

Dynamic Multimodal Freight Routing using a Co-Simulation Optimization Approach

Yanbo Zhao, *Member, IEEE*, Petros A. Ioannou, *Fellow, IEEE* and Maged M. Dessouky

Abstract— The complexity and dynamics of multimodal freight transportation networks make the optimum routing of freight demand a challenging task. Route decision-making in a dynamical and complex urban multimodal transportation environment aims to minimize a certain objective cost relying on the accurate prediction of the traffic network states and the estimation of the route costs that are not readily available. The purpose of this paper is to develop a methodology to be used by a central coordinator who generates individual routing decisions for shippers by minimizing an overall cost assuming that all participating shippers send their demands to this central coordinator. We propose, analyze and evaluate a multimodal freight routing system with hard vehicle availability and capacity constraints based on a hierarchical Co-Simulation Optimization (COSMO) approach. The COSMO approach consists of a simulation layer which provides traffic state predictions and cost estimations to an upper optimization layer which incorporates a load balancing methodology to speed up the convergence of the optimization algorithm. A simulation testbed consisting of a road traffic simulation and a rail simulation model for the Los Angeles/Long Beach Ports regional area is developed and used to demonstrate the efficiency of the proposed approach.

Index Terms—Freight Routing, Load Balancing, Co-Simulation, Multimodal Transport

I. INTRODUCTION

The growth of worldwide trade has significantly increased air pollution due to increased congestion in the urban transportation infrastructure especially in metropolitan areas with major ports such as the Los Angeles/Long Beach Ports where there is a high concentration of freight traffic. One of the biggest challenges for freight transport efficiency in such a multimodal environment arises from the fact that both freight and passenger traffic share the same infrastructure which leads to non-homogeneous traffic. This non-homogeneity has a detrimental impact on the urban transport performance because of the differences of vehicle sizes and dynamics between passenger and freight vehicles. Freight vehicles such as freight trains and heavy trucks take longer distances to stop and longer time to accelerate from a stopping position, consume more fuel

The research reported in this paper was supported in part by the National Science Foundation under grant 1545130 and in part by the METRANS Transportation Center under the following grants: Pacific Southwest Region 9 University Transportation Center (USDOT/Caltrans), National Center for Sustainable Transportation (USDOT/Caltrans) and Metrorail and SCAQMD.

Y. Zhao and P.A. Ioannou are with the Department of Electrical Engineering, University of Southern California, Los Angeles, CA 90089 USA (email: yanbozha@usc.edu, ioannou@usc.edu)

and generate more air pollution compared to passenger vehicles. The situation becomes even worse during disruptions that lead to network capacity reductions such as road incidents or railway closures when rapid response and redistribution of freight traffic across the multimodal network are required. Without efficient management of the freight transport, the whole transportation network can face severe capacity shortages, inefficiencies, load imbalances, and have a negative environmental impact across the network in space and time. Therefore a more efficient freight routing system will not only save freight delivery time and cost but can also contribute to improving mobility, efficiency and sustainability of urban transportation systems.

Due to the important role of freight transport, numerous researchers have addressed the issue of multimodal freight transportation especially in multimodal network modeling as well as routing and scheduling of freight traffic. As a fundamental issue in routing and scheduling algorithms, the shortest route problem in freight transport has been studied by many researchers [1]-[4]. The shortest route algorithms can satisfy the routing requirement of low demand since the interaction between the loaded traffic and current traffic is not significant. For high demand levels that may change the network state and cost, optimization techniques have been commonly used to solve the multimodal routing and scheduling problem with a formulation of a simplified network state and cost model. Guelat and Florian proposed a linear approximation algorithm to solve the multimodal and multiproduct freight assignment problem [5]. Castelli et al. used a Lagrangian-based heuristic procedure to solve the freight scheduling problem [6]. Ham, Kim and Boyce showed the application of Wilson's iterative balancing method in interregional multimodal shipment planning [7]. Zografos et al. developed a dynamic programming based algorithm for multimodal scheduling [8]. Moccia et al. solved a multimodal routing problem with timetables and time windows by integrating a heuristic methodology with the column generation algorithm [9]. Crainic et al. proposed meta-heuristic methods for freight demand distribution in congested urban areas in [10] and [11]. The main difficulty is that these approaches use mathematical models which may not have a closed form solution when applied to complex networks such as large scale multimodal freight

M. M. Dessouky is with the Daniel J. Epstein Department of Industrial Engineering, University of Southern California, Los Angeles, CA 90089 USA (e-mail: maged@usc.edu).

networks that exhibit complex and nonlinear interactions between the routing decisions and traffic network states.

The availability of fast computers and software tools open the way for new approaches that go beyond the limitations of network modeling complexity [12]. The traffic flows and states can be better predicted using simulation models that are more complex and can capture phenomena that cannot be formulated with mathematical models [13]. Then decisions could be developed by combining the simulation environment with proper optimization algorithms such as in [12], [14] and [15]. Peeta and Mahmassani formulated and developed a simulation based method for the dynamic user equilibrium problem given fixed demand for the road transport mode [16]. The proposed method was also applied for multimodal transport [17]-[19]. The user equilibrium among supply and demand also has been studied in order to identify which trip costs from all shippers to the same destination are in equilibrium [20] [21]. Other solution algorithms such as cross entropy based [22] and gap-based [19][23] methods were proposed to give better performance than the method of successive average (MSA) that is widely used for user equilibrium problems. The system optimal routing problem can also be solved by the above algorithms by using the marginal costs of the routes in the equilibrium solution instead of the trip costs [24]. Due to the fact that the number of routes increases exponentially with the size of the transportation network, it is computationally prohibitive to evaluate the marginal costs of all candidate routes by using simulations.

Besides the computational issues associated with using simulation based user equilibrium approaches to solve the system optimal problem, there are other difficulties in applying these approaches for optimum multimodal freight routing. First, the equilibrium of routes may not be achievable in some cases where vehicle availability and hard capacity constraints exist. These types of constraints need to be considered in the freight model especially when considering the rail mode of transport since there is a limited number of trains available for dispatching on a particular day and the rail network has capacity for a finite number of trains before deadlock occurs. Second, the coordination of shippers has not been considered in most previous approaches where it is typically assumed that each shipper conducts its own route augmentation and load balancing separately. Although the interaction of the different shippers will be evaluated in the simulation stage, it may lead to a slow convergence of load balancing.

The contributions of this paper are as follows. First, we use a hierarchical modeling methodology to formulate the centralized multimodal freight routing problem in which hard vehicle availability and capacity constraints exist in portions of the transportation network. The multimodal freight routing problem is formulated in two levels: service graph and transportation network, which could handle the complex freight vehicle constraints and improve the solving procedure. Moreover, we propose a CO-Simulation Optimization (COSMO) approach to deal with the route decision-making problem of complex dynamical systems such as a multimodal transportation network. In the proposed routing approach, we

use a novel loading balancing based methodology that coordinates the individual route decisions for multiple shippers. Using computational experiments based on real traffic data from the Ports of Los Angeles and Long Beach, we show that the proposed COSMO approach can reduce the total delivery cost during traffic conditions and shipping demand changes by utilizing centralized load balancing. In addition, the convergence speed of our load balancing methodology is faster than other approaches in the literature.

The paper is organized as follows. Section II gives the problem formulation. Section III demonstrates how to solve the formulated multimodal routing problem with the proposed hierarchical COSMO approach. Section IV shows the experimental results of the proposed approach on portions of the transportation network in Southern California. Finally conclusions are discussed in Section V.

