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Authors
Ioannou, Petros
Giuliano, Genevieve
Dessouky, Maged
et al.

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Freight Load Balancing and Efficiencies in Alternative Fuel Freight Modes

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A Research Report from the National Center for Sustainable Transportation

Petros Ioannou, University of Southern California

Genevieve Giuliano, University of Southern California

Maged Dessouky, University of Southern California

Pengfei Chen, University of Southern California

Sue Dexter, University of Southern California

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16. Abstract The current freight transportation network is highly unbalanced as routing decisions are made by individual users without coordination. Certain routes may become congested when chosen based on current traffic information without any anticipation that if other users do the same, these routes are no longer the best. This project developed a centrally coordinated load balancing system that considers all user demands and generates individual routes that balance freight loads across the network by minimizing cost. It is initially assumed that all vehicles are diesel and then gradually increases zero emissions vehicles such as electric trucks for a mixed fleet of trucks. The electric trucks add additional constraints due to limitation of range and charging time of batteries. As the number of electric trucks increases, the emissions reduce as expected; however, the cost of charging does not make their use less operational costly than the corresponding diesel trucks. The experiments show that for electric trucks to compete with diesel, charging should occur when drivers are off duty or in idle mode since the cost of charging is mainly due to the labor cost of the waiting driver. Several simulation experiments show the benefits of deploying electric trucks in a freight fleet with respect to environment and operational cost, provided charging is scheduled appropriately. It is shown that the proposed centrally coordinated load balancing system can easily incorporate different concepts such as the empty container re-use where the exchange of containers between users can be optimized to reduce empty trips. In order to better understand the implementation issues of a load balancing system, the report also includes results from interviews of individuals responsible for trucking operations in the Los Angeles region. All interviewed trucking companies are either drayage operations (hauling freight to and from ports or intermodal facilities) or short-haul operators that move goods between manufacturers, distribution center, and retail facilities. The answer for load balancing system varies between interviewees and it is recommended to follow an iterative fashion by first targeting trucking companies who already work collaboratively in associations and vertical markets. These clusters of firms have built working relationships, engage in communication, and have trust between members.		

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Freight Load Balancing and Efficiencies in Alternative Fuel Freight Modes

A National Center for Sustainable Transportation Research Report

June 2020

Petros Ioannou, Department of Electrical Engineering Systems, University of Southern California

Genevieve Giuliano, Sol Price School of Public Policy, University of Southern California

Maged Dessouky, Department of Industrial and Systems Engineering, University of Southern California

Pengfei Chen, Electrical, Electronics, and Communications Engineering, University of Southern California

Sue Dexter, Urban Planning and Development, University of Southern California

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Glossary

Abbreviations	Explanation
GHG	Green House Gases
CO2	Carbon dioxide
NOx	Oxides of nitrogen
PM10	Inhalable particles, with diameters that are generally 10 micrometers and smaller
A TRI	American Transportation Research Institute
ITS	Intelligent Transportation Systems
VRP	Vehicle Routing Problem
TSP	Traveling Salesman Problem
O/D	Origin/Destination
GPS	Global Positioning System
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
COSMO	Co-SiMulation Optimization
SCAG	Southern California Association of Governments
MSA	Method of Successive Average
ZEFV	Zero Emission Freight Vehicle
NREL	National Renewable Energy Laboratory
LA/LB	Los Angeles/Long Beach
FHWA	Federal Highway Administration

Freight Load Balancing and Efficiencies in Alternative Fuel Freight Modes

EXECUTIVE SUMMARY

Recent advances in sensing and navigation technologies makes it easier to route vehicles from origin to destination based on traffic characteristics obtained from historical and available real time traffic data. Google maps and Waze are some of the most popular commercial applications used for routing instructions. These applications however do not distinguish between different classes of vehicles and associated dynamics which often have a big impact on travel time and traffic flow characteristics. In areas where the volume of trucks is relatively high, the impact of heterogeneous vehicle dynamics can be quite pronounced, making these apps less reliable for navigation guidance. This heterogeneity may become more pronounced as the truck fleet becomes more diversified. Battery electric trucks are beginning to enter some markets, and hydrogen fuel heavy duty trucks are in development. These trucks may have different performance attributes with respect to speed, acceleration, or deceleration as well as different charging/refueling constraints.

