Resource Replenishment Location Planning for Service Trucks under Network Congestion and Routing Constraints

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ABSTRACT

It is often very challenging to plan expedient and cost-effective operations for service trucks under network design constraints, particularly on congested urban roadways. Hence, it is beneficial to simultaneously account for truck facility location design and network expansion decisions to mitigate the additional congestion caused by trucks and facilitate their routing. This paper develops an integrated mathematical model for the facility location design under network routing and congestion constraints. The model determines the optimal number and location of replenishment facilities, minimizes truck routing costs based on the proposed network design, assigns traffic in the network (for both general roadway users and service trucks), and selects candidate links for possible roadway capacity expansion. The model aims to minimize the total cost for new facility construction, truck routing, transportation infrastructure expansion, and transportation delay. A genetic algorithm framework is developed that incorporates a continuous approximation model for truck routing cost estimation and a traffic assignment algorithm. The numerical results show that the integrated solution technique can solve the problem effectively.

Keywords: facility location; continuous approximation; traffic assignment; truck routing cost estimation; transportation infrastructure expansion; optimization; genetic algorithm
1 Introduction

Service trucks assist community priorities and support safe, reliable, and efficient movement of goods and people. It is important that public works agencies serve urban and regional roadways in a way so as to minimize truck routing costs. However, service trucks are relatively heavy in weight and thus, they often encounter difficulty in their maneuvers, particularly at intersections and local roads. Hence, they can significantly interfere with the existing roadway activities and contribute to additional congestion. Expanding roadways (e.g., widening roadway shoulders at network bottlenecks), in turn, can increase truck driver comfort, improve roadway capacity, and facilitate public traffic operations. On the other hand, performance of service trucks is subject to the network design, i.e., the number and location of resource replenishment facilities that these trucks need to visit during their operations. To satisfy the service demand, resources are to be replenished from a variety of supply areas. There is always a trade-off between using a few large centralized facilities (to benefit from production economies of scale) versus using more decentralized network systems (to save transportation cost among resource replenishment facilities and demand regions). Furthermore, truck routing cost influences various network design decisions. These issues affect the overall service reliability, especially in high priority regions where timely service is vital (e.g., emergency response needs). Thus, a strategic plan that accounts for replenishment facility location design and transportation network expansion under network routing constraints is needed. Such a strategic plan helps mitigate additional congestion and facilitate truck routing, especially in the neighborhood of the replenishment locations and local roadways.

This paper proposes an integrated mathematical model for strategic planning of a network design problem that encompasses resource replenishment number and location, transportation planning based on the optimal network design, and possible infrastructure capacity expansion. To reduce the complexity of the problem, the general public traffic flow has been assumed to follow a system optimal principle (Aziz and Ukkusuri 2012; Hajibabai and Ouyang 2013) instead of a user equilibrium principle (e.g., see Hajibabai et al. 2014a). Figure 1 illustrates the relationship among these components. The objective of the proposed model is to minimize the total cost including the transportation costs (i.e., truck routing and deadheading and public travel) and the infrastructure investments (in both new facility construction and network capacity expansion). A set of algorithms are developed that account for multiple components of the problem: a) the resource replenishment location is modeled as a fixed-charge facility location problem, b) the existing roadway users' transportation is modeled as a traffic assignment problem, and c) the service truck routing is estimated by a continuous approximation model to determine the routing cost under optimal network design.

The integration of facility location, truck routing, public transportation, and infrastructure expansion makes the problem very complex. This paper proposes a genetic algorithm (GA) framework to handle the facility location and infrastructure expansion parts of the problem. Besides, an embedded convex combination algorithm is used to solve for the traffic assignment decisions (Hajibabai and Ouyang 2013). To help reduce the computational efforts, a continuous approximation algorithm is incorporated within the GA framework to estimate the truck routing cost; otherwise, solving the truck routing itself is extremely difficult.

The exposition of this paper is as follows. Section 2 introduces the existing models and methodologies for strategic planning of network infrastructure development and network routing of vehicles. Section 3 focuses on the mathematical formulation and further introduces the solution.
Section 4 details the empirical case study for the Lake County network, Illinois and presents the numerical results. Finally, concluding remarks and trends for future research are presented in Section 5.