II. PROBLEM FORMULATION

A. Transportation Network and Service Graph

In this paper, we deal with the centralized routing of freight traffic that is container flow between origin and destination nodes. We assume all shippers send their demands to a central coordinator who generates individual routing decisions for each shipper by minimizing an overall delivery cost based on multimodal transportation network states. A multimodal freight transportation network can be represented as a directed graph consisting of a set of nodes (N) with a set of directed arcs (A) connecting the nodes. A node in the transportation network can be a road intersection, railway station, port terminal, or warehouse etc. An arc in the transportation network can be one segment of a roadway or railway track. Both passenger and freight traffic start and end at certain network nodes. Let I and J be the sets of origin nodes and destination nodes respectively. Both I and J are a subset of N .

In practice, the available freight vehicles are constrained in portions of the transportation network. For example, the number of available trains is limited between two rail stations or there is an upper bound for the number of assigned trucks among some truck depots. It is hard to describe and formulate these freight vehicle constraints with transportation nodes and arcs directly. Therefore, a multimodal service graph model is proposed to formulate the overall freight routing problem in this paper. The service graph G is also represented as a directed graph consisting of a set of service nodes (NS) with a set of modal segments (L) connecting these nodes. The set NS is a subset of N consisting of all origin and destination nodes as well as other nodes that support the formulation of freight vehicle constraints such as port terminals, truck depots, and rail stations. A modal segment is a transport segment served by a unique transport mode (e.g., road trucks or rail trains). An intermodal route from an origin node to destination node consists of a collection of one or multiple modal segments of the service graph that could be applied to deliver the demand between the corresponding origin and destination. The freight service graph can be seen as an abstracted upper layer of its corresponding physical transportation network. Fig.1 shows an example of a

service graph and corresponding traffic network.

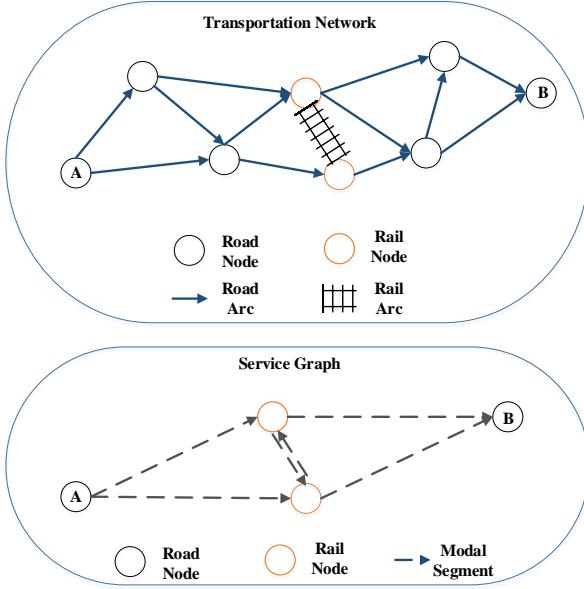


Fig. 1. Traffic network and service graph

The overall freight routing problem in the central coordinator has two levels of decisions: the routing decisions i.e. freight load allocation in the service graph level and the freight vehicle dispatching in the transportation network. The routing decisions in the service graph that minimize the total cost depend on the transportation network dynamics (e.g., traffic congestion, arc travel time, vehicle setup costs etc.). Moreover, the transportation network dynamics are also impacted by the service graph decision since the travel time and congestion for a road segment or rail segment are determined by the allocated freight traffic. The constraints for allocating freight demand in a service graph include available modal segments and intermodal routes as well as the freight vehicle availability and capacity constraints while the freight vehicle dispatching constraints include transportation arc capacities and vehicle characteristics as well as other possible operation constraints such as safety headway between freight vehicles.

B. Problem Formulation

In this paper, we solve the routing decision problem of freight demand i.e. cargo containers across the multimodal transportation network between the origin and destination nodes that minimizes the total delivery cost by the central coordinator. The analysis time horizon is discretized into $/K$ time intervals and used to formulate the problem. The notations that are used throughout the paper are defined as follows:

- i The index of an origin node, $i \in I$;
- j The index of a destination node, $j \in J$;
- k The index of a time interval, $k \in K$ where $K = \{0, 1, \dots, |K|\}$;
- l The index of a modal segment in service graph G , $l \in L$;
- $R_{i,j}$ The set of all feasible intermodal routes from an origin i to a destination j ;
- r The index of an intermodal route from an origin i to a

destination j ;

$d_{i,j}$ The total demand in the number of containers from an origin node i to a destination node j ;

$X_{i,j}^r(k)$ The freight demand in units of containers from origin node i to destination node j using an intermodal route r with a departure time k ;

$x_l(k)$ The number of containers using modal segment l at time k ;

$u_l(k)$ The vehicle availability in the number of freight vehicles for modal segment l at time k ;

$v_l(k)$ The vehicle capacity in units of containers per freight vehicle for modal segment l at time k ;

$S_{i,j}^r(k)$ The average service cost per container on intermodal route r from node i to node j at time k consisting of the non-travel time vehicle cost $C_{i,j}^r(k)$ and the cost of intermodal route travel time $T_{i,j}^r(k)$;

P_l The set of all feasible vehicle paths in the transportation network serving the delivery of freight demand of modal segment l with the same transport mode as modal segment l ;

p The index of a vehicle path in transportation network for modal segment l , $p \in P_l$;

$c_l^p(k)$ The non-travel time vehicle cost of a vehicle path p for modal segment l at time k ;

$t_l^p(k)$ The travel time of a vehicle path p for modal segment l at time k ;

$y_l^p(k)$ The number of containers using path p for demand of modal segment l at time k ;

$z_a(k)$ The traffic volume of transportation network arc a at time k ;

$w_a(k)$ The travel time of transportation network arc a at time k ;

The freight routing problem of the service graph that considers vehicle availability and capacity constraints can be expressed as follows:

$$\begin{aligned} \min TC(X) &= \sum_{k \in K} \sum_{i \in I} \sum_{j \in J} \sum_{r \in R_{i,j}} S_{i,j}^r(k) X_{i,j}^r(k) \\ &= \sum_{k \in K} \sum_{i \in I} \sum_{j \in J} \sum_{r \in R_{i,j}} (C_{i,j}^r(k) + \kappa_r T_{i,j}^r(k)) X_{i,j}^r(k) \end{aligned} \quad (1)$$

subject to the following constraints:

$$\sum_k \sum_{r \in R_{i,j}} X_{i,j}^r(k) = d_{i,j}, \quad \text{for } \forall i \in I, \forall j \in J \quad (2)$$

$$\sum_{i \in I} \sum_{j \in J} \sum_{r \in R_{i,j}} \sum_{\tau \leq k} X_{i,j}^r(\tau) \delta_{l,r,\tau,k} = x_l(k), \quad \text{for } \forall l \in L, \forall k \in K \quad (3)$$

$$0 \leq x_l(k) \leq u_l(k) v_l(k) \quad \text{for } \forall l \in L^R, \forall k \in K \quad (4)$$

$$X_{i,j}^r(k) \geq 0 \quad (5)$$

given $d_{i,j}$, $u_l(k), v_l(k)$, for $\forall i \in I, j \in J, l \in L, k \in K$ (6)

Equation (1) is the problem objective that minimizes the total cost TC to deliver the demand where X is the routing decision consisting of the distribution of freight demand on all possible intermodal routes in the service graph. κ_r is the value of travel time of intermodal route r . Equation (2) represents the demand conservation constraints. Equation (3) is the modal segment demand model where $\delta_{l,r,\tau,k} = 1$ when the demand of intermodal route r with departure time τ uses modal segment l at time k . Otherwise, $\delta_{l,r,\tau,k} = 0$. Equation (4) is the vehicle availability and capacity constraints where L^R is the set of modal segments where vehicle constraints exist. In this paper, we only consider the vehicle availability constraints existing in part of the modal segments served by the rail mode but the proposed approach can also be extended to a more general problem where constraints exist on all service modes. Since the explicit forms of the cost functions in the problem objective are not available directly due to the nonlinearities and complex variable interactions, transportation network simulation models are used to estimate the service graph state and cost variables in problem (1-6) for more accurate routing decisions.