Today's vehicle navigation systems have limited ability to predict. For example, when many vehicles with similar origins and destinations are routed on what appears at the time as a minimum time route, the route may turn out to be non-optimal as a result of the increased traffic assigned to the route. The lack of coordination among different shippers and of information on the transport network make it difficult to predict changes in the transportation networks due to upcoming loads.

In general, the current freight transportation system is full of inefficiencies leading to imbalances in traffic with respect to space and time, and these imbalances have significant individual and environmental costs. Information technologies, software and hardware technologies offer a strong potential for dramatic improvements in balancing freight loads in multimodal networks.

This project addresses the design and evaluation of a freight load balancing system by taking into account advances in theory, software and hardware technologies. The freight load balancing system is based on a co-simulation optimization approach that combines real time traffic simulators with a route optimization algorithm in a feedback configuration. The system takes into account the nonlinear impact of loads on traffic conditions. It assumes a "system manager" that allocates loads to time, space, and mode windows. The load balancing system is first developed for one type of truck (diesel) in a multimodal environment that includes the road and rail network. The purpose is to evaluate computational speeds of different optimization techniques. Then the system is extended to two type of trucks, diesel and battery electric. Battery electric trucks are assumed to be those that qualify as zero emission freight vehicles (ZEFV) under current California law and that are part of demonstrations in drayage service. The use of mixed fleet of diesel and electric trucks introduces additional constraints

and cost criteria to be considered, as electric trucks have a higher capital cost, shorter range, and longer refueling time than diesel trucks.

Finally, the concept of empty container reuse has been incorporated into the proposed load balancing system. Empty container reuse seeks to reduce the number of empty container moves via better matching of loads and containers. The purpose of incorporating empty container reuse into the proposed load balancing system is to demonstrate its flexibility and capability to be integrated with future freight management concepts and technologies.

Several scenarios from the Southern California area that incorporates the Los Angeles and Long Beach Ports are used for evaluation of the proposed load balancing system with mixed fleet of vehicles namely diesel and electric ones. The main outcomes of these evaluations are listed as follows:

- *The proposed centrally coordinated freight load balancing system has potential for improvements in balancing freight loads across the road and rail networks in terms of overall cost and impact on the environment. All simulated scenarios showed consistent improvements whose level depends on traffic network conditions*
- *Vehicle technologies such as electric trucks can be incorporated in the proposed load balancing system despite the added constraints of range, charging times, location of charging stations.*
- *Based on models of diesel and electric engines and tests with different speed cycles the electric engines are found to consume less energy than diesel except during congestion when traffic speeds are very low. In such environment the electric engine is very inefficient when compared with diesel. These engine characteristics are taken into account in load balancing.*
- *In a mixed fleet of diesel and electric vehicles the total energy cost without including charging cost decreases as the percentage of electric vehicles increases. However, this does not imply that for a specific route the use of electric vehicle is always less costly than that of a diesel vehicle.*
- *The total cost that also includes the charging cost tends to increase in general with increasing number of electric vehicles in the fleet. The assumption made is that the charging cost includes the labor cost of the Driver waiting for the vehicle to charge. If charging is done off-duty this cost can be reduced considerably and, in such case, the total cost reduces with increasing number of electric vehicles*
- *As expected, the emissions go down drastically as the number of electric vehicles increases in the fleet.*
- *The concept of empty container reuse can be easily incorporated in the proposed load balancing approach with a mixed fleet of diesel and electric trucks. The removable of unnecessary empty container trips contributes to improved load balancing across the road network.*

The practical implementation of the proposed load balancing system has been discussed with practitioners and SCAQMD board member who is in the tracking industry via interviews and a questionnaire. A total of six extended interviews were conducted. Common themes are summarized as follows:

- *Servicing customers is the number one priority. Disruptions in the ability to deliver services on time would have significant impacts to businesses.*
- *Shippers are very sensitive to costs and, in general, open to new technologies as long as they can see the benefit. Shippers are reluctant to change schedules and time windows and pass that control over to some central coordinator; they will consider it if they can see individual benefits.*

The response of the practitioners is to be expected and it is something that is common to all new technologies. People will use them when they can perceive benefits. The goal of this and future projects on freight load balancing is to identify and better quantify these potential benefits in order to accelerate acceptance and implementation.