2 Literature Review

Despite its importance, facility location design, network capacity expansion, and truck routing optimization have not been intensively studied in the literature, particularly when existing traffic congestion is taken into consideration. This section summarizes the existing models and solution strategies for facility location design, transportation cost estimation, and network infrastructure expansion.

Both discrete and continuous facility location problems have been widely researched (e.g., Daskin (1995) and Drezner (1995)). Besides, there is a set of research studies in the context of supply chain network design as follows. Eathington and Swenson (2007) have developed expedited decision-making for refinery location, size, and technology using Geospatial Information Systems (GIS). Their approach has considered various scenarios for energy demand level, industry growth, and impacts on the job market. Traffic congestion (e.g., network travel time), on the other hand, has been recently incorporated into facility location design as a cost metric. Instances include (Konur and Geunes, 2011) and (Jayaram, 2005) that have evaluated the traffic congestion impact on facility location design, distribution networks, and supply chains and manufacturers. However, numerous studies have overlooked the congestion impact and simply considered distance in measuring the transportation cost (e.g., Graves and Willems, 2005). Although this approach simplifies the problem, it leads to non-realistic results. On the other hand, López and Monzón (2010) have developed strategic freight planning models that incorporate sustainability constraints in facility location plan and economic analysis. Another study, motivated by the biofuel industry
expansion, has explored the interactions among biorefinery location and bio-materials shipment decisions under network congestion (Bai et al., 2011). The problem has been jointly formulated into a fixed-charge facility location model with a traffic assignment model and solved by Lagrangian relaxation (Fisher, 1981) with an embedded convex combination approach (Frank and Wolfe, 1956; Sheffi, 1985). Besides, Hajibabai and Ouyang (2013) have integrated the supply chain network design and multi-modal transportation infrastructure expansion to mitigate congestion.

Transportation cost (public travelers’ travel time and service trucks deadhead time) is often determined by network traffic assignment (Frank and Wolfe, 1956; Sheffi, 1985) and route design of the trucks. Routing of the service trucks involves a variety of complex design requirements. Examples of the models and solution techniques for various truck routing applications follow. Sochor and Yu (2004) have proposed heuristic algorithms to route trucks so as to minimize the total system cost, including the penalty cost for using extra vehicles from the depots. In their solutions, certain depots have been repeatedly over- or under-utilized, suggesting that the quantity and/or distribution of available vehicles may be sub-optimal. Perrier et al. (2006) have developed meta-heuristic approaches (i.e., simulated annealing, tabu search, and elite route pool) for winter road maintenance to determine a route design that serves all road segments under a set of operational constraints. Their approach aims to minimize deadhead travel time, fixed costs of vehicles and depots, and the number of alternations between deadheading and servicing. The level of service for each class of highways is determined according to their priority. Later, Perrier et al. (2007a,b) have optimized the truck depot location, fleet sizing, and replacement decisions to satisfy service requirements for multiple road classes. The vehicle fleet replacement decision addresses the trade-off between costs for keeping older vehicles and expenses for purchasing newer fleet assets. In addition, Perrier et al. (2008) have introduced a heuristic method to find the optimal routes that minimize the service truck routing time. The model is based on a multi-commodity network flow structure to ensure the connectivity of the route covered by each truck. More recently, Salazar-Aguilar et al. (2012) have formulated a mixed integer non-linear program to minimize the longest route service time while ensuring that all lanes in each directional road segment are plowed simultaneously by synchronized vehicles. The set of snow routes are determined by an adaptive large neighborhood search heuristic. Haghani and Qiao (2001) and Wang et al. (1995) have formulated a capacitated rural postman problem to design efficient truck routes and applied a combination of different heuristics to solve the problem. Most recently, Hajibabai et al. (2014b) have developed a mixed integer linear program to minimize the total operation time of all service trucks to complete a given set of routes with multiple service priorities and to reduce the longest individual truck operation time. They have solved the problem by customized construction and local search solution algorithms. A branch of locational analysis that accounts for vehicle routing aspects has also been studied in the literature. Location routing problem, in general, involves locating a number of facilities among candidate locations and simultaneously establishing optimal routes to a set of demand regions in such a way that the total system cost is minimized. Interested readers are referred to Laporte (1987), Min et al. (1998), and Nagy and Salhi (2007) for more details on location routing models and associated solution algorithms.