In a traffic network, the freight vehicles are used to deliver the container demand based on the routing decision of the service graph using different vehicle paths. The demand of containers on a modal segment l determines the required volume of freight vehicles for the transportation network according to the service mode (rail, road, etc.) and freight vehicle capacity in the number of containers per vehicle.

Let $Z(k) = [z_1(k), z_2(k), \dots, z_{|A|}(k)]'$ be the vector of traffic volumes on the transportation network arcs 1 to $|A|$ at time k . Then the relationship of the traffic volume on arc a with the departure of the freight traffic and other parameters in the network can be expressed as a nonlinear dynamical equation:

$$z_a(k+1) = f_a(z_a(k), q_a(k), Y(k), k), \text{ for } \forall a \in A, \forall k \in K \quad (7)$$

where

$$Y(k) = [y_l^p(k) : \forall l \in L, \forall p \in P_l] \quad (8)$$

In (7), f_a is a nonlinear and time-dependent function of the traffic volume of arc a . The impact of the traffic volumes from the adjacent arcs at time k is denoted by $q_a(k)$ and $Y(k)$ is the vector of departure freight traffic from all the origin nodes at time k as in (8). Since $z_a(k)$ and $q_a(k)$ contain the impact of the previous departure container traffic before time k (i.e., $Y(\tau)$ for $\forall \tau < k$), only $Y(k)$ is included in equation (7). The arc volumes in the transportation network are time-dependent due to various factors such as time-dependent passenger traffic, network changes, accidents and incidents.

Let $W(k) = [w_1(k), w_2(k), \dots, w_{|A|}(k)]'$ be the vector of travel time (unit: Δt) of arcs 1 to $|A|$ at time k . The arc travel time is a function of the arc volume at time k which is time-dependent because of the impact of the time-dependent passenger traffic, network incidents and railway dispatching

decisions. The travel time of an arc is dependent not only on the arc flow but also on the flows of the other arcs therefore,

$$W(k) = g(Z(k), k), \text{ for } \forall k \in K \quad (9)$$

Let $t_l^p(k)$ be the travel time of a path p if a freight vehicle departs from the origin node on modal segment l at time k . Assume a path p contains arcs $a_{p,1} \rightarrow \dots \rightarrow a_{p,N_p}$ where N_p is the total number of arcs on this path p . Define $e_{a_{p,n_p}}(k)$ as the entering time at arc a_{p,n_p} for a freight vehicle using path p with a departure time of k from the origin. Then the path travel time can be computed as follows:

$$t_l^p(k) = \sum_{n_p=1}^{N_p} w_{a_{p,n_p}}(e_{a_{p,n_p}}(k)) \quad (10)$$

where

$$e_{a_{p,1}}(k) = k, \quad (11)$$

$$e_{a_{p,n_p+1}}(k) = e_{a_{p,n_p}}(k) + w_{a_{p,n_p}}(e_{a_{p,n_p}}(k)), \text{ for } n_p = 1, \dots, N_p - 1 \quad (12)$$

Then the vehicle dispatching problem in the transportation network given the service graph decision can be expressed as follows:

$$\min \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} (c_l^p(k) + \eta_l^p t_l^p(k)) y_l^p(k) \quad (13)$$

where η_l^p is the value of vehicle travel time along path p for modal segment l .

The problem constraints consist of (7) – (12) and

$$\sum_{p \in P_l} y_l^p(k) = x_l(k), \text{ for } \forall l \in L, \forall k \in K \quad (14)$$

$$y_l^p(k) \geq 0 \text{ for } \forall l \in L, \forall p \in P_l, \forall k \in K \quad (15)$$

$$\text{given } X \in \Omega \quad (16)$$

The objective function (13) is the total cost of the transportation network generated by the freight vehicles which is equal to TC if X is a feasible solution for problem (1-6). Constraints (14) and (15) are the constraints for demand balancing for each modal segment. The feasible set Ω in (16) is defined by constraints (2-6). Since the explicit forms of the dynamical functions in (7-9) are difficult to mathematically express directly due to the nonlinearities and complex traffic interactions, we use simulation models to replace the mathematical functions to generate more accurate arc traffic volumes and travel times. For freight vehicles using the road mode, the problem can be seen as a system optimal traffic assignment problem. For the subnet of freight vehicles using the rail service mode, the problem can be seen as a train dispatching problem. The resulting modal segment travel time are used to update the intermodal route travel time variables in (1) with a similar method as in (10-12) which reconstructs the travel time of a path as the sum of the travel times of the transportation arcs belonging to this path.

III. PROPOSED METHODOLOGY

A. Overall Framework

The proposed approach to solve the freight routing problem is shown in Fig. 2. It consists of the following layers:

1) *Interface layer*: This layer connects the physical traffic network and the upper routing optimization layers. It involves the sensing of the physical transportation network data achieved by various available techniques including GPS (global positioning system), V2I (vehicle to infrastructure) & V2V (vehicle to vehicle) communication, sensor detection of the traffic status and incidents, etc. All the collected data are fed into the simulation model which reconfigures itself to match the measurements in order to provide accurate state and cost prediction to the upper optimization layer. In addition, the routing decision is transferred to the physical network after the optimization is carried out.

2) *Simulation models*: The simulation models are developed to capture the main characteristics and dynamics of the multimodal transport network under the impact of the service graph routing decisions, passenger traffic and network changes (network incidents, road closures, etc.).

3) *Simulation-based cost evaluation*: This part is used to estimate the intermodal route state and cost which is required by the service graph decision-making. The system optimal dynamic assignment is used to find the optimal paths of the trucks on the road subnetwork. Then, the trip time and costs of the trucks are collected for updating the cost of the service graph segments served by the road mode. A train dispatching algorithm is used to find the best schedule of freight trains that minimizes the total cost without generating deadlocks by considering the impact of the passenger trains. The schedule of freight trains is used to update the cost of the service graph segments served by the rail mode.

4) *Service graph optimization*: This layer controls the overall decision process. An optimization algorithm searches for new candidate routing decisions that can reduce the total cost until certain stopping criteria are satisfied. The stopping criteria include reaching the maximum number of iterations or the change in the total cost is less than a predefined value between two consecutive iterations. Once one of the stopping criteria is satisfied the final decision is sent to the actual transportation network to implement the routing decision of freight traffic for the shippers.

B. Optimization Algorithm

The optimization problem (1-6) can be relaxed to the form with penalty functions as follows:

$$\min J(X) = TC + \sum_{k \in K} \sum_{l \in L^R} \sigma_l \phi_l(x_l(k), u_l(k), v_l(k)) \quad (17)$$

subject to constraints (2), (5-6) where σ_l is the penalty factor of modal segment l and ϕ_l is the modal segment penalty function depending on the freight on the modal segment, and the modal segment vehicle availability and capacity levels. According to the KKT (Karush-Kuhn-Tucker) conditions, the necessary conditions for a minima of problem (17) are all used intermodal routes for the same group of demand share the same intermodal route marginal cost which is less than the marginal costs of the other unused intermodal routes. The marginal cost of an intermodal route is defined as the partial derivative of the revised total cost $J(X)$ with respect to the intermodal route load.

The incremental penalty algorithm [25] is applied to solve problem (1-6) where hard constraints exist by solving the relaxed problem (17) repeatedly.