We have to emphasize that the research performed is a preliminary step toward a centrally coordinated freight load balancing and by no means captures the full complexity of freight transport. Some of the assumptions made need to be validated with experiments and some of the scenarios tested are rather simple when compared with the complexity of freight operations. This research however sets the foundations of the concept of centrally coordinated freight load balancing system by solving some challenging problems whose solutions point the directions for future research. Complexity and scalability are some of the future topics to be addressed in order to deal with larger scale scenarios, more complex demands and practices and additional constraints. Such topics will bring load balancing closer to practical implementation.

1. Introduction

The efficient movement of freight is a critical factor in US competitiveness. As globalization proceeds, the volume of international trade will increase, and the US will face growing competitive pressures. It is therefore essential that the freight transport system operates as efficiently as possible. Worldwide container trade is growing at a 9.5% annual rate, and the US growth rate is around 6%. Current forecasts expect US commodity trade to approximately double by 2030 [1]. Forecasts predict significant increases in highway congestion around US ports, air cargo, and border crossing nodes [2]. Growth in average ocean vessel size concentrates port activity into the largest ports, further intensifying bottleneck problems on the surface transport system. The concentration of truck traffic in metro areas with major ports (e.g., New York, Los Angeles) and trade nodes (e.g., Chicago, Atlanta) adds significantly to congestion and air pollution. Congestion results in enormous costs to shippers, carriers, and the economy. According to [3], the total cost of truck congestion amounts to approximately $23 billion in 2010 for 439 US urban areas. Freight bottlenecks on highways throughout the United States cause more than 243 million hours of delay to truckers annually [4]. At a delay cost of $26.70 per hour, the conservative value used by FHWA's Highway Economic Requirements System model for estimating national highway costs and benefits, these bottlenecks cost truckers about $6.5 billion per year [4]. Freight transport is a significant contributor of NOx, CO2, PM10 and other pollutants. Of the Greenhouse Gases (GHG) emissions coming from transportation related sources, freight movement (trucks, ships, trains, airplanes, and pipelines) accounts for 29 percent of total; trucks were responsible for emitting 68 percent of GHG coming from these freight sources [5].

Of all the motor vehicle traffic fatalities reported in 2009, 9.6 percent (2,987) involved large trucks and over one-third of the crashes took place in urban areas [6]. Truck crashes add disproportionately to highway congestion, because of their longer duration. Despite the continued growth of rail freight, trucks continue to retain the largest market share. Of the nearly 20 billion tons of freight moved in 2012, 13 billion moved by truck [7]. Dominance of truck increases as haulage distance decreases; for trips of less than 100 miles (about half of all freight haulage), the truck mode share is 84% [7]. Trucks dominate due to shipment size, trip length, and ubiquity of the road network, [8]–[11]. Due to size and differences in vehicle dynamics, freight transport by trucks has a bigger impact on the road network especially in urban areas. For example, trucks have different dynamics than passenger vehicles, they are often restricted to outside highway lanes, take longer distances to stop, have smaller deceleration and acceleration values, and more importantly pollute more and consume more fuel. In addition, they affect traffic flow much more than passenger vehicles especially during turns, stop and go traffic, lower speeds in highways etc.

In European Union the impact of trucks on CO2 emissions is also significant relative to that of other vehicle classes as according to [12] about 26% of the CO2 emissions are due to heavy–duty vehicles in comparison to 61% for passenger vehicles, 12% for vans and 1% for two-wheelers. According to [12] while the emissions from other sectors have been dropping during the last 3 decades those due to freight road transport have been rising.

The fuel cost accounts for about one third of the total cost of owning and operating a truck [13]. In the US the cost of operating a truck averaged $1.69 per mile, a 6% increase in 2017 according to a report released Oct. 2, 2018 by the American Transportation Research Institute (ATRI) [14]. Broken down hourly, the report said it cost $66.65 per hour to operate a truck in 2017, compared with $63.66 in 2016 and $58 in 2009 [14]. On a percentage basis, driver salaries, benefits and bonuses account for 43% of the cost of operating a truck, fuel is 22%, lease and truck payments make up 16%, and repairs and maintenance are 10%. Other costs including vehicle insurance, permits, tolls and tires make up the remaining 9% [14]. These statistics suggest that the driver is the highest cost of operating a truck followed by the fuel cost and these statistics hold in the US as well as EU in general.

