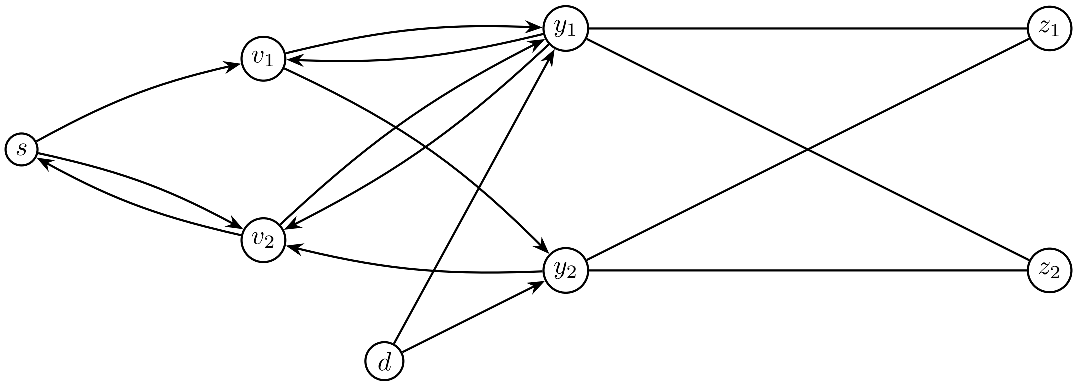

Figure 1: A topology of an integrated evacuation network.

3. AN INTEGRATED EVACUATION SCENARIO

In an integrated evacuation scenario, evacuees collected at the pickup locations Y in $\mathcal{N}_1$ are assigned to transit-buses in the appropriate route across $\mathcal{N}_2$ and are finally sent to the sinks. In such embedding, the set Y works as the sink for $\mathcal{N}_1$ but as the source in $\mathcal{N}_2$.

The arrivals of evacuees at different pickup locations are usually probabilistic, which are categorized by a constant arrival rate or by a random variable that is, deterministic or stochastic, time-dependent or flow-dependent. Evacuees have gathered themselves at different pickup locations relative to the population density of the transit-dependent people nearby them in Pyakurel et al. (2015) with no specific arrival patterns. Pereira and Bish have considered the constant arrival rate of evacuees at the predetermined pickup locations in Pereira and Bish (2014). However, such an assumption is still unrealistic as the actual arrival process is probabilistic and will likely vary over time. Two of the prominent BEPP formulations as in Goerigk et al. (2013) and Bish (2011) have considered the evacuees at the pickup locations, but these approaches do not speak about the specific arrival patterns. However, they take into account whether the number of evacuees is the integral multiples of the busloads or not. Such a problem BEPP is extended to a robust BEPP by assuming that the number of evacuees is not known exactly but a set of estimates for the number of evacuees at each source Goerigk and Grün (2014).

In this section, we are presenting the earliest arrival pattern of evacuees in $\mathcal{N}_1$, their assignment to vehicles in $\mathcal{N}_2$ and the mathematical model in $\mathcal{N}$.

3.1 The earliest arrival pattern of evacuees

When preparing for an evacuation, the time it actually takes is uncertain, and hence it is preferential to plan at each point of time to execute the maximum flow, which is offered by the earliest arrival flow. It is better-suited for evacuation planning as it maximizes the flow of evacuees simultaneously at each instance within the given time horizon. Such an evacuee arrival pattern is more appropriate for the integrated evacuation scenario.

An s-y flow of evacuees over time is a non-negative function f on $A \times \mathbb{R}_+$, for given time $\mathbf{T} = \{0.1. \ldots, T\}$ satisfying the flow conservation and capacity constraints (1-3). The inequality flow conservation constraints allow waiting for flow at intermediate nodes. However, the flow conservation constraints force that flows entering an intermediate node must leave it again immediately.

$$\sum_{\sigma=\tau_a}^{T} \sum_{a\in A_i^{in}} f(a,\sigma-\tau_a) - \sum_{\sigma=0}^{T} \sum_{a\in A_i^{out}} f(a,\sigma) \quad = \quad 0,\ \forall\, i \notin \{s,y\}, \tag{1}$$

$$\sum_{\sigma=\tau_a}^{\theta} \sum_{a\in A_i^{in}} f(a,\sigma-\tau_a) - \sum_{\sigma=0}^{\theta} \sum_{a\in A_i^{out}} f(a,\sigma) \quad \geq \quad 0, \forall i \notin \{s,y\}, \theta \in \mathbf{T}, \tag{2}$$

$$0 \ \leq\ f(a,\theta) \ \leq\ u_a, \qquad \forall\, a \in A,\ \theta \in \mathbf{T}. \tag{3}$$

Here, $A_i^{out} = \{a = (i,j) \in A\}$ and $A_i^{in} = \{a = (j,i) \in A\}$ are the sets of outgoing and incoming arcs, respectively for the node $i \in V$. For the source node s, we get the flow value be $\nu_f(s) > 0$, and for the sink y the flow value becomes $\nu_f(y) < 0$, whereas $\sum_{i\in V} \nu_f(i) = 0$. If the supply and demand on sources and sinks $\nu_f(i)$ is a fixed value for all $i \in \{s,y\}$, then the earliest arrival evacuee problem maximizes value(ν_f,θ) for all $\theta \in \mathbf{T}$, as in Equation (4) satisfying the constraints (1-3).

$$(\nu_f,\theta) = \sum_{\sigma=0}^{\theta} \sum_{a\in A_s^{out}} f(a,\sigma) = \sum_{\sigma=\tau_a}^{\theta} \sum_{a\in A_y^{in}} f(a,\sigma-\tau_a) \tag{4}$$

We consider a flow over time problem with zero transit time function $f : A \times \mathbb{Z}_+ \to \mathbb{R}_+$.