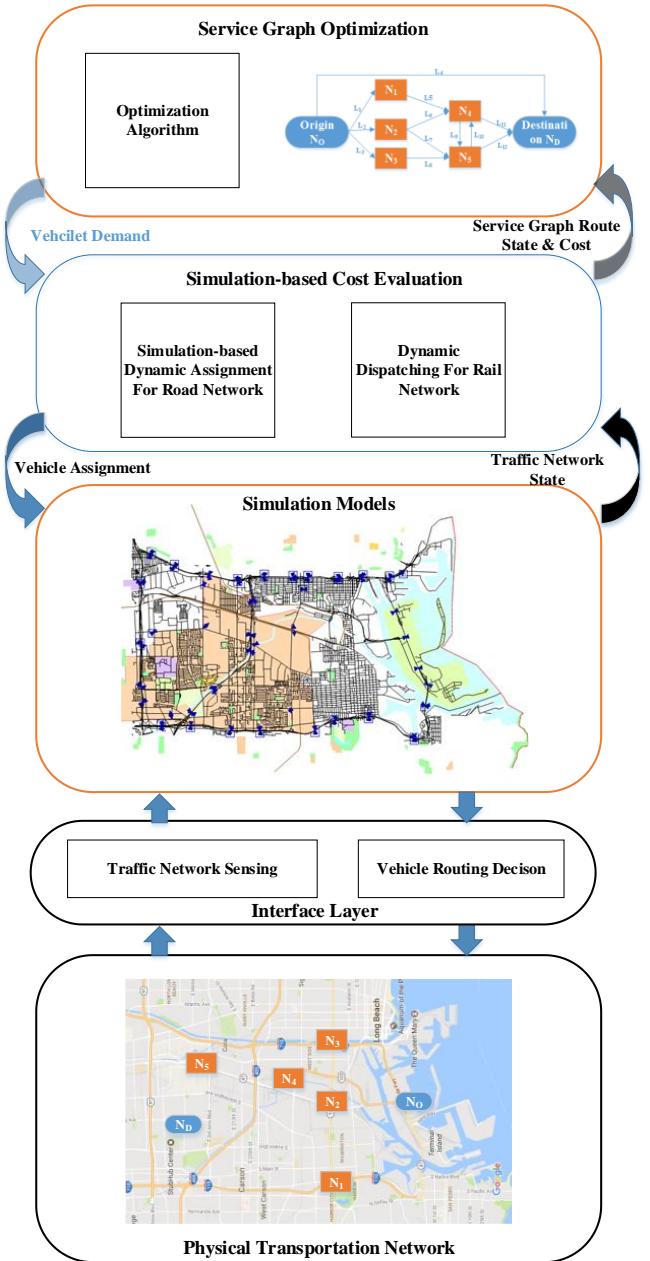


Fig. 2. Framework of Proposed Freight Routing System

The procedure of the incremental penalty algorithm is:

Step 0: Choose initial penalty factors σ_l^0 for $\forall l \in L^R$ and set master iteration round to $n = 0$;

Step 1: Find an optimal solution of the relaxed problem (17) with given values of $\sigma_l^n, \forall l \in L^R$ by the iterative COSMO approach using the idea of column generation [26] as shown in Fig. 3.

The key step of the COSMO approach is to find new routes that can improve the total delivery cost which depends on the marginal cost information of the possible routes. Considering the fact that it is difficult to find the explicit functional form of

TC , the marginal costs with respect to feasible intermodal routes cannot be obtained directly. The method that leads to the best marginal cost estimation for the candidate routes is to run the simulation models repeatedly by adding one more unit of demand to these routes and then check the change of delivery costs. However, it is impractical to enumerate all routes due to the fact that the number of possible routes grows exponentially with respect to the service graph size. An alternative way is to estimate the route marginal costs with the updated service graph states and costs from the traffic network simulation models.

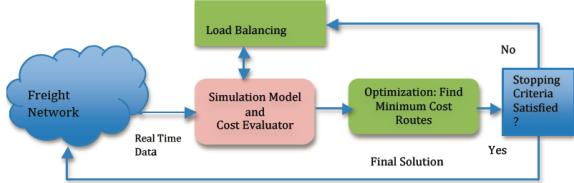


Fig. 3. COSMO Iterative Approach for Freight Routing

The procedure of COSMO is:

Step 1.1: Set the initial solution

In the n th round of the master procedure, set the iteration counter $m = 0$ and update the modal segment cost function with penalty factors $\sigma_i^n, \forall i \in L^R$. Assign the freight demand according to the routing decision in the previous round as the initial solution $X^{(0)}$. $R_{i,j}^{(0)}$ is the set of the used service routes.

Step 1.2: Update the service graph states using the simulation models

Set the current freight vehicle demand for the transportation network based on routing decision $X^{(m)}$ and conduct system optimal dynamic assignment of trucks and optimal train dispatching to update the transportation network states to estimate the marginal costs of the service graph based on the updated transportation network states. Since the marginal costs of the used vehicle paths belonging to the same modal segment are in equilibrium after system optimal assignment, the marginal cost $MC_l(k)$ for a modal segment l at time k can be estimated by the marginal cost of the vehicle paths plus the derivative of the penalty value, i.e.

$$MC_l(k) + \frac{\sigma_l \partial \phi_l(x_l(k), u_l(k), v_l(k))}{\partial x_l(k)} \quad (18)$$

In this paper we use $(\max\{x_l(k) - u_l(k)v_l(k), 0\})^2$ as the derivative of the modal segment penalty value. We give the details of how to obtain the modal segment marginal cost in (18) in the following section.

Step 1.3: Route augmentation (Column generation)

With the revised marginal cost as in (18), find intermodal routes that can reduce the revised total cost $J(X)$. The time-dependent shortest route algorithms in references [1]-[4] can be applied to find the shortest route. The new intermodal route is augmented in the available intermodal route set.

Step 1.4: Check for Convergence

Check whether the convergence criteria are satisfied. Considering the complexity and nonlinearity of the problem, it is intractable to give theoretical conditions for the optimal

solution and usually it is hard to find the optimal solution within an acceptable computation time for large scale problem sizes. Therefore, we use heuristic criteria to decide when to stop the search procedure. The stopping criteria used in this paper is the cost difference between two successive iterations is less than a predefined threshold or the maximum number of iterations has been reached. If one of the criteria is reached, go to Step 2 of the main procedure. Otherwise, go to step 1.5 for load balancing.

Step 1.5: Perform load balancing

For a shipper having an intermodal route with less marginal cost, conduct load balancing by redistributing the freight load from the current used intermodal routes to the new found route then return to step 1.2 to continue the optimization algorithm. The load balancing algorithm starts from constructing an auxiliary solution $X_{Aux}^{(m)}$ for example all-or-nothing assignment, i.e. the current demand of this shipper is loaded to the intermodal route with minimum marginal cost. Then the new routing decision can be generated by selecting a proper step size $\alpha^{(m)} \in [0, 1]$,

$$X^{(m+1)} = X^{(m)} + \alpha^{(m)} (X_{Aux}^{(m)} - X^{(m)}) \quad (19)$$

There are many ways to determine the step size in (19), such as the enumeration method i.e. redistributing only one unit of demand which is the most conservative step size, the MSA method [16][18], the revised MSA method, and the optimal step size method in the Frank-Wolfe algorithm [27] etc. The enumeration method has a very slow convergence despite the fact that it is guaranteed to find the optimal step size. One issue with the MSA group methods is that the step size only depends on the iteration without considering the current solution quality. Another issue is that they may exhibit solution oscillations around the hard constraints when the values of the penalty factor are large for the problem in this paper.