The above statistics together with the efforts of cutting down emissions motivate a number of key technologies and set the trend for the future of the trucking industry. These technologies can be divided into two major parts: Hardware changes and Software/intelligence. Hardware changes include hybrid and electric propulsion systems, tires with reduced rolling resistance, vehicle design with improved aerodynamics etc. Software/intelligence includes intelligence on the vehicle level such as improved lateral and longitudinal control systems, optimized engine control actions, connectivity and use of intelligent transportation systems (ITS).

ITS connects the vehicle with the infrastructure and addresses issues such as optimum routing in order to minimize travel times, energy consumption, reduce emissions and cut additional costs such as using less number of drivers as in the case of truck platoons. However, some of these technologies whether hardware or software are often interconnected. For example, the use of electric trucks brings up the constraint of available charging stations and charging times which will affect optimum routing decisions. The battery range and charging time as well as availability of charging stations where needed are some of the challenges of electric trucks [15]. Nevertheless the industry is moving ahead with companies like Volvo and Tesla producing electric trucks [16] for short-haul operations in urban areas where the need for cutting down pollution is much higher.

Research on vehicle routing is very rich and many optimization tools have been developed over the years which will become very useful in addressing some of the issues mentioned above. The Vehicle Routing Problem (VRP) formulation was first introduced by Dantzig and Ramser [17], as a generalization of the Traveling Salesman Problem (TSP) presented by Flood [18]. Since then, there is a significant amount of research on this topic which can be divided into 4 main categories. First, in static and deterministic problems, all inputs are known beforehand and vehicle routes do not change once they are in execution. This classical problem has been extensively studied in the literature, and we refer the interested reader to the recent reviews of exact and approximate methods by Baldacci et al. [19], Cordeau et al. [20], Laporte [21], [22], and Toth and Vigo [23]. Second, static and stochastic problems are characterized by inputs partially known as random variables, which realizations are only revealed during the execution of the routes. Additionally, it is assumed that routes are selected a priori and only minor changes are allowed afterwards. Uncertainty may affect any of the input data like stochastic times where either service or travel times are modeled by random variables [24], [25]; and stochastic demands [26]–[30]. Third dynamic and deterministic problems have part or all of the inputs as unknown and appear dynamically during the design or execution of the routes. For these problems, vehicle routes are redefined in an ongoing fashion, requiring technological support for real-time communication between the vehicles and the decision maker (e.g., mobile phones and global positioning systems). Fourth, dynamic and stochastic problems have part or all of their inputs unknown and appear dynamically during the execution of the routes, but in contrast with the latter category, exploitable stochastic knowledge is available on the dynamically revealed information. As before, the vehicle routes can be redefined in an ongoing fashion with the help of technological support. For a comprehensive review of both the deterministic and the stochastic dynamic VRP, we refer the interested reader to [26]–[30]. Additional work on shortest route problems which cover the four categories mentioned can be found in [31]–[39] which also include work on multimodal routing and planning.

With respect to electric vehicle routing, Ambrose and Jaller [40] examined the result of electric drayage trucks at the Port of Los Angeles and assessed emissions reductions with increased electrification of port truck operations. Nan et al. presented a mathematical programming model and solution method for path- constrained traffic assignment problem for electric vehicles in congested networks [41]. Bahrami et al. proposed a complementarity equilibrium model for electric vehicles without violating driving range constraints [42]. Based on the assumption of large adoption of electric vehicles, Faridimehr et al. [43] proposed a two-stage stochastic programming model to determine the optimal network of charging stations for a community as well as the charging decision for each electric vehicle in this community. For a more detailed topic for electric vehicle traffic assignment, Yao et al. [44] compared electric vehicle's energy consumption rate on different road types from the floating car data collected from the road networks in Beijing.