Problem 1. Given a flow over time sub-network $\mathcal{N}_1 = (s, V, A, u_a, \tau_a, Y)$ with supplies at s, auxiliary nodes V, arc capacity u_a and arc transit time τ_a for $a \in A$. The earliest arrival evacuee problem is to find the earliest arrival of evacuees at Y with partial arc reversal capability.

Let the reversal of an arc $a = (i,j)$ be $a' = (j,i)$, then the transformed network of $\mathcal{N}_1$ consists of the modified arc capacities and constant transit times as,

$$b_{\overline{a}} = b_a + b_{a'}, \ \text{ and } \ \tau_{\overline{a}} = \begin{cases} \tau_a, & \text{if } a \in A \\ \tau_a', & \text{otherwise} \end{cases} \tag{5}$$

where an edge $\overline{a} \in \overline{A}$ in a transformed network, if $a \vee a' \in A$ in $\mathcal{N}_1$. The remaining graph structure and data are unaltered. For the sake of simplicity, we use $\mathcal{N}_1$ for a transformed network, in which $\overline{a}$ and $\overline{A}$ are replaced by a and A, respectively, in the rest of the works. In the transformed network $\mathcal{N}_1$, we have solved the earliest arrival transshipment problem with zero transit times on each arc as in Schmidt and Skutella (2014) and saved all unused arc capacity as in Pyakurel et al. (2019).

The total flow amount out of the source s that reached to the pickup locations Y in $\mathcal{N}_1$ for all time up to $\theta' \in \mathbb{Z}_+$, with zero transit times $\tau_a = 0$, is given by

$$|\nu_f|_{\theta'} = \sum_{\theta=1}^{\theta'} |\text{value}(Y,\theta)|. \tag{6}$$

For the given time bound T, the value in 6 is denoted by $|\nu_f| = \sum_{\theta=1}^{T} |\text{value}(Y,\theta)|$.

For the earliest arrival flow over time reached to Y in $\mathcal{N}_1$, the net amount of flow given by Equation (6) should be maximum at every point in time within the given time horizon. Such a flow over time will simultaneously maximize the flow that has already reached the sinks for all points in time. For details, we refer to Pyakurel and Dhamala (2017b); Schmidt and Skutella (2014).

In the case of arbitrary transit times, no earliest arrival transshipment exists even in a one-source-two-sinks, Baumann and Skutella (2009). However, every in-or out-tree with the depth of at most two always allows for the earliest arrival transshipment for every choice of capacities and flow values for zero transit Schmidt and Skutella (2014).

Hence, the existence of such flow with zero transit times is based on the depth of the network considered. A directed graph with exactly one path from i to j for every node i is the in-tree with root j. Likewise, the directed graph with exactly one path from j to i for every node i is the out-tree with root j. The depth of an in-or out-tree is the number of edges on the longest path contained in it.

Lemma 1. Consider $\mathcal{N}_1$ with zero transit times. Then every in-or out-tree with a depth of at most two in $\mathcal{N}_1$ always allows for the earliest arrival transshipment regardless of capacities and balance values, Schmidt and Skutella (2014).

Theorem 1. There exists an earliest arrival transshipment with zero transit times in a type $\mathcal{N}_1$ network of single-source and multi-sink, where the depth is at most two.

Proof. The earliest arrival $s-y$ flow exists for a single-source-single-sink network as in Gale (1959). However, the earliest arrival transshipment does not exist for arbitrary transit times, even in a single-source and double-sink network. But from Lemma 1, the earliest arrival transshipment with zero transit times exists for all networks with a depth of at most two, and is satisfied for the single-source and multi-sink network. □

Now, Algorithm 1 is presented to solve the earliest arrival evacuee problem with zero transit times with partial arc reversal capability in polynomial-time complexity.

Algorithm 1: The earliest arrival evacuee algorithm

Input : A flow over time sub-network $\mathcal{N}_1 = (s, V, A, u_a, \tau_a, Y)$ with $\tau_a = 0$ for each $a \in A$.
1 Construct a transformed network $\mathcal{N}_1$ as in Equation 5.
2 Determine the maximum number of evacuees at every possible time instance at each Y from s as in Schmidt and Skutella (2014).
3 For each $\theta \in \mathbf{T}$ and reverse $a' \in A$ up to capacity $c_a - u_a$ iff $c_a > u_a$, u_a replaced by 0 whenever $a \notin A$, in $\mathcal{N}_1$, where c_a denotes the static $s-y$ flow value in each $a \in A$ for such sub-network.
4 For each $\theta \in \mathbf{T}$ and $a \in A$, if a is reversed, $\kappa_a = u_{\overline{a}} - c_{a'}$ and $\kappa_{a'} = 0$. If neither a nor a' is reversed, $\kappa_a = u_a - c_a$, where κ_a is saved capacity of a, Pyakurel et al. (2019).
Output: Earliest arrival of evacuees at Y with $\tau_a = 0$ for each $a \in A$.

Theorem 2. Algorithm 1 sends the evacuees at the earliest arrival time to Y at each instances and saves the unused arc capacity.

Proof. The construction of a transformed network for a given network in Step 1 is feasible. Steps 2 and 4 are feasible. As there is no cycle flow in Step 2, the flow is either on arc a or a' but never in both directions simultaneously. And such a flow is not greater than the modified capacities of each arc in the transformed . So, Step 3 is also feasible. Hence, Algorithm 1 is feasible.