Movement of service trucks, on the other hand, induces higher transportation demand that originates or ends at the depots or replenishment facilities. Such demand possibly causes additional congestion delay in the transportation network, particularly on roadway bottlenecks where public traffic demand is close to or has reached the roadway capacity or there is not enough space for the service trucks to maneuver (especially on local roads near the resource replenishment facilities). This increases the travel time of the general roadway users, which sequentially shall
affect the replenishment facility location decisions. These endogenous relationships have been considerably overlooked in the context of service truck operations. While there have been strategic transportation planning models that integrate sustainability issues into facility location design, network analysis, and spatial and regional economic analysis (e.g., López and Monzón (2010)), the most pertinent study is probably Hajibabai and Ouyang (2013), which shows that integrating facility location, multi-modal shipment routing, and infrastructure expansion decisions could help mitigate congestion impacts. Thus, adding lanes to existing roadways in the neighborhood of replenishment facilities (or building local access roads to newly constructed facilities) shall be considered as an integral part of the strategic planning for service trucks management.

Nevertheless, integration of the vehicle routing problem into the network design model that includes facility location design, transportation planning, and roadway capacity expansion makes the problem extremely difficult to solve. The routing algorithms require tedious computations, particularly with a considerable network size. Hence, they affect the efficiency of the aforementioned strategic configuration. Perhaps, an effective approach to tackle the computational problem is to utilize an approximation technique (e.g., Shen and Qi (2007)) as an embedded routing cost estimation module within the overall framework.

3 Model Development and Solution Approach

This section presents a mixed integer non-linear program (MINLP) that simultaneously addresses resource replenishment location, service truck routing, and infrastructure expansion decisions under traffic congestion in 3.1. The objective of the proposed model is to minimize the total costs for the entire planning and operations including the investments in new resource facility construction and network capacity expansion, as well as routing and transportation cost (for service trucks and public travel delay). This section further discusses in 3.2 the genetic algorithm framework developed to solve the proposed problem.

3.1 Optimization Model

Assume service trucks move from multiple replenishment locations to demand areas. We let \( I^d \) represent the set of service truck demand locations. Let \( J \) denote the set of candidate locations for resource replenishment facilities, including the existing ones and new candidates. Trucks dispatch from location \( j \in J \) with supply \( h^s_i \) to region \( i \in I^d \) that has maintenance demand \( h^d_i \).

The construction of a replenishment facility at location \( j \in J \) involves a fixed cost of \( m_j \) and a resource (e.g., fuel, salt, chemicals, etc.) capacity of \( C_j \). In this study, we simply assume a fixed resource capacity for each candidate location (similar to Hajibabai and Ouyang (2013)). The selection of locations for replenishment facilities is determined by decision variables \( Y_j = \{0, 1\} \), where it is 1 if a replenishment facility is built at \( j \in J \), and 0 otherwise.

Each replenishment facility \( j \) is assumed to dispatch trucks to serve task links from the set of available tasks \( A \) at a fixed frequency; we use \( \mathcal{X}_r \) to denote the number of visits of a task link in a year. Let \( \gamma_j \) be the total number of tasks served in a specific facility \( j \) neighborhood, \( \lambda \) be the number of tasks each truck can serve (i.e., truck capacity), \( D_{r,j} \) be the distance between

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3 The unit of \( h^d_i \) is hourly passenger car equivalents (PCE), which are estimated based on full-truck load (salt capacity) in volume and hourly passenger car flow equivalent for trucks (HCM, 2000).