Despite the amount of research in vehicle routing, there are many issues that need to be addressed and new techniques need to be developed in order to make full use of these emerging technologies in a way that benefits the overall system and the environment. The complexity of the traffic network is immense due to the nonhomogeneous dynamics of different vehicle classes at the vehicle level to traffic nonlinear behavior at the traffic flow level. Mathematical models whether static, dynamic or stochastic used by most routing schemes cannot possibly capture the complexity of the real system in order to achieve the best possible outcomes especially due to the added constraints of the electric trucks. A true optimum route for a truck for example may end up been far away from the optimum generated from a model due to uncertainties not captured by the mathematical model that optimality is based on. The development of accurate mathematical models to describe traffic characteristics has always been a challenge and is becoming more of a challenge if electric trucks are included in traffic. The availability of fast computers and advanced software tools allows for the first time the development of traffic simulation models which can run in real time to provide the information and predicted states of the traffic network in order to choose routes that are more likely to be close to optimality than those based on simplified mathematical models. The challenge is how these simulation models can be integrated with optimization tools in order to generate more realistic outcomes.

In our past work [39], [45] we considered the use of real time traffic simulators as part of a centralized coordinated multimodal freight load balancing, where we successfully showed the significance of traffic simulators in planning freight routes to achieve a good balance of freight loads across the road and rail network. In this project we extended the work of [39], [45] which was focused on diesel trucks to include electric trucks in mixed fleets with diesel trucks. Electric trucks will be entering the market due to efforts to reduce emissions and most companies will be operating mixed fleets of trucks. Therefore, routing mixed fleets of trucks in a coordinated manner that will have additional benefits to the environment and costs is an important research problem this project focused on. Empty container reuse, an important concept developed by this team in the early 2000 [46] utilized by several trucking companies is also attractive for mixed fleet of trucks as electric trucks may be more appropriate due to lower weight with lower impact on battery life. This concept has also been addressed in this project as part of the load balancing approach together with implementation issues in general.

The report is organized as follows. Section 2 deals with the problem formulation. Respectively Section 2.1 presents the formulation of the diesel truck multimodal freight load balancing system and Section 2.2 presents the corresponding mixed truck multimodal freight system. Section 3 presents the experimental results of the proposed freight load balancing system and in Section 4 the empty container reuse concept is incorporated in the freight load balancing system. Section 5 discusses the implementation issues for such system and presents the results of interviews with individuals in the industry. Finally, conclusions are presented in Section 6.

2. Problem Formulation

Our problem relies on a centrally coordinated freight routing system where different shippers send their demand to a central coordinator. Demand is characterized in terms of volume, origin and destination, and time windows. The central coordinator seeks to allocate or balance loads across the network in order to minimize the overall social cost. The balancing process generates routes for each user. Load balancing can be done in advance as part of scheduling and planning or in real time in case of unpredictable traffic changes due to incidents.

We use a directed graph consisting of a set of nodes (N) with a set of directed arcs (A) connecting the nodes to represent the transportation network. A node in the network can be a road intersection, railway station, port terminal, charging station or warehouse etc. An arc in the network is regarded as 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 and destination nodes respectively. Both I and J are a subset of N. In the following section we present the formulation of a multi modal freight load balancing system involving only one type of truck namely diesel. We extend the formulation to include a mixed fleet in the subsequent section.

2.1 Models for Load Balancing

In practice, one of the important problems in assigning diesel freight vehicles is that the available number of freight vehicles are constrained in parts of the transportation network. For example, the number of available trains is limited between two rail stations or there is an upper bound on 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. The service graph G is 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 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. Figure 1 shows an example of a service graph and corresponding traffic network where A and B are the origin and destination nodes respectively. The traffic network can be represented by a service graph with four nodes including nodes A, B, and the two rail nodes.