Now, we show that Algorithm 1 gives an optimal solution. In the transformed network, we compute the maximum number of evacuees reached to each pickup location in Y at every possible time point with zero transit times on each arc using the algorithm of Schmidt and Skutella (2014). As in Theorem 1, there are some characteristic networks with the depth bounded by two in which the earliest arrival flow exists. As the maximum amount of flows are assigned from the source s across different auxiliary nodes to Y at each instance, by using Equation (6) for the maximum flow value, it gives the evacuees at the earliest arrival time to such pickup locations at each instance. Moreover, the obtained solution is equivalent to the solution of the earliest arrival evacuee problem in the original sub-network $\mathcal{N}_1$ with the arcs reversed up to the necessary capacity as in Step 3, Pyakurel et al. (2019). The capacities of the arcs not used by the flow after partial arc reversals are recorded in Step 4. This completes the proof. □

Theorem 3. The earliest arrival evacuee problem with zero transit times can be solved in polynomial-time complexity using Algorithm 1 in the sub-network $\mathcal{N}_1$.

Proof. As Steps 1, 3, and 4 of Algorithm 1 are solved in linear time, its time complexity is dominated by the time complexity of computation of the earliest arrival evacuees at the pickup locations Y with zero transit times on each arc as in Schmidt and Skutella (2014) in Step 2, which is solved in polynomial-time. Thus, we solve the earliest arrival evacuee problem in polynomial-time complexity in the sub-network $\mathcal{N}_1$. □

Theorem 4. The earliest arrival evacuee problem having zero transit times with partial arc reversal capability follows the principle of temporally repeated flows and can be solved in polynomial-time complexity.

Proof. The flow over time problem having zero transit times that reached to each of the pickup locations determines the maximum number of evacuees at every possible time instance from the beginning in the primary sub-network $\mathcal{N}_1$ as in Schmidt and Skutella (2014). That means the earliest arrival of evacuees at Y from s with zero transit times on the transformed network follows the principle of temporally repeated flows which is equivalent to the solution with arc reversals capability on the original network, Pyakurel and Dhamala (2017b). It can be obtained in polynomial-time complexity as in Theorem 3. Hence the theorem is proved. □

3.2 Assignment of vehicles

Transit-vehicles are assigned in an appropriate route across $\mathcal{N}_2$ to send the evacuees to the sinks. It is similar to the BEPP as presented by Bish (2011) and Goerigk et al. (2013) to minimize the duration of evacuation by using a given number of homogeneous buses satisfying all evacuee demands respecting the sink and vehicle capacity constraints. In such a problem formulated as in Bish (2011), the number of evacuees at the demand node might be greater than the capacity of a bus, and it demands the split delivery (SD) service within the pickup locations. However, the split delivery service does not improve the solution, as illustrated in Example 1, based on Dror and Trudeau (1990).

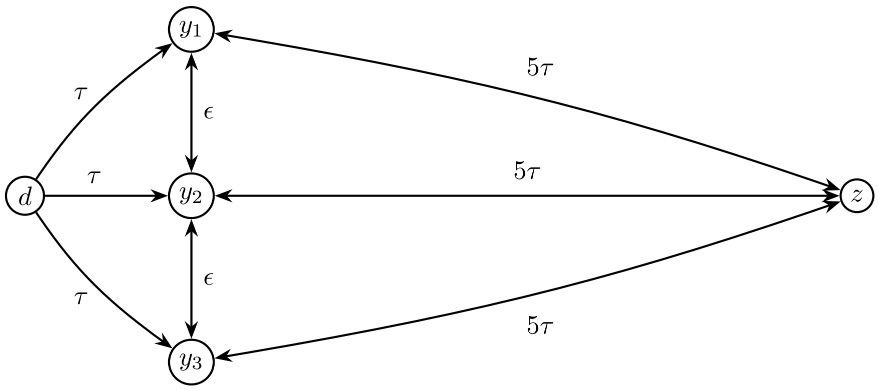

Figure 2: An instance of evacuation network.

$\|B\|$	Π & ED without SD	Π & ED with SD	Bound
1	$d-y_1-z-y_2-z-y_3-z=26\tau$	$d-y_1-y_2-z-y_2-y_3-z=16\tau+2\epsilon$	1.625
2	$d-y_1-z-y_2-z=16\tau$	$d-y_1-y_2-z=6\tau+\epsilon$	
	$d-y_3-z$	$d-y_3-y_1-z$	2.67
3	$d-y_1-z=6\tau$	$d-y_1-z=6\tau$	
	$d-y_2-z$	$d-y_2-z$	1
	$d-y_3-z$	$d-y_3-z$	
4	$d-y_1-z=6\tau$	$d-y_1-z=6\tau$	
	$d-y_2-z$	$d-y_2-z$	1
	$d-y_3-z$	$d-y_3-z$	
	ϕ	ϕ	

Table 1: The split delivery does not always improve the solution in transit-based evacuation.

Example 1. Consider an evacuation network in Figure 2, where d, $\{y_1, y_2, y_3\}$, and z are the bus depot, pickup locations, and the sink, respectively. Consider $|B|$ buses are located at d with a homogeneous capacity of 50 evacuees. Let the demands at pickup locations y_1, y_2, and y_3 be 30, 40, and 30, respectively. Consider the pickup locations are at equal distance, τ each, from the depot and are at 5τ from the sink. Here, ϵ is used to denote that the pickup locations are sufficiently close to each other and connected by edges. Consider the sink capacity to be 100.

The tour plan Π and the respective evacuation duration (ED) without and with SD, and their respective bounds are shown in the second, third, and fourth columns of Table 1, where the buses were scheduled simultaneously. Here, the bound denotes the corresponding ratio of the ED obtained in column 2 to that in column 3, for the network considered. The bound greater than 1 indicates that the SD service improves the solution. During their route assignments, sometimes the SD service is also appropriate though it may not always improve the ED. Here, no improvement in the solution by applying the SD service for $|B|$ equals 3 and 4.