4 Task links refer to the roadway segments that trucks shall visit for maintenance or providing service. Tasks are the services performed by trucks.
task link $i' \in A$ and facility $j$, and $\mathcal{A}'$ present the total service area. Shen and Qi (2007) show that the optimal vehicle routing problem (VRP) distance $\mathcal{V}_j$ can be approximated by the following formulation:

$$\mathcal{V}_j \approx 2/\lambda \left( \sum_{i' \in A} \frac{\mu_{i'}}{\mathcal{X}_{i'}} \mathcal{D}_{i'j} \right) + (1 - 1/\lambda) \Phi \gamma_j \left( \frac{\mathcal{A}'}{N} \right)^{0.5},$$  \hspace{1cm} (1)$$

where $\mu_{i'}$ is the yearly maintenance demand at task link $i'$, given total tasks $\mathcal{N}$ uniformly scattered in area $\mathcal{A}'$. $\Phi$ is a constant value that is assumed 0.75 for Euclidean metrics (Shen and Qi, 2007). Figure 2 illustrates the clusters for each replenishment facility neighborhood (truck routing is only shown in one of the clusters). Trucks will be dispatched from the main depot to each facility neighborhood and tasks will be performed within each facility neighborhood following a routing procedure. Trucks will then go back to the main depot. Such truck travel costs are estimated using (1), which includes, in the first term, the weighted average maintenance demand in each cluster according to the distance of each task link to its assigned replenishment facility. The second term estimates the traveling salesman cost in each cluster, which is the major cost component (higher weight, as $\lambda$ is large) in this estimation.

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**Figure 2: Routing cost approximation.**

Suppose that service trucks move through a transportation network containing a set of roadway links $A$. Similar to Hajibabai and Ouyang (2013), an imaginary node, $S^d$, is added as a source node for the demand transportation, which is connected by a set $V$ of virtual links to candidate location $j \in J$ if there is an open facility (i.e., $Y_j = 1$); see Figure 2. This can be interpreted as considering node $S^d$ as the only origin of truck transportation to the set of demand points $I^d$ as destinations. This ensures that all the flows from the source node will pass through at least one open replenishment facility.

Let $K^{d,i}$ denote the set of roadway paths from the source node $S^d$ to a demand point $i \in I^d$. Demand flow $f^{d,i}_k$ travels from $S^d$ to $i \in I^d$ on a possible path $k \in K^{d,i}$. Link-arc incidence

\footnote{The continuous approximation approach is accurate for large-scale networks (i.e., when total tasks, $\mathcal{N}$, is large enough). More discussion on the accuracy of this method can be found in Shen and Qi (2007) and Cui et al. (2010).}
parameter \( \delta_{a,k} \) (Sheffi, 1985) is further introduced as \( \delta_{a,k} = \{0,1\} \), where it is 1 if path \( k \in K_{d,i} \) includes link \( a \in A \), and 0 otherwise. Similarly, parameter \( \Delta_{j,k} \) is defined for the virtual links connected to roadway network, as \( \Delta_{j,k} \), where it is 1 if path \( k \in K_{d,i} \) includes node \( j \in J \), and 0 otherwise.

Link flows on these virtual links \( v_{j}^{d} \) represent replenishment facility throughput at location \( j \in J \). It can be expressed as \( v_{j}^{d} = \sum_{i \in I^{d}} \sum_{k \in K_{d,i}} f_{k}^{d,i} \Delta_{j,k} \). In addition to the roadway maintenance demand flows, we assume that there are passenger traffic flows on the roadway transportation network from a set of origins, \( O \) to a set of destinations, \( D \). Let \( K_{o,d}^{a} \) denote the set of paths connecting a passenger flow origin \( o \in O \) and destination \( d \in D \) through the roadway network, and let \( f_{k}^{o,d} \) represent the flow on path \( k \in K_{o,d}^{a} \). On each roadway link \( a \in A \), the total passenger flow is \( \sum_{o \in O} \sum_{d \in D} \sum_{k \in K_{o,d}} f_{k}^{o,d} \delta_{a,k} \), where \( \delta_{a,k} = 1 \) if path \( k \in K_{o,d}^{a} \) contains link \( a \in A \), and 0 otherwise.