In the optimal step size method, the step size is determined by solving a linear search problem as follows.

$$\alpha^{(m)} = \arg \min_{\alpha^{(m)} \in [0, 1]} J(X^{(m)} + \alpha^{(m)} (X_{Aux}^{(m)} - X^{(m)})) \quad (20)$$

The linear search optimal step size is computationally intensive because running simulation models is required to construct the cost evaluation J in (20). As an alternative approach, a discrete set of predefined candidate step sizes is selected and evaluated in order to speed up the algorithm; however, the optimum step size is not guaranteed.

A common issue with the above load balancing algorithms is that all shippers are considered in the same way when selecting the step sizes, leading to slow convergence for multimodal routing when vehicle availability and capacity are considered. In order to speed up the algorithm, we propose the following revised algorithm which gives priority to some shippers in the step size selection. The step sizes of the different shippers are determined with respect to the potential cost reduction that is evaluated approximately by the standard deviation of the marginal costs of the used intermodal routes. Therefore,

$$\alpha_{i,j}^{(m)} = \min \left\{ \alpha_{\max}, \sum_{(i,j)} \alpha^{(m)} \frac{\xi(d_{i,j})}{\sum_{(i,j)} \xi(d_{i,j})} \right\} \quad (21)$$

where α_{\max} is the upper bound of the step size and $\xi(d_{i,j})$ is the standard deviation of the marginal cost of all the used routes by demand $d_{i,j}$.

Step 2: Compute $\phi_l^n(x_l(k), u_l(k), v_l(k))$ in the current solution. If $\phi_l^n(x_l(k), u_l(k), v_l(k)) = 0$, for $\forall l \in L^R$, terminate the algorithm because the problem solution is found;

Step 3: Update the penalty factors as follows then set $n = n + 1$ and go to step 1;

$$\sigma_l^{n+1} = \begin{cases} \sigma_l^n + \Delta_l^n \phi_l^n & \text{if } \phi_l^n(x_l(k), u_l(k), v_l(k)) > 0 \\ \sigma_l^n & \text{if } \phi_l^n(x_l(k), u_l(k), v_l(k)) = 0 \end{cases} \quad (22)$$

where $\Delta_l^n > 0$ is the increasing scalar to update the penalty factor of modal segment l at round n . In the experimental study of this paper, we select $\sigma_l^n = 10$ and $\Delta_l^n = 0.001$.

The computation time of the entire solution procedure mainly depends on the required amount of execution time of the simulation models. Therefore, accurate estimation of the route marginal cost for best route searching and efficient load balancing to improve the current solution are two critical parts of the algorithm.

C. Marginal Cost of the Service Graph

Assume we have a current container vehicle dispatching solution Y , the marginal cost of a vehicle path demand can be computed by the following equation:

$$\begin{aligned} MCP_{l'}^{p'}(k') &= \frac{\partial TC}{\partial y_{l'}^{p'}(k')} = \frac{\partial \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} (c_l^p(k) + \eta_l^p t_l^p(k)) y_l^p(k)}{\partial y_{l'}^{p'}(k')} \\ &= c_{l'}^{p'}(k') + \eta_{l'}^{p'} t_{l'}^{p'}(k') + \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} \eta_l^p y_l^p(k) \frac{\partial t_l^p(k)}{\partial y_{l'}^{p'}(k')} \end{aligned} \quad (23)$$

$MCP_{l'}^{p'}(k')$ is the change in the total cost in (12) if $y_{l'}^{p'}(k')$ is changed by one unit of containers. The first two terms are the cost of the current path and the last term is the cost change due to the impact on the arc travel time which can be computed approximately using the outputs of the simulation models.

$$\begin{aligned} \frac{\partial t_l^p(k)}{\partial y_{l'}^{p'}(k')} &= \sum_{n_p=1}^{N_p} \frac{\partial w_{a_{p,n_p}}(e_{a_{p,n_p}}(k))}{\partial y_{l'}^{p'}(k')} \\ &= \sum_{n_p=1}^{N_p} \frac{\partial w_{a_{p,n_p}}(e_{a_{p,n_p}}(k))}{\partial z_{a_{p,n_p}}} \frac{\partial z_{a_{p,n_p}}(e_{a_{p,n_p}}(k))}{\partial y_{l'}^{p'}(k')} \end{aligned} \quad (24)$$

The term $\frac{\partial w_a}{\partial z_a}(k)$ in (24) is the change in the arc travel time

at time k when the arc vehicle volume changes by one vehicle. It can be approximately estimated using the simulated arc traffic volume $z_a(k)$ and arc capacity at time k .

For a road segment, the travel time derivative with respect to the traffic volume can be obtained using the fundamental diagram of traffic flow [28] with the observed arc volume and density. The travel time derivative can also be determined using a road travel time model such as the Bureau of Public Roads (BPR) function in [29] or other estimated functions in [30]. Take the BPR function as an example,

$$w_a = t_{a_free} \times \left(1 + \alpha_a \left(\frac{z_a}{cap_a} \right)^{\beta_a} \right) \quad (25)$$

where w_a is the arc travel time, t_{a_free} is the arc free-flow travel time, z_a is the arc vehicle volume and cap_a is the arc capacity for vehicles. $\alpha_a \geq 0, \beta_a \geq 0$ are model parameters that can be estimated from historical data. The arc travel time derivative in (25) can be computed by the following equation,

$$\frac{\partial w_a}{\partial z_a}(k) = \frac{\alpha_a \beta_a t_{a_free}}{cap_a(k)} \left(\frac{z_a(k)}{cap_a(k)} \right)^{\beta_a-1} \quad \text{for } \forall a \in A, \forall k \in K \quad (26)$$

For the railway segments, considering the impact of the passenger train schedule and the freight dispatching constraints, the travel time of a rail arc is not an explicit function so the corresponding travel time derivative cannot be computed by a simple model. Therefore, the travel time with respect to the number of used freight trains are estimated by running the rail simulation models repeatedly or using historical operations data. Lu et. al. provide a detailed description of how to find the schedule of freight trains by deadlock-free dispatching in [31].

Ignoring the arc interactions to simplify the problem computation, we get,

$$\frac{\partial z_{a_{p,n_p}}(e_{a_{p,n_p}}(k))}{\partial y_{l'}^{p'}(k')} \approx \begin{cases} \frac{1}{v_{a_{p,n_p}}(k) \Delta t}, & a_{p,n_p} = a_{p',n_{p'}} \text{ and } e_{a_{p,n_p}}(k) = e_{a_{p',n_{p'}}}(k') \\ 0, & \text{otherwise} \end{cases} \quad (27)$$

Finally, the marginal cost of a vehicle path in (23) can be approximately computed by,

$$\begin{aligned} MCP_{l'}^{p'}(k') &\approx c_{l'}^{p'}(k') + \eta_{l'}^{p'} t_{l'}^{p'}(k') + \\ &\quad \sum_{n_p=1}^{N_p} \left[\eta_{l'}^{p'} y_{l'}^{p'}(e_{a_{p,n_p}}(k')) \frac{1}{v_{l'}(e_{a_{p,n_p}}(k')) \Delta t} \frac{\partial w_{a_{p,n_p}}}{\partial z_{a_{p,n_p}}}(e_{a_{p,n_p}}(k')) \right] \\ &\quad \text{for } \forall l' \in L, \forall p' \in P_{l'}, \forall k' \in K \end{aligned} \quad (28)$$

Since the first and second terms in (28) are decomposable with respect to the arcs, the marginal costs of the used paths belonging to the same modal segment will be in equilibrium by running a dynamic assignment algorithm in which the path marginal cost is computed by (23-28). Then the marginal cost for a modal segment can be approximately estimated by the resulting vehicle path marginal cost, i.e.

$$MC_{l'}(k') = MCP_{l'}^{p'}(k') \quad \text{for } \forall l' \in L, \forall k' \in K \quad (29)$$

IV. EXPERIMENTAL ANALYSIS

A. Evaluation Environment and Scenarios

This section shows the experiments of the proposed approach on a regional transportation network which covers the LA/LB Ports and surrounding area. The simulation models used in the COSMO approach consist of a macroscopic road network model and a rail simulation model. We use the macroscopic traffic simulator VISUM to develop the road network traffic flow model to achieve fast network state predictions computationally. The simulator parameters including lane number, length, speed limit and road capacity etc. are configured based on the practical transportation network. The inputs including passenger and freight traffic for the road network are expressed as the number of trips between zones that are the origins and destinations within the road network. We assume that the trucks can only carry one container so in our formulation the number of truck trips between each OD pair will be the number of containers to be delivered. Historical passenger traffic data of year 2012 that are obtained from the Southern California Association of Governments (SCAG) are used to tune the simulation models.