Here, we consider the modified version of the BEPP as in Problem 2, as formulated in Goerigk et al. (2013).

Problem 2. Let $(\tau_{ij})_{i\in Y, j\in Z}$ be a matrix of source-sink travel times, τ_{di} be a vector of depot-source travel times, $(_i)_{i\in Y}$ be a vector of evacuees number and $(\mu_j)_{j\in Z}$ be a vector of sink capacities. Then the BEPP is to find a tour plan to minimize the maximum travel times overall buses such that all the evacuees are transported to the sinks.

For this, it is assumed that the number of evacuees at every source is known in terms of the integral multiples of the bus loads, which do not require any split delivery service. Assume that every bus has a capacity of one unit.

Moreover, the capacity of the sink is also in terms of bus loads. The movement between a source to another source is ignored, and the same situation is considered between the sinks. It is assumed that, the set of tours of the buses cannot be changed any more after they start to move. Let $\sum_{i\in Y} l_i$ and $\sum_{j\in Z} \mu_j$ be the total number of evacuees and the total sink capacities, respectively. The maximum number of rounds R for the evacuation process is given by $\sum_{i\in Y} l_i$. The nonnegative travel cost of τ_{ij} on each edge $e = (i, j) \in E$ is taken symmetric and satisfies the triangle inequality.

The variables τ_{to}^{br} and τ_{back}^{br} give the travel time for the vehicle b within the round r from a source to a sink, and from that sink to another source, respectively. The binary variable $x_{ij}^{br} \in \{0, 1\}$ denotes whether the vehicle b travels from source i to sink j in the round r. Let $\mathcal{T}_{\max}$ be the duration of evacuation overall vehicles. The problem can be formulated as follows.

$$\begin{aligned}
\text{minimize} \quad & \mathcal{T}_{\max} && (7)\\
\text{such that} \quad \mathcal{T}_{\max} &\geq \sum_{i\in Y}\sum_{j\in Z} \tau_{di} x_{ij}^{b1} + \sum_{r\in R} \tau_{to}^{br} + \sum_{r\in R} \tau_{back}^{br}, \quad \forall b \in B, && (8)\\
\tau_{to}^{br} &= \sum_{i\in Y}\sum_{j\in Z} \tau_{ij} x_{ij}^{br}, \quad \forall b \in B, r \in R, && (9)\\
\tau_{back}^{br} &\geq \sum \tau_{ij} [\sum_{k\in Y} x_{kj}^{br} + \sum_{l\in Z} x_{il}^{b,r+1} - 1], \quad \forall b \in B, r \in R-1, && (10)\\
\sum_{i\in Y}\sum_{j\in Z} x_{ij}^{br} &\geq \sum_{i\in Y}\sum_{j\in Z} x_{ij}^{b,r+1}, \quad \forall b \in B, r \in R-1, && (11)\\
\sum_{i\in Y}\sum_{j\in Z} x_{ij}^{br} &\leq 1, \quad \forall b \in B, r \in R-1, && (12)\\
\sum_{j\in Z}\sum_{b\in B}\sum_{r\in R} x_{ij}^{br} &\geq {}_i, \quad \forall i \in Y, && (13)\\
\sum_{i\in Y}\sum_{b\in B}\sum_{r\in R} x_{ij}^{br} &\leq \mu_j, \quad \forall j \in Z, && (14)\\
x_{ij}^{br} &\in \{0, 1\}, \quad \forall \tau_{to}^{br}, \tau_{back}^{br}, \mathcal{T}_{\max} \in \mathbb{R}. && (15)
\end{aligned}$$

Constraint (8) needs $\mathcal{T}_{\max}$ to be greater than or equal to the maximal travel cost incurred by all buses, which is to be minimized on (7). Constraints (9) and (10) are the measure of travel time for the bus b within the round r from a source to a sink, and from that sink to the next source, respectively. Constraint (11) tells that the tours are connected and can stop whenever they like. Constraint (12) allows a bus from a source to sink per round. Constraint (13) and (14) are the bus capacity and shelter capacity constraints, respectively. Constraint (15) represents whether the bus b travels from source i to sink j in the round r.

Let τ_{ij}, τ_{di}, ${}_i$ and μ_j for $i \in Y$ and $j \in Z$ be as in Problem 2. For $k \in \mathbb{R}$, is there a tour plan with $\mathcal{T}_{\max} \leq k$, for the complete evacuation? Regarding the complexity of such a decision version of BEPP, the following result is .

Theorem 5. The decision version of BEPP is $\mathcal{NP}$-complete, even if $\tau_{di} = 0$ and $\tau_{ij} = \tau_{i'j}$ for all $i, i' \in Y$ and $j \in Z$.

During the solution of BEPP, authors in Goerigk et al. (2013) have presented the branch and bound algorithms with four different upper bounds and three lower bounds for time, three branching rules to minimize the number of branches, and two tree reduction strategies to avoid the equivalent branches. Upper bounds are constructed in polynomial-time complexity by four heuristics. Among them, the first three heuristics are based on a greedy distribution of tours on buses with precomputed tour lists, and the last one uses an iterative way without any precomputed tour lists.

1. **Heuristic H1:** Initially, a set of tours (i, j) for $i \in Y$ and $j \in Z$ is to be constructed for each source node i and $l_i \geq 0$ from i to the nearest sink j with $\mu_j > 0$ resulting $l_i \to l_i - 1$ and $\mu_i \to \mu_j - 1$ such that l_i should vanish. One of the randomly chosen tours from the tour list is assigned to a transit-vehicle with the minimum total travel cost. It is continued in a similar fashion to have a complete evacuation.