In summary, the total link flow \( x_{a} \) for all \( a \in A \) is the summation of the public traffic flow and the demand flow, that is

\[
x_{a} = \sum_{o \in O} \sum_{d \in D} \sum_{k \in K_{o,d}} f_{k}^{o,d} \delta_{a,k} + \sum_{i \in I^{d}} \sum_{k \in K_{d,i}} f_{k}^{d,i} \delta_{a,k}, \forall a \in A.
\]  

(2)

Roadway link capacity expansion (especially in local areas close to replenishment facilities) is considered as an option here. Let decision variable \( Z_{a} \in \{0,1,2,\ldots\}, \forall a \in A \) be the number of lanes added to link \( a \), and each additional lane yields a known extra capacity of \( q_{a} \). The capacity of link \( a \) after the capacity expansion is the summation of the original link capacity \( Q_{a} \) and the additional capacity; that is, \( Q_{a} + Z_{a} q_{a} \). The travel time on link \( a \in A \), denoted by \( t_{a}(x_{a}, Z_{a}) \), is assumed to take the following Bureau of Public Roads (BPR) function form based on the traffic volume and expanded link capacity \( t_{a}(x_{a}, Z_{a}) = t_{0} \left( 1 + \alpha \left( \frac{x_{a}}{Q_{a} + Z_{a} q_{a}} \right)^{\beta} \right) \), \( \forall a \in A \), where constant parameters \( \alpha = 0.15 \) and \( \beta = 4 \) (BPR, 1970). The cost for roadway link capacity expansion, \( c_{a}(Z_{a}) \), \( \forall a \in A \), can be expressed as the product of link length \( l_{a} \), the additional capacity \( q_{a} Z_{a} \), and a cost coefficient \( w \) (Unnikrishnan et al., 2009), that is \( c_{a}(Z_{a}) = w l_{a} q_{a} Z_{a}, \forall a \in A \).

\[
\text{minimize } \sum_{j \in J} \left( m_{j} Y_{j} + \rho' V_{j} \right) + \sum_{a \in A} \left( c_{a}(Z_{a}) + \rho x_{a} t_{a}(x_{a}, Z_{a}) \right)
\]  

(3a)

subject to

\[
v_{j}^{d} = \sum_{i \in I^{d}} \sum_{k \in K_{d,i}} f_{k}^{d,i} \Delta_{j,k}, \forall j \in J,
\]  

(3b)

\[h_{i}^{d} = \sum_{k \in K_{d,i}} f_{k}^{d,i}, \forall i \in I^{d},\]

(3c)

\[v_{j}^{d} \leq C_{j} Y_{j}, \forall j \in J,\]

(3d)

\[\sum_{i \in I^{d}} h_{i}^{d} \leq C_{j} Y_{j}, \forall i \in I^{d}, j \in J,\]

(3e)

\[Y_{j} \in \{0,1\}, \forall j \in J, \text{ integer}, \]

(3f)

\[f_{k}^{d,i} \geq 0, \forall i \in I^{d}, k \in K_{d,i},\]

(3g)

\[f_{k}^{o,d} \geq 0, \forall o \in O, d \in D, k \in K_{o,d}.\]

(3h)
The mathematical optimization model that integrates location design, routing cost approximation, network expansion, and transportation decisions can be expressed as (3a)-(3h). The objective function \( (3a) \) minimizes the total system cost, which includes replenishment facility construction investment, routing cost, infrastructure capacity expansion cost, and public travel cost, respectively. Parameter \( \rho \) converts link travel time to travel cost and reflects a relative weight of total travel cost against the construction costs. Constraints (1) estimate the routing cost in each replenishment facility \( j \) neighborhood. Constraints (2) indicate that the traffic flow on each roadway network link is the sum of the background traffic and the passenger car equivalent demand truck flows on roadway network. Constraints (3b) ensure that the flow on each virtual link is the sum of the demand flow from all paths which contain node \( j \in J \). Constraints (3c) show that the sum of all demand flows into a demand point shall be equal to the demand at that point. Constraints (3d) ensure that the flow \( v^j_d \) can be any non-negative value no greater than the capacity of the replenishment facility at candidate location \( j \in J \) (if there is a replenishment facility at that node). Constraints (3e) ensure that the total capacity of replenishment facilities shall exceed the total demand. Finally, constraints (3f)-(3h) define the binary and non-negative variables.