For the rail simulator, we use the railway simulation system of Lu et al. in [31] developed based on the ARENA simulation software. The rail simulator is used to evaluate the dynamical train movements for a complex rail network. The track network is divided into different segments based on their speed limits, length, and locations. Then, an abstract track graph is constructed with these segments. The inputs for the rail simulator are the passenger and freight train schedules including their planned departure times, origin stations, and destinations. Then the train movements in the track network are simulated to calculate the travel times and delays of all involved trains.

The integration of the two models has been realized by sharing the container demands and simulation outputs. The road network simulator sends the freight traffic i.e. the number of containers as well as corresponding origin and destination stations that will be delivered by the freight trains to the rail simulator. Then, the rail simulator creates the freight train schedule based on the train capacity and the simulated train movements with the planned passenger trains. After receiving the train schedule of the rail simulator, the road network simulator will generate the necessary truck flows to dispatch containers from the rail stations to their final destinations. The execution time of the simulation models to update the service graph is about 15 to 30 CPU seconds depending on the freight vehicle amount and passenger traffic conditions. The optimization program is implemented using MATLAB. Both the simulation models and optimization program were run on a desktop computer with 3.10GHz CPU and 8.0G memory.

We evaluated the routing between six main destinations (D1 – D6) and three main terminals (A, B, C) according to the practical distributions of warehouses and terminal ports in the region as shown in Fig. 4. The average weight of all the containers is assumed to be 25 tons and the transportation costs per unit (price/ton-mile) are assumed to be 8 cents for the road

network and 3 cents for the railway network [32]. The three shippers communicate their demand and current routing decision to a coordinator who runs the COSMO approach to generate the routing decisions by minimizing the overall cost that is defined by the transportation cost plus the travel time cost. The baseline demand for each shipper is 1020 containers. The detailed amounts of containers for the six destinations are provided in Table I.

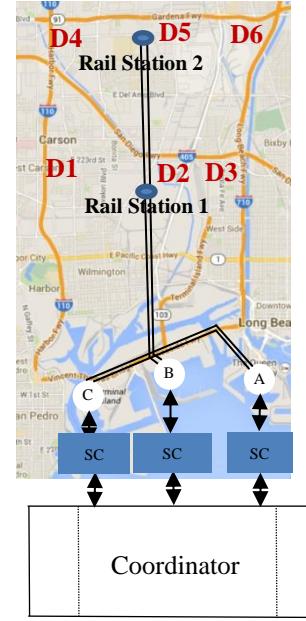


Fig. 4. Region of Study

TABLE I
BASELINE DEMAND OF DESTINATIONS

Destination	1	2	3	4	5	6
Supply from A	0	60	400	0	0	560
Supply from B	0	390	0	0	630	0
Supply from C	350	0	0	600	70	0
Total Demand	350	450	400	600	700	560

Five rail stations including three port terminals and two rail stations are located in the studied region. We assume that the freight trains have a unified capacity of 50 containers. The number of available freight trains from the port terminals to the two rail stations in the evaluated scenarios are: (1) Terminal A to station 1: 6 trains; (2) Terminal B to station 1: 2 trains; (3) Terminal C to station 1: 4 trains; (4) Station 1 to station 2: 10 trains.

B. Comparison of Load Balancing Methods

In this section, we computationally evaluate different methods for load balancing. First, we found that the custom MSA method has traffic flow oscillation issues for large penalty factors, which will result in slow convergence under the used stopping criteria in this paper. Besides custom MSA method, we evaluate four other step size selection methods: (1) Enumeration method in which the step size is selected in the most

conservative manner; (2) MSA with shipper priority in which the step size is computed by equation (21) and $\alpha^{(m)} = 1/(m+1)$; (3) Optimal step size method in which the step size is found by model (20); (4) the new proposed algorithm – optimal step size with shipper priority in which the step size is selected by model (10) and equation (21).

Since the enumeration method selects the most conservative step size, it will guarantee finding the optimal load balancing solution; however this method has the problem of slow convergence due to repeatedly execution of the simulation models. According to our evaluations, the CPU time keeps increasing with respect to the increased demand. The enumeration method becomes very slow to solve the problem with hard vehicle constraints that requires multiple rounds of load balancing for different penalty factors. We evaluated the CPU time of cases with hard vehicle constraints under normal traffic conditions. When the demand loads are 1.0 and 2.0 times of the default values, more than 13 and 22 CPU hours are required to find the solutions until convergence respectively. When the demand load is 2.5 times of the baseline demand, the enumeration method was not able to converge to a solution within 24 hours, which makes the method impracticable to apply for decision-making for large scaled demand.

Table II compares the performances of the step size selection methods for different demand loads (0.5, 1.0, 2.0, and 2.5 times the baseline demand) under the same normal traffic condition. In Table III, four different road traffic conditions are compared by fixing the demand to the baseline demand: 1) normal traffic in which the road traffic is set as the daily average traffic volumes; 2) widely congested traffic in which the network level road passenger traffic is increased by 50%; 3) partial congested traffic in which the traffic in one segment of freeway 405 is congested as shown in Fig. 5 a); 4) traffic under incidents in which the lane closures are introduced at two locations on the main freeways I-710 and I-110 causing the capacities of the two freeway segments to be reduced by a half as in Fig. 5 b).

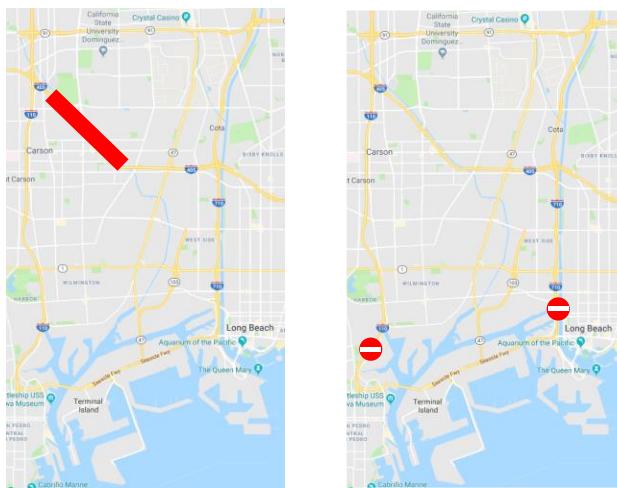


Fig. 5. Traffic conditions a) I405 freeway congestion and b) freeway capacity reduction due to lane closure