2. **Heuristic H2:** Initially, a set of all possible tours (i, j) for $i \in Y$ and $j \in Z$ is to be constructed and is sorted on non-decreasing cost provided by $l_i, \mu_j > 0$. Such a set of tours sorted until l or μ vanishes. The initially available transit-vehicle is assigned to the tour with the highest cost, and then it continues the next expensive tour, and so on. It is based on the longest processing time first rule as in Pinedo (2008).

3. **Heuristic H3:** For the precomputed tour list (i, j) for $i \in Y$ and $j \in Z$ having $\min\{d_{i'j'}\}$ with $l_{i'} > 0, \mu_{j'} > 0$ for all i' and j' as in heuristic $H2$, transit-vehicles are assigned by reversing the set of such tours for each vehicle. For the assignment of such vehicles, the long tour may have a long return tour, which might be beneficial. But, the vehicles having a long tour need not have a long return tour at the end. It is a simple modification of $H2$ and needs no guarantee for the improvement of the solution.

4. **Heuristic H4:** This begins with the best possibility to bring one evacuee back from the sink to the source and is continued iteratively. For this, let Y and Z be the available sources and sinks, respectively, provided for $l_i > 0$ and $\mu_j > 0$. Let t_i^b be the distance of the current position of the vehicle to the source and offset_b be the distance of the vehicle $b \in B$, which is already planned. Initially, for all the vehicles in the depot, we get $t_i^b = \tau_i$ and $\mathit{offset}_b = 0$. In such a case, the best possibility to assign the vehicle is with a minimum possible value of the sum of offset_b, τ_i and τ_{ij}, which is given by $\min\{\tau_i + \tau_{ij}\}$, same as the minimum total travel cost. Updating the t_i^b for each $l_i \to l_i - 1$ and $\mu_j \to \mu_j - 1$ in an iterative procedure for the next assignment, and so on, the feasible solution is obtained in minimum possible time.

All three lower bounds are also computed with polynomial-time complexity. The first lower bound is based on the estimation of the travel times from sources to sinks and from sinks to sources, respectively. The second lower bound is based on the fact that the lower bound for the maximum travel time is the average travel time. To address this, the objective is to minimize the sum of travel times and has been formulated by replacing the relations (7) and (8) by,

$$\text{minimize} \quad \sum_{i\in Y}\sum_{j\in Z} \tau_{di} x_{ij}^{b1} + \sum_{b\in B}\sum_{r\in R} \tau_{to}^{br} + \sum_{b\in B}\sum_{r\in R} \tau_{back}^{br} \tag{16}$$

The third lower bound is the simplification of model formulation, assuming that sinks are far away from the dangerous zone, and the pickup locations Y are nearby with negligible distances between such pickups. Consider all the pickups be at y_0 as the super pickup node with $l_{y_0} = \sum_{i\in Y} l_i$. Let the sinks $j \in Z$ and the depot d are at a distance of τ_j and τ_d respectively from y_0, where $\tau_j = \min_{i\in Y} \tau_{ij}$, for $(i, j) \in E$ and $\tau_d = \min_{i\in Y} \tau_i$. Here, τ_d is the same for all vehicles available in the network and can be neglected. Let y_j^b be the number of tours for the vehicle b from y_0 to sink Z and z_j^b be the number of tours for the vehicle b from sink Z to y_0, then the model as in Equations (7-15), can be reformulated as:

$$\begin{aligned}
\text{minimize} \quad & \mathcal{T}_{\max} && && (17)\\
\text{such that} \quad & \mathcal{T}_{\max} && \geq \sum_{j\in Z} \tau_j (y_j^b + z_j^b), && (18)\\
& \sum_{b\in B}\sum_{j\in Z} y_j^b && \geq l_{y_0}, && (19)\\
& \sum_{b\in B} y_j^b && \leq \mu_j, \quad \forall j \in Z, && (20)\\
& \sum_{b\in B} z_j^b && = x_j^b - 1, \quad \forall j \in Z, && (21)\\
& y_j^b, z_j^b && \in \mathbb{N}, \forall b \in B, \quad j \in Z, && (22)\\
& \mathcal{T}_{\max} && \in \mathbb{R}. && (23)
\end{aligned}$$

By analyzing these four heuristics used to construct the feasible solutions on their upper bounds, we have proved Theorems 6 and 7, with respect to their dominating relations. Here, the dominance on heuristics is followed with respect to the superiority of having minimum evacuation duration for their better performance in the network considered. A solution S_1 is said to dominate another solution S_2 if the solution S_1 is either no worse than S_2 or is strictly better than S_2 for the objective considered. Example 2 verifies the dominating relations of these heuristics.

Theorem 6. Heuristic H1 dominates heuristics H2 and H3 in evacuation duration.

Proof. The shortest processing time first dispatching rule is superior over the longest processing time first dispatching rule in minimizing the total completion time criteria, Pinedo (2008). Nevertheless, the longest processing time first dispatching rule balances the loads on the network and does not guarantee the optimality. Hence, H1 dominates H2 and H3 with respect to the evacuation duration, where H3 is a simple modification of H2. □

Theorem 7. Heuristic H4 dominates heuristics H2 and H3 in evacuation duration.