### 3.2 The Genetic Algorithm Framework

The integrated mathematical model (1)-(2) and (3a)-(3h) is very challenging as it involves non-linearity and mixed integer variables. Thus, a hybrid solution approach that integrates the genetic algorithm (Goldberg, 1989), continuous approximation (Daganzo, 2005; Shen and Qi, 2007), and traffic assignment algorithm (Frank and Wolfe, 1956; Sheffi, 1985) is proposed to overcome the complexity of this problem.

The GA has been used to effectively solve transportation network design problems (e.g., Ukkusuri et al., 2007; Putha et al., 2012). The general framework for our GA approach includes a basic parameter setting (e.g., population size \( n \) and probabilities of crossover and mutation). A chromosome is defined to be a binary vector representation of the integer variables \( \{Y_j\} \) and \( \{Z_a\} \), such that the length of the chromosome depends on \( |J|, |A| \), and the maximum number of lanes to expand. Thus, the length of the chromosome will simply be \( |J| + |A| \) if capacity expansion is limited to only adding one lane to each link (i.e., \( Z_a \in \{0, 1\}, \forall a \in A \)).

In the initialization step, chromosomes are randomly generated for the first population, and each chromosome shall satisfy constraints (3e) to ensure feasibility of the solution; that is, the total service demand shall not exceed the total capacity of the replenishment facilities. Each chromosome in the population contains information on the facility location and road expansion decisions. Thus, traffic assignment is performed based on this information and the near-optimal link traffic volumes on roadway network \( \{x_a\} \) will be determined.

Task links \( i' \in A \) are clustered into \( j \) optimal replenishment facility locations and the truck routing cost \( V^j \) is estimated for the current network design according to (1). Besides, a

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6 There are global optimization methods that solve transportation network design problems under user equilibrium traffic congestion constraints (e.g., Ouyang et al., 2015; Liu and Wang, 2015; Yang et al., 1994). However, our proposed integrated model includes four components with their inter-relationships (i.e., facility location, roadway capacity expansion, traffic assignment, and truck routing cost estimation) and is too difficult to solve using such methods. Therefore, a GA framework is employed to handle the integer decision variables (i.e., facility location and infrastructure expansion decisions) so that the remaining problem becomes a simpler non-linear one.
convex combination algorithm is used to solve the remaining routing decisions (general roadway users traffic volume). For any given chromosome, the sets of decision variables \( \{Y_j\} \) and \( \{Z_a\} \) are known, therefore model (2) and (3a)-(3h) reduces to a simpler non-linear program. Then, the convex combination method can be applied to solve the routing problem. Here, the fitness function to evaluate and rank each chromosome is the inverse of the objective value.

GA creates chromosomes for new populations through a series of operations including selection, crossover, and mutation. The tournament selection technique is used to choose the chromosomes for later perturbations in crossover and mutation operations. The crossover uses a multi-point technique where cross points are randomly selected for each part of the chromosome (e.g., those corresponding to location decisions \( \{Y_j\} \) and capacity expansion decisions \( \{Z_a\} \)). Then, a bit-wise mutation is used, that is, each cell of the chromosome (i.e., gene) is randomly flipped according to the probability of mutation. All parts of the chromosome are mutated in the same way but the cells representing the location decision are never switched with the cells representing the capacity expansion decision. Again, any newly generated chromosome shall satisfy constraints (3e) or otherwise it will be discarded. Finally, the algorithm terminates either once the predetermined maximum number of generations is reached, or if the best solution has not been improved over a certain number of consecutive generations. The best chromosome over all generations is recorded as the solution to the problem.

4 Real-World Case Study

The proposed solution algorithm in Section 3.2 is implemented and applied on a real-world case study for strategic planning of salt dome location design and winter maintenance operations for the Lake County, Illinois. This section presents the case study network and discusses the numerical results.

4.1 Network Dataset

The roadway network database of the Lake County Division of Transportation (LCDOT) contains 1,354 nodes and 3,350 links. Each task link in the network is considered as a demand location for plowing and salting service. A dataset including 162 links for possible capacity expansion in the neighborhood of salt dome facilities is chosen. There are 19 candidate locations for salt replenishment facility construction, including 12 existing facility locations and 7 new locations that are selected based on socioeconomic factors such as access to major transportation facilities. If one of these candidates are selected for facility construction, a set of roadway segments will also be built to connect the facility to the existing roadway network. The demand for plowing and salting service is calculated based on the historical service demand (passenger cars per hour (pc/hr)).