TABLE II
EVALUATION OF DIFFERENT DEMAND LOADS

Demand	MSA with Priority		Optimal Step		Optimal Step with Priority	
	Avg. cost (dollar)	Time (sec)	Avg. cost (dollar)	Time (sec)	Avg. cost (dollar)	Time (sec)
0.5	43.40	19415	43.38	508	43.56	162
1.0	48.34	28810	48.02	4051	48.39	1827
2.0	60.19	41568	61.18	9931	61.14	4187
2.5	68.32	90465	68.99	13045	68.72	11690

TABLE III
EVALUATION OF DIFFERENT TRAFFIC CONDITIONS

Traffic Condition	MSA with Priority		Optimal Step		Optimal Step with Priority	
	Avg. cost (dollar)	Time (sec)	Avg. cost (dollar)	Time (sec)	Avg. cost (dollar)	Time (sec)
Normal Traffic	48.34	28810	48.02	4051	48.39	1827
Congested Traffic	65.61	50571	66.34	8647	66.43	5214
I405 Congested	48.62	38651	48.35	2345	48.61	1824
Lane Closures	66.20	39900	67.04	6305	67.13	5441

In Table II, when the demand load increases, the average delivery cost increases because the overall vehicle delay will be added due to more freight vehicles. Meanwhile, more CPU computation time is required for increasing demand due to larger problem size. Therefore, the scalability issue of load balancing needs further study to deal with increased demand. As shown in Tables II and III, although in most cases the load balancing algorithm with the MSA method generates a slightly better solution in reducing the total cost, its CPU time is much higher, which limits its practical application. The MSA with priority method faces obvious larger computation time due to two reasons: (1) more rounds of load balancing are implemented in the incremental penalty algorithm compared to the optimal step group methods; according to the experimental results, the number of rounds of the load balancing procedure with MSA with priority method were nearly double of the optimal step group method; (2) more executions of the simulation models in Step 1.2 are required until the stopping criteria is satisfied for the MSA method especially when the penalty factors are large. The load balancing with the optimal step size methods has a much quicker convergence than the MSA method. Compared to the optimal step size method without priority, the proposed load balancing algorithm combining the optimal step size selection and shipper priority can save from 10% to 68% on the CPU time. The main reason is that the shipper priority considers the potential impact of the step size in reducing the total objective cost. One new solution can achieve better cost reduction which reduces the total number of iterations of Step 1. In summary, the proposed load balancing algorithm with priority provides the best convergence performance in reducing the computation time while providing nearly the same total costs compared to the other methods.

C. Application of Load Balancing

In this section, we compare the proposed load balancing system with a system without a centralized coordinator for different changes in traffic conditions and demand. For the system without load balancing, we assume the shippers optimize their own daily routing decisions based on observing historical traffic conditions and thus they follow a user equilibrium based solution. However, we also assume that a shipper will not change its predefined decisions when other shipper demand or traffic condition are changed since this shipper does not have the information about demand changes to the other shippers without the coordinator.

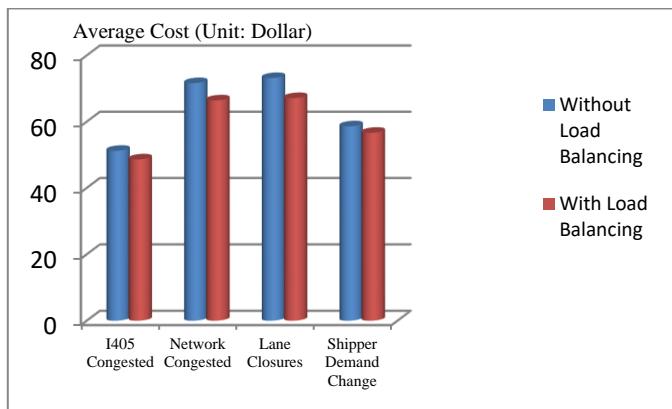


Fig. 6. Load balancing impact for traffic condition and shipper demand changes

Fig. 6 shows the impact of utilizing the proposed load balancing system in responding to traffic condition and shipper demand changes. In the first three cases, the traffic conditions are changed but the shippers' demand is the same as the baseline demand. In case 4 the demand of shipper 3 to destinations 1 and 3 becomes two times of the baseline demand; however there is no change on the road traffic condition. In all cases with load balancing, the coordinator can collect the shipper demand and traffic condition then make a centralized decision of redistributing the freight demand of the shippers across the multimodal network. According to the results, the delivery cost can be reduced in all the evaluated cases. The proposed load balancing system reduces the total cost by 6% to 9% compared to the cases without load balancing in the three traffic condition changes. For the last case, the average cost has been reduced by 2 dollars per container. Therefore, the proposed system can generate better routing decisions for the participating shippers with a centralized coordinator.

V. CONCLUSION

In this paper we proposed a regional freight routing system in which a hierarchical Co-Simulation Optimization control methodology based on an iterative load balancer is proposed to deal with hard vehicle availability and capacity constraints. We use a multimodal transport simulation testbed which covers the road and rail network in the Los Angeles/Long Beach Port area and a realistic scenario to evaluate the performance of the proposed freight routing system. The performance of different

step size selected methods in the load balancing algorithm has been compared and the experimental results demonstrate that the proposed load balancing method with shipper priority has a much faster convergence rate. The application of load balancing in handling changes in traffic conditions and shipper demand is also demonstrated. As future work, the scalability of the proposed methodology will be further studied to deal with larger traffic networks with increased demand.

REFERENCES

- [1] P. Modesti, A. Sciomachen, "A utility measure for finding multiobjective shortest paths in urban multimodal transportation networks," in *European Journal of Operational Research*, vol. 111, no.3, 1998, pp. 495-508.
- [2] A. Lozano, G. Storchi, "Shortest viable path algorithm in multimodal networks," in *Transport. Res. A: Pol.*, vol. 35, no. 3, 2001, pp. 225-241.
- [3] K. F. S. Abdelghany, "Stochastic dynamic traffic assignment for intermodal transportation networks with consistent information supply strategies," *Dissertation of The University of Texas at Austin*, 2001.
- [4] S. Demeyer, P. Audenaert, M. Pickavet, and P. Demeester, "Dynamic and stochastic routing for multimodal transportation systems," *IET Intelligent Transportation Systems*, vol. 8, no. 2, 2014, pp. 112-123.
- [5] J. Guelat, M. Florian, T. G. Crainic, "A Multimode multiproduct network assignment model for strategic planning of freight flows," in *Transportation Science*, vol. 24, no. 1, 1990, pp. 25-39.
- [6] L. Castelli, R. Pesenti, W. Ukovich, "Scheduling multimodal transportation systems," in *European Journal of Operational Research*, vol. 155, no. 3, 2004, pp. 600-613.
- [7] H. Ham, T. J. Kim, D. Boyce, "Implementation and estimation of a combined model of interregional, multimodal commodity shipments and transportation network flows," in *Transport. Res. B: Meth.*, vol. 39, no. 1, 2005, pp. 65-79.
- [8] K. G. Zografos, K. N. Androultsopoulos, "Algorithms for itinerary planning in multimodal transportation networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 9, no. 1, 2008, pp. 175-184.
- [9] J. Moccia, J. Cordeau, G. Laporte, S. Ropke, M. Valentini, "Modeling and solving a multimodal transportation problem with flexible time and scheduled services," in *Networks*, vol. 57, no. 1, 2011, pp. 53-68.
- [10] Crainic T. G., Gobbato L., Perboli G., Rei W., "Logistics capacity planning: A stochastic bin packing formulation and a progressive hedging meta-heuristic," in *European Journal of Operational Research*, vol 253, pp. 404-417, 2016.
- [11] Crainic T. G., Ricciardi N., Storchi G., "Advanced freight transportation systems for congested urban areas," *Transportation Res. Part C: Emerging Tech.* vol. 12, no. 2, pp. 119–137, 2004.
- [12] A. Abadi, P. A. Ioannou, M. M. Dessouky, "Multimodal dynamic freight load balancing," *IEEE Transactions on Intelligent Transportation System*, vol. 17, no. 2, 2016, pp. 356-366.
- [13] T. G. Crainic, G. Perboli, M. Rosano, "Simulation of intermodal freight transportation systems: a taxonomy," in *European Journal of Operational Research*, vol. 270, no. 2, 2018, pp. 401-418.
- [14] Y. Zhao, P. Ioannou, M. M. Maged, "Routing of multimodal freight transportation using a co-simulation optimization approach," *Transportation Research Board 96th Annual Meeting*, January, 2017.
- [15] G. Perboli, M. Rosano, M. Saint-Guillain, P. Rizzo, "Simulation-optimisation framework for city logistics: an application on multimodal last-mile delivery," *IET Intelligent Transportation Systems*, vol. 12, no. 4, 2018, pp. 262-269.
- [16] S. Peeta, H. S. Mahmassani, "System optimal and user equilibrium time-dependent traffic assignment in congested network," in *Annals of Operations Research*, vol. 60, no. 1, 1995, pp. 81-113.
- [17] H. S. Mahmassani, K. Zhang, J. Dong, C. C. Lu, V. C. Arcot, and E. Miller-Hooks, "Dynamic networks simulation-assignment platform for multiproduct intermodal freight transportation analysis," in *Transportation Research Record*, no. 2032, 2007, pp. 9-16.
- [18] X. Zhou, H. S. Mahmassani, K. Zhang, "Dynamic micro-assignment modeling approach for integrated multimodal urban corridor management," in *Transport. Res. C-Emer.*, vol. 16, no. 2, 2008, pp. 167-186.
- [19] C. C. Lu, H. S. Mahmassani, X. Zhou, "Equivalent gap function-based reformulation and solution algorithm for the dynamic user equilibrium problem," in *Transport. Res. B: Meth.*, vol. 43, no. 3, 2009, pp. 345-364.