Proof. Heuristic H4 is initialized with $t_i^b = \tau_i$ and $offset_b = 0$ for all vehicles in the depot and gives the minimum initialization on the vehicle assignment with respect to the rest with $\min\{\tau_i + \tau_{ij}\}$, i.e. the same as the minimum total travel cost as in H1. Routes are considered iteratively with the best possibility to have the link (j, i) for each route (i, j) considered for the better choice of minimum evacuation time for their to-distance and back-distance than that for such distances with respect to H2 and H3. The updated t_i^b in each iteration with $l_i \to l_i - 1$ and $\mu_j \to \mu_j - 1$ minimizes the route assignment to have a feasible solution in minimum time. Hence, heuristic H4 dominates H2 and H3 both. □

Example 2. Let the pickup locations Y be at a distance $\tau_{di} = \begin{bmatrix} 1 & 3 \end{bmatrix}$ from d, and the transit times to the sinks Z from Y be $\tau_{ij} = \begin{bmatrix} 3 & 1 \\ 5 & 2 \end{bmatrix}$. Consider a scenario with the demands at Y as $l_i = (2, 1)$ and capacity of Z as $\mu_j = (2, 3)$, respectively.

For the given data in Figure 3, we construct the tour plans Π using heuristics H1, H2, H3, and H4 and calculate the corresponding ED as represented in the second, third, fourth, and fifth columns of Table 2, respectively. It shows that heuristic H1 dominates heuristics H2 and H3 (as proved in Theorem 6). Similar result holds in case of heuristic H4 as well (cf. Theorem 7).

This also helps to estimate the threshold number of the transit-vehicles. Here, the threshold number for $|B|$ is 3 as for $|B| = 4$, the fourth bus is left with no tour.

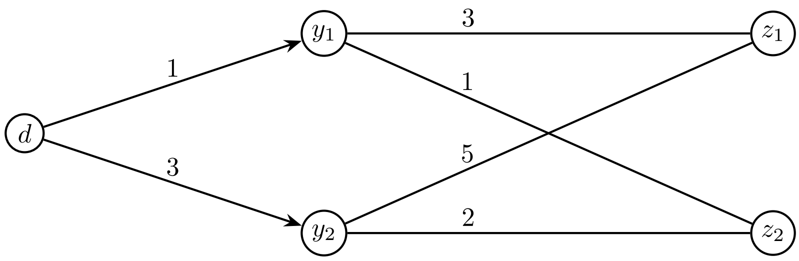

Figure 3: An instance of bus assignment problem.

$\|B\|$	Π & ED w.r.t. H1	Π & ED w.r.t. H2	Π & ED w.r.t. H3	Π & ED w.r.t. H4
1	$\tau_1 + 3\tau_{12} + 2\tau_{22} = 8$	$\tau_2 + \tau_{21} + 3\tau_{11}$ $+\tau_{12} = 18$	$\tau_1 + 2\tau_{12} + \tau_{11}$ $+2\tau_{21} = 16$	$\tau_1 + 3\tau_{12}$ $+2\tau_{22} = 8$
2	$\tau_1 + \tau_{12} + 2\tau_{22} = 6$	$\tau_2 + \tau_{21}$	$\tau_2 + \tau_{21} = 8$	$\tau_1 + \tau_{12} + 2\tau_{22} = 6$
	$\tau_1 + \tau_{12}$	$\tau_1 + 2\tau_{11} + \tau_{12} = 8$	$\tau_1 + 2\tau_{12} + \tau_{11}$	$\tau_1 + \tau_{12}$
3	$\tau_1 + \tau_{12}$	$\tau_2 + \tau_{21} = 8$	$\tau_2 + \tau_{21} = 8$	$\tau_1 + \tau_{12}$
	$\tau_1 + \tau_{12}$	$\tau_1 + \tau_{11}$	$\tau_1 + \tau_{11}$	$\tau_1 + \tau_{12}$
	$\tau_2 + \tau_{22} = 5$	$\tau_1 + \tau_{12}$	$\tau_1 + \tau_{12}$	$\tau_2 + \tau_{22} = 5$
4	$\tau_1 + \tau_{12}$	$\tau_2 + \tau_{21} = 8$	$\tau_2 + \tau_{21} = 8$	$\tau_1 + \tau_{12}$
	$\tau_1 + \tau_{12}$	$\tau_1 + \tau_{11}$	$\tau_1 + \tau_{11}$	$\tau_1 + \tau_{12}$
	$\tau_2 + \tau_{22} = 5$	$\tau_1 + \tau_{12}$	$\tau_1 + \tau_{12}$	$\tau_2 + \tau_{22} = 5$
	ϕ	ϕ	ϕ	ϕ

Table 2: Tour plan Π with evacuation duration ED w.r.t. different heuristics.

Note that, heuristic H1 construed with precomputed tour lists and assigned to the closest sink approach, and heuristic H4 constructed iteratively without any precomputed tour lists and assigned as above, are very closed to each other and are dominating the rest. However, for the vehicle assignment in N_2, we prefer H4 as it does not require precomputed tour list.

3.3 A mathematical model in an integrated network

For large scale disasters with a sufficiently large number of evacuees, all the evacuees may not arrive at Y at the same time, and it requests certain waiting time at Y before to start the bus assignment in $\mathcal{N}_2$. It is obvious that those who are delivered to Y earlier will have comparatively more waiting time. Meanwhile, for the evacuees, waiting at Y is comparatively better than to be at s. On the other hand, buses available at d request a certain time to be assigned to Y and are given by τ_{di}. Hence the effective waiting time in $\mathcal{N}$ can be denoted by $\Omega = \max\{\sum \omega_i, \tau_{di}\}$, for ω_i be the waiting at $y_i \in Y$. To address this in an integrated evacuation network, where the evacuees collected in $\mathcal{N}_1$ are to be assigned in $\mathcal{N}_2$, the objective function given by Equation (8) is modified. For this, let $\mathcal{T}_{\max}$ be the duration of evacuation overall vehicles, then the integrated evacuation planning problem can be reformulated as follows:

$$\text{minimize} \quad \mathcal{T}_{\max} \tag{24}$$

$$\text{such that} \quad \mathcal{T}_{\max} \geq \Omega + \sum_{r\in R} \tau_{to}^{br} + \sum_{r\in R} \tau_{back}^{br} \quad \forall b \in B. \tag{25}$$

$$\text{with the constraints} \quad (9-15). \tag{26}$$

Constraint (25) needs $\mathcal{T}_{\max}$ to be greater than or equal to the maximal travel cost incurred by all vehicles and is to be minimized in (24). Other constraints are the same as in Equations (9-15).