Furthermore, the maximum capacity of salt dome facilities is considered to be 4,000 tons/year, except for the main depot that is 10,000 tons/year. The annual prorated cost of constructing new salt dome facilities of size 4,000 tons/year and roadway link connectors to the existing network links will be $1,297,000 (i.e., $10^6$ to build a facility of that size and $297,000 to expand the roadway network by adding links for connecting the new facility to the existing roadway; the roadway capacity expansion cost is calculated according to Unnikrishnan et al. (2009) for 0.3 miles roadway length and the cost coefficient factor of $10^3$ $/lane – mile$). The salt dome facility construction cost is further prorated into hourly cost by assuming 20 years of service life and
60 days per year and 8 hours per day as the effective working time for the snow plowing/salting work shift.

Traffic flow is converted to passenger car equivalent (PCE) per hour. Information on the hourly passenger car traffic flow and the existing capacity of the roadway links are obtained from Illinois Department of Transportation (IDOT, 2011). The capacities of the interstate highways and local arterials are assumed to be 2,200 and 1,045 pcp/hpl, respectively (HCM, 2000). We set \( \rho = 20 \, \text{$/hr - PCE} \), \( \rho' = 10^3 \, \text{/plowspeed$/hr - PCE} \) (where 30 is assumed for the average speed of snow plow trucks’ operation), and the cost coefficient factor for capacity expansion is \( 10^3 \, \text{$/lane-mile} \) (Unnikrishnan et al., 2009). Furthermore, we assume that at most one roadway lane will realistically be added to each link if road capacity expansion is required (i.e., \( Z_a \in \{0, 1\} \)).

Routing cost is estimated by (1), which uses parameter values as follows. We assume each task link is visited 100 times in a year (i.e., \( X_{i'} = 100, \forall i' \in A \)). According to each GA solution for location decisions (i.e., \( Y_j \)), we cluster tasks into zones (i.e., assign each task to each salt dome facility \( j \)). The total number of tasks served in each zone (i.e., \( \gamma_j \)) is the number of task links in each cluster \( j \) to be served by a truck. Truck service capacity is determined based on LCDOT data; i.e., \( \lambda \) is assumed to be equal to total available tasks in the network that total trucks in LCDOT can serve per one operation cycle without salt replenishment along the way. We assume equal trucks with equal capacity of service. The yearly maintenance demand at task link \( i' \) (i.e., \( \mu_{i'} \)) is calculated by the product of number of visits per year, \( X_{i'} \), length of each task link, and the salt application rate of trucks divided by average salt carrying capacity of trucks. Constant parameter \( \Phi \) is assumed 0.75 (Shen and Qi, 2007). We derived the total routing area \( A' \) as well as total tasks, \( N \), from Lake County dataset.

4.2 Numerical Results and Discussion

This proposed algorithm is coded in Visual C++ and run on a desktop computer with 2.67 GHz CPU and 3.00 GB memory. In the GA framework, the selection pressure is chosen to be 20, the population size 300, probability of crossover 0.8, probability of mutation 0.01, chromosome length 181 (i.e., 19 candidate locations and 162 candidate links for expansion close to salt replenishment facilities), and random seed value 0.025. Candidate facilities 1, 2, ..., 12 are chosen from the existing facilities in LCDOT network and the rest are new candidate locations. The program terminates when the best fitness value does not improve across a number of generations. For all numerical cases, the GA converges within 100 generations, taking less than an hour of CPU time.