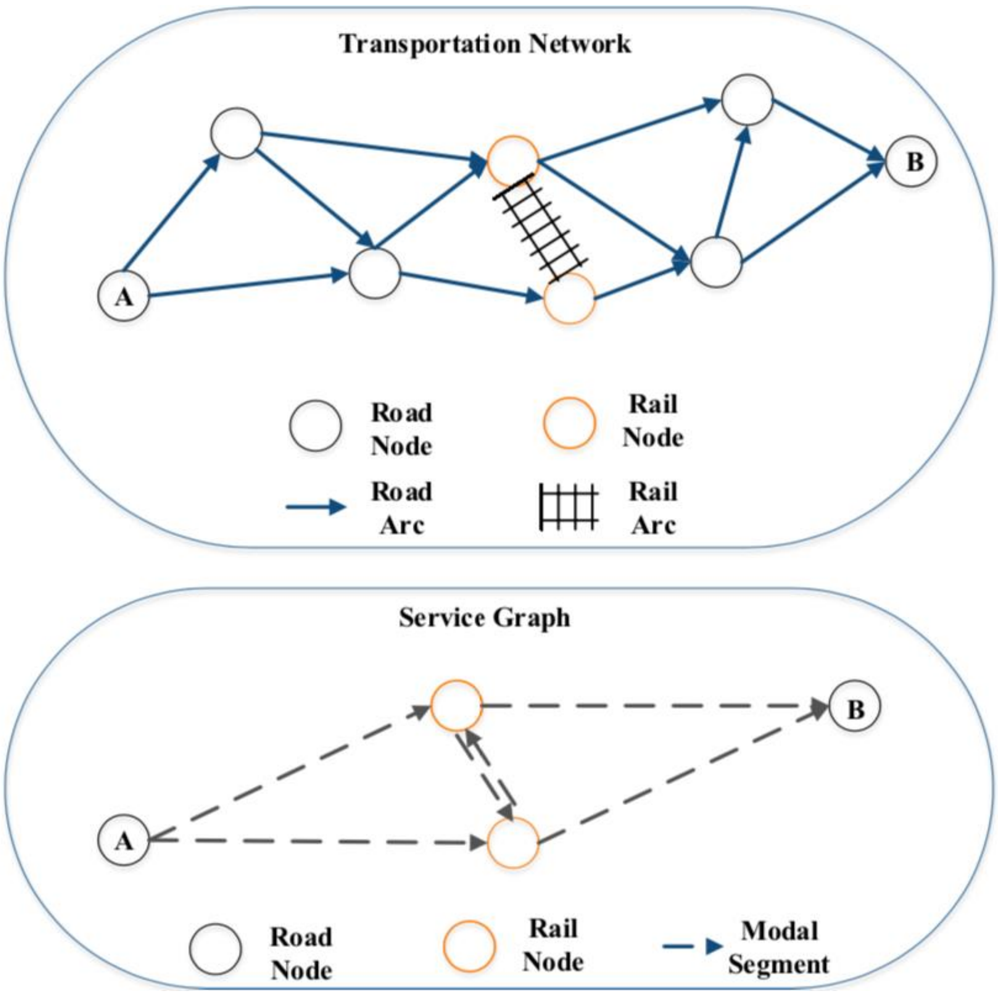

Figure 1. Traffic network and service graph

In this subsection we present the formulation of the freight load balancing system assuming one type of trucks namely diesel so the constraints of limited range, battery life, charging times etc., are not included. This formulation and understanding of how to do load balancing with one type of trucks is found to be helpful in dealing with the more complicated case of including mixed fleets of electric and diesel trucks and added constraints.

The overall freight routing problem 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 the 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 the safety headway between freight vehicles etc. The formulation of the model of a multimodal freight assignment and routing problem uses the following symbols and notation:

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 $K = \{0,1,\ldots,|K|\}$;

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 consisting of arcs of the same transport mode as modal segment l;

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

$c_l^p(k)$: 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 is described as follows:

$$\min TC(X) = \sum_{k\in K}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R_{i,j}} S_{i,j}^{r}(k)\, X_{i,j}^{r}(k) = \sum_{k\in K}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R_{i,j}} (C_{i,j}^{r}(k) + k_r T_{i,j}^{r}(k))\, X_{i,j}^{r}(\mathrm{k}) \tag{1}$$

subject to the following constraints:

$$\sum_{k\in K}\sum_{r\in R_{i,j}} X_{i,j}^{r}(k) = d_{i,j}, \forall i \in I, \forall j \in J \tag{2}$$