For the solution of our integrated model, we adopt the branch and bound algorithm of Goerigk et al. (2013) in which the computation of upper bounds, lower bounds, branching rules, and reduction strategies are described in Subsection 3.2. However, based on the effective waiting time at each pickup locations, the objective as in Equation (16) in the second lower bound becomes

$$\text{minimize} \quad \Omega + \sum_{i\in Y}\sum_{j\in Z} \tau_{di} x_{ij}^{b1} + \sum_{b\in B}\sum_{r\in R} \tau_{to}^{br} + \sum_{b\in B}\sum_{r\in R} \tau_{back}^{br} \tag{27}$$

Whereas, for the third lower bound, the relations (17) and (18) can be replaced by

$$\text{minimize} \quad \mathcal{T}_{\max} \tag{28}$$

$$\text{such that} \quad \mathcal{T}_{\max} \geq \Omega_0 + \sum_{j\in Z} \tau_j (y_j^b + z_j^b) \tag{29}$$

where, $\Omega_0 = \max\{\omega_0, \tau_j\}$, for ω_0 be the waiting time for the earliest arrival of evacuees at the super pickup node y_0.

As the problem (24-26) is not easier than the problem (7-15), we state the following result.

Theorem 8. The decision version of the integrated evacuation planning problem is $\mathcal{NP}$-complete.

4. SOLUTION IN AN INTEGRATED EVACUATION NETWORK

In this section, we deal with an integrated evacuation network $\mathcal{N}$. As discussed in Subsection 3.2, the number of evacuees at each pickup location is given, but their approach does not speak about the arrived pattern at Y. The main aim of our work is to present an analytical investigation of an appropriate network flow model and give an efficient solution algorithm, as considered in Subsection 3.1 that provides information on the number of evacuees arriving at the pickup locations for the BEPP. Evacuees are collected on the earliest arrival flow pattern from s. Such evacuees at Y are considered as the supplies for $\mathcal{N}_2$ and are to be assigned to the available transit-vehicles in an integrated evacuation network.

Problem 3. Given an evacuation network $\mathcal{N} = (s, d, V, Y, A, E, u_a, \tau_a, \tau_e, Z)$, having supplies and demands at s and Z, respectively. The transit-vehicle assignment problem is to assign the vehicles for evacuees transshipment with minimum clearance time.

Algorithm 2: The transit-vehicle assignment algorithm for minimum clearance time.

Input : An embedded evacuation network $\mathcal{N} = (s, d, V, Y, A, E, u_a, \tau_a, \tau_e, Z)$.
1. In $\mathcal{N}_1 = (s, V, A, u_a, \tau_a, Y)$, consider Y as the sinks and determine the earliest arrival of evacuees for $\tau_a = 0$ at different Y from s, by using Algorithm 1.
2. Assign the transit-vehicles from d to $\mathcal{N}_2 = (d, Y, E, \tau_e, Z)$ for the supplies provided by Step 1 at Y, as guided by the dominant vehicle assignment approach as in Subection 3.2.
3. Stop, if all the supplies at each of Y are fulfilled, respecting the capacity constraints of Z.
4. Otherwise, return to Step 2.

Output: Transit-vehicle assignment with the minimum clearance time from $s \to Z$.

Theorem 9. The transit-vehicle assignment algorithm as in Algorithm 2 gives the dominating solution for the transit-vehicle assignment problem as in Problem 3 with minimum clearance time.

Proof. Step 1 is feasible, since $\mathcal{N}_1$ is constructed in which the earliest arrival flow of evacuees exists for $\tau_a = 0$. As $\mathcal{N}_2$ is embedded in $\mathcal{N}_1$ for the appropriate vehicle assignment in $\mathcal{N}$, Step 2 is feasible. Feasibility of Step 3 is obvious as the flow respects the supplies as well as the demands in the network $\mathcal{N}$. Step 4, is of course, feasible. Hence, the algorithm is feasible.

Now, we show that Algorithm 2 gives a dominating solution. The maximum amount of flows are assigned from s across different auxiliary nodes to Y in $\mathcal{N}_1$, as in the form of the earliest arrivals of evacuees by using Algorithm 1. So, it gives the maximum possible flow of evacuees at each instance in the earliest arrival time and saves the unused capacity by Theorem 2. These resulting flows of such evacuees arrived at Y are taken as an input in $\mathcal{N}_2$ for the transit-vehicle in the subsequent evacuation process with the dominating vehicle assignment approach as in Subsection 3.2. Such an assignment of vehicles is continued until the last evacuee on such pickup locations reached to the sinks without violating their capacities. Hence, the resulting vehicle assignment in the integrated evacuation network gives the dominating solution with minimum clearance time. Hence, the theorem is proved. □