It shall be noted that following our chromosome setting, constraints (3e) will be satisfied with a probability of 99.7% as follows. Constraints (3e) ensure that the total capacity of replenishment facilities shall exceed the total maintenance demand. This affects the salt dome facility location design. In this case study, enough number of facilities with average capacity of 4315.8 tons shall exist to satisfy the total demand (\( \geq 14 \times 10^3 \) tons). The probability of selecting \( k' \) number of salt dome facilities by GA out of a total of \( n' \) candidate facility locations follows a binomial distribution as \( \binom{n'}{k'} \, p^{k'} \, (1-p)^{n'-k'} \), where, \( p \) is the probability of selecting the candidate facilities. Therefore, the probability of selecting at least \( x' \) facilities (i.e., minimum number of required facilities to satisfy total maintenance demand: \( 14 \times 10^3 / 4315.8 = 3.2 \)) is represented as \( \sum_{k' \geq x'} \binom{n'}{k'} \, p^{k'} \, (1-p)^{n'-k'} \).

As GA assigns 0’s and 1’s to the facility location decision variables with 0.5 probability, the probability of satisfying constraints (3e) is computed as \( 1 - \sum_{k' \in \{0,1,2,3\}} \binom{19}{k'} \, 0.5^{n'} = 99.7\% \). As such, these constraints are mostly satisfied and only in a few instances GA has to generate a
new solution in the initialization step to satisfy the constraints. In the following generations, the constraints are hardly violated as GA pushes the solutions towards the regions of the feasibility area with lower costs that happen to have more facilities as shown in the numerical results.

Table 1 presents the computation results for $\rho = 20$ and $\omega = 10^3$. Figure 3 shows the locations selected for salt domes as well as the roadway links considered for expansion for this case. For comparison, we also compute the optimal solution of a benchmark scenario where the existing salt replenishment facilities are selected and the model excludes roadway link capacity expansion.

<table>
<thead>
<tr>
<th>scenario</th>
<th># of domes</th>
<th>loc. cost for domes ($\times 10^6$)</th>
<th># of added domes</th>
<th>cost for exp. cost ($\times 10^6$)</th>
<th>trans. cost ($\times 10^6$)</th>
<th>rout. cost ($\times 10^6$)</th>
<th>sys. cost ($\times 10^6$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>proposed model</td>
<td>11</td>
<td>9,10,11,14</td>
<td>0.25</td>
<td>31</td>
<td>0.37</td>
<td>4.07</td>
<td>2.29</td>
</tr>
<tr>
<td>benchmark solution</td>
<td>12</td>
<td>6,7,8,9</td>
<td>0</td>
<td>–</td>
<td>–</td>
<td>4.87</td>
<td>2.66</td>
</tr>
<tr>
<td>difference</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>16.4%</td>
<td>13.9%</td>
</tr>
</tbody>
</table>

The proposed solution selects 7 existing facilities and 4 new candidate locations for facility construction. In the benchmark solution, all facilities are the existing ones, thus the facility construction cost is equal to 0. The computation results show that our joint optimization model (i.e., proposed model including capacity expansion decisions in the model) efficiently reduces the transportation cost (travel time of the roadway users) by 16.4% and the routing cost (estimated routing cost of the service trucks) by 13.9%, and in fact reduces the total system cost by 7.2%. Figure 3 shows the facility location design and roadway capacity expansion decisions on the Lake County, Illinois map.

5 Conclusion

This study presents an integrated mathematical model for resource replenishment facility location design. The model determines the optimal number and location of facilities, routing cost estimation for service trucks, and candidate roadway links for capacity expansion. The objective is to minimize the total cost associated with facility construction, roadway capacity expansion, routing of service trucks, and transportation delay. The congestion pattern and total transportation costs are determined based on system optimal flows on transportation routes under expanded capacity. The truck routing cost, on the other hand, is estimated under optimal facility location design. To find the optimal solution to the proposed model, a hybrid GA framework is developed that incorporates convex combination and continuous approximation algorithms. A real-world case study for the Lake County, Illinois is conducted and the computational results show that the proposed algorithm is capable of solving the problem effectively.

A possible extension for the future research is to develop a heuristic solution algorithm to evaluate the performance of the proposed framework with embedded routing cost estimation. It
Figure 3: The algorithm results in the Lake County, Illinois network.

would also be interesting to apply the proposed model and solution approach to a comprehensive list of diverse networks for additional real-world case studies (e.g., incident response stations, urban freight distribution facilities).

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References