- [20] J. E. Fernandez, J. D. Cea, A. Soto, "A multi-modal supply-demand equilibrium model for predicting intercity freight flows," in *Transport. Res. B-Meth.*, vol. 37, no. 7, 2003, pp. 615-640.
- [21] Z. C. Li, W. H. Lam, S.C. Wong, and A. Sumalee, "An activity-based approach for scheduling multimodal transit services," in *Transportation*, vol. 37, no. 5, 2010, pp. 751-774.
- [22] T. Y. Ma, J. P. Lebacque, "Dynamic system optimal routing in multimodal transit network," in *Transport. Res. Rec.*, no. 2351, 2014, pp. 76-84.
- [23] O. Verbas, H.S. Mahmassani, M. F. Hyland, "Gap-based transit assignment algorithm with vehicle capacity constraints: Simulation-based implementation and large-scale application," in *Transport. Res. B: Meth.*, vol. 93, part A, 2016, pp. 1-16.
- [24] W Shen, Y. Nie, and H. Michael Zhang, "Route-based system optimal dynamic traffic assignment model: formulations and solution methods," *IEEE Conference on Intelligent Transportation Systems*, pp. 1298-1303, 2006.
- [25] M. Fukushima, "Restricted generalized Nash equilibria and controlled penalty algorithm," in *Computational Management Science*, vol. 8, no. 3, 2011, pp. 201-218.
- [26] J. Desrosiers and M. E. Lübecke, "A primer in column generation," *Column Generation*, pp. 1-32, 2005.
- [27] M. Frank, P. Wolfe, "An algorithm for quadratic programming". *Naval Research Logistics*, vol. 3, no.1, pp. 95-110, 1956.
- [28] N. Geroliminis; C.F. Daganzo, "Existence of urban-scale macroscopic fundamental diagrams: some experimental findings," in *Transport. Res. B: Meth.*, vol. 42, no. 9, 2008, pp. 759-770.
- [29] Traffic Assignment Manual, U.S. Department of Commerce, Bureau of Public Roads, 1964.
- [30] G. A. Davis, H. Xiong, "Access to destinations: travel time estimation on arterials," *Technical Report MN/RC 2007-35*, University of Minnesota, 2007.
- [31] Q. Lu, M. Dessouky, and R.C. Leachman, "Modeling train movements through complex rail networks," in *ACM Transactions on Modeling and Computer Simulation*, vol. 14, no. 1, 2004, pp. 48-75.
- [32] D. J. Forkenbrock, "Comparison of external costs of rail and truck freight transportation," in *Transport. Res. A: Pol.*, vol. 35, no. 4, 2001, pp. 321-337.



Yanbo Zhao (M'12) received his Ph.D. degree in Electrical Engineering from the University of Southern California, Los Angeles, in 2017. He earned his M.S. degree in Control Science and Engineering from Tsinghua University, Beijing, China in 2009 and B.S. degree in Measurement, Control Technology and Instrument from Harbin Institute of Technology, Harbin, China in 2006 respectively. He is currently working as a Postdoctoral Research Associate of the METRANS Transportation Center at the University of Southern California. He worked as a Researcher Assistant with Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, in 2011 and a Project Engineer at Beijing National Railway R&D Institute of Signal & Communication from 2009 to 2011. His research interests lie in the intersection of complex system modeling, control, machine learning and nonlinear optimization. His research topics include Cyber-Physical transportation systems, traffic control systems with connected and autonomous vehicles, and urban policy study based on urban data analytic.

Petros Ioannou (F'97) received the B.Sc. degree with First Class Honors from University College, London, England, in 1978 and the M.S. and Ph.D. degrees from the University of Illinois, Urbana, Illinois, in 1980 and 1982, respectively. In 1982, Dr. Ioannou joined the Department of Electrical Engineering-Systems, University of Southern California, Los Angeles, California. He is currently the A.V. 'Bal' Balakrishnan Professor in the same Department, the Director of the Center of Advanced Transportation Technologies and Associate Director for Research of METRANS. He holds a courtesy appointment with the Department of Industrial Engineering and the Department of Aerospace and Mechanical Engineering. His research interests are in the areas of adaptive control, neural networks, vehicle dynamics and control, aerospace control, freight transportation, and intelligent transportation systems. In 1984 he was a recipient of the Outstanding Transactions Paper Award by the IEEE Control System Society and the recipient of a 1985 Presidential Young Investigator Award. In 2009 he received the IEEE ITSS Outstanding Application Award for his work on Adaptive Cruise Control Systems. He also received the 2009 IET Achievement Medal in control systems by the Institute of Engineering and Technology (IET). In 2012 he received the IEEE ITSS Outstanding Research Award and in 2016 the IEEE Transportation Technologies Field Award. He is currently the Editor in Chief of the IEEE Transactions on Intelligent Transportation Systems. Dr. Ioannou is a Fellow of IEEE, IFAC IET and AAAS and the author/co-author of 8 books and over 300 research papers.

Maged M. Dessouky is Professor and Chair in the Daniel J. Epstein Department of Industrial & Systems Engineering at the University of Southern California and the Director of the Epstein Institute. He received B.S. and M.S. degrees from Purdue University and a Ph.D. in Industrial Engineering from the University of California, Berkeley. He is area/associate editor of *Transportation Research Part B: Methodological*, *IIE Transactions*, and *Computers and Industrial Engineering*, on the editorial board of *Transportation Research Part E: Logistics and Transportation Review*, and previously served as area editor of the *ACM Transactions of Modeling and Computer Simulation* and associate editor of *IEEE Transactions on Intelligent Transportation Systems*. He is a Fellow of IIE and was awarded the 2007 *Transportation Science and Logistics Best Paper Prize*.