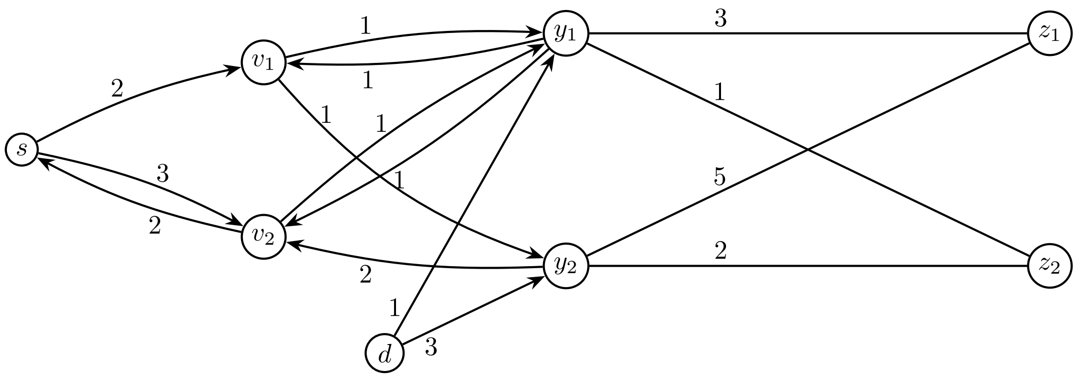

Figure 4: An instance of an integrated evacuation network $\mathcal{N}$

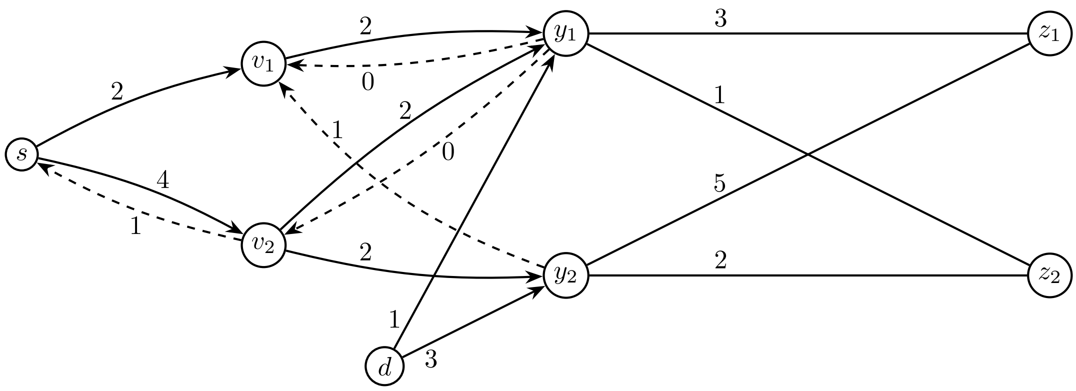

Figure 5: An instance of an integrated evacuation system with partial arc reversal in $\mathcal{N}_1$.

Example 3. Consider an instance of integrated evacuation system in $\mathcal{N}$, as in Figure 4. Consider a scenario with 12 units of evacuees at s, and with the pickup demands 8 and 4 for y_1 and y_2, respectively. Let the capacity of the sinks be 6 and 10 for z_1 and z_2, respectively.

Each of the paths $s - v_1 - y_1$, $s - v_2 - y_1$ and $s - v_1 - y_2$ can be assigned with 1 unit of flow as the earliest arrival flow of evacuees at zero transit time. Such flow is temporally repeated as in Theorem 4 and will collect 8 and 4 units of flows at y_1 and y_2, respectively, after 4-time units. Similarly, for the arc reversal capability, 2 units of flow can be assigned on each of the above-mentioned paths at zero transit time and are also temporally repeated. It can collect 8 and 4 units of flows at y_1 and y_2 respectively after 2-time units by using Algorithm 1 and also helps to improve the waiting instance.

We seek to find an optimal tour plan of this scenario using the dominating vehicle assignment approach as demanded by heuristic H4 (cf. Subsection 3.2), without violating the demands and the capacity constraints. Let the transit-vehicles be located at the depot d. Then their respective $\mathcal{T}_{\max}$ on $\mathcal{N}$, without and with arc reversal capability in $\mathcal{N}_1$, can be estimated as 41 and 39, respectively for $|B| = 1$.

Here, we have $\mathcal{T}_{\max}$ is 7 and 5 respectively, concerning to without and with arc reversal capability, for all $|B| \geq 12$. It also gives the threshold number of transit-buses. Moreover, the saved capacities obtained from partial arc reversals are shown along with the dotted arcs in Figure 5.

5. CONCLUSIONS

A solution of an evacuation planning problem is preferential to plan within the available time horizon to execute the maximum flow in each possible time unit and is offered by the earliest arrival flows. The earliest arrival flow does not exist in the network with multiple sinks for general transit times. Under some characterizations, some of the specific networks always permit for the earliest arrival transshipments regardless of all choices of the capacities and balances in zero transit times.

In our work, we are focused on the new and better-suited form of arrival pattern of evacuees in the earliest arrival flow pattern for the integrated evacuation planning problem. It will maximize the arrival of evacuees at every possible instance at the pickup locations with zero transit times from a source. We present a polynomial-time earliest arrival evacuee algorithm following the principle of temporally repeated flows to solve the earliest arrival evacuee problem with zero transit times and partial arc reversal capability. Such evacuees collected at different pickup locations of the primary sub-network are considered as the supplies during the subsequent evacuation process of vehicle assignment for the secondary sub-network. The partial arc reversal approach for the collection of evacuees also reduces the waiting instances at different pickup locations by collecting them earlier and helps to improve the solution of our integrated evacuation model. The assignment of transit-vehicles in such an integrated evacuation network is also carried in a dominating solution approach for the minimum evacuation duration. Different analytical issues are addressed to improve the performance of the evacuation in an integrated framework, though the problem itself, in general, is challenging. Its extensions for the arbitrary time setting and their different approximation approaches, including the experimentation and different case studies closer to the real scenarios, are the further research interests.

Conflict of interest. There is no conflict of interest regarding the publication of this paper.

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