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

$$0 \le x_l(k) \le u_l(k)v_l(k), \forall l \in L^R, \forall k \in K \tag{4}$$

$$X_{i,j}^{r}(k) \ge 0, \forall i \in I, \forall j \in J, \forall r \in R_{i,j}, \forall k \in K \tag{5}$$

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

Equation (1) is the problem objective that minimizes the total cost TC to process the demand by choosing X, the routing decisions consisting of the distribution of freight demand on all possible intermodal 10 routes in the service graph. κ_8 is the travel time of intermodal route r. Equation (2) represents the demand conservation constraint. 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. Since the explicit forms of the cost functions in the problem objective are not available directly due to the nonlinearities and complex variable interactions, traffic network simulation models are used to estimate the service graph states and costs for more accurate routing decisions.

In order to investigate $\delta\delta_{l,r,\tau,k}$: whether at time k, a truck departing from the beginning of route r at time τ is on segment l , $l \in R_{i,j}$, we need to look into the time spent on each segment. Let $Z(k)$ = $[z_1(k), z_2(k), \ldots, z_{|A|}(k)]'$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 departed freight traffic and other parameters in the network can be expressed as a nonlinear dynamical equation:

$$z\,(k+1)=f_{a}(z_{a}\,(k),q_{a}\,(k),Y(k),k),\forall a \in A,\forall k \in K \tag{7}$$

where

$$Y(k) = [y_l^p(k): \forall l\ \in L, \forall p\ \in P]' \tag{8}$$

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 $q_{\mathrm{a}}(k)$ and $Y(k)$ is the vector of departed freight traffic from all the origin nodes at time k as in (8). Since $z_{\mathrm{a}}(k)$ and $q_{\mathrm{a}}(k)$ contain the impact of the previous departure container traffic before time k (i.e., $Y(\tau)$, $\forall\tau$ < 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 times (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 depends not only on the arc flow but also on the flows of the other arcs. Therefore,

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

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

$$\mathrm{t}_{\mathrm{l}}^{\mathrm{p}}(\mathrm{k}) = \sum_{\mathrm{n_p}-1}^{\mathrm{N_p}} \mathrm{w}_{\mathrm{a}_{\mathrm{p,n_p}}}(\mathrm{e}_{\mathrm{a}_{\mathrm{p,n_p}}}(\mathrm{k})) \tag{10}$$

Where

$$\mathrm{e}_{\mathrm{a}_{\mathrm{p,1}}}(\mathrm{k}) = \mathrm{k} \tag{11}$$

$$\mathrm{e}_{\mathrm{a}_{\mathrm{p,n_p+1}}}(\mathrm{k}) = \mathrm{e}_{\mathrm{a}_{\mathrm{p,n_p}}}(\mathrm{k}) + \mathrm{w}_{\mathrm{a}_{\mathrm{p,n_p}}}\left(\mathrm{e}_{\mathrm{a}_{\mathrm{p,n_p}}}(\mathrm{k})\right), \forall \mathrm{n_p} = 1, \dots, \mathrm{N_p} - 1 \tag{12}$$

The vehicle dispatching problem in the transportation network given the service graph solution is expressed as follows:

$$\min \sum_{\mathrm{k}\in\mathrm{K}} \sum_{\mathrm{l}\in\mathrm{L}} \sum_{\mathrm{p}\in\mathrm{P_l}} (\mathrm{c}_{\mathrm{l}}^{\mathrm{p}}(\mathrm{k}) + \eta_{\mathrm{l}}^{\mathrm{p}} \mathrm{t}_{\mathrm{l}}^{\mathrm{p}}(\mathrm{k}))\mathrm{y}_{\mathrm{l}}^{\mathrm{p}}(\mathrm{k}) \tag{13}$$

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

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

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

Given $X \in \Omega$ (16)

The objective function (13) is the total cost of the transportation network generated by the freight demand 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 mathematic functions and generate more accurate arc traffic volumes and travel times. For freight vehicles using the road network, 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 costs are used to update the intermodal route service cost variables in (1) with a similar method as in (10-12) which reconstructs the travel time of a path as the sum of travel times of the transportation arcs belonging to this path. The approach used to solve the freight routing problem is shown in Figure 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 parameters achieved by various 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 to provide accurate state and cost prediction for the upper optimization layer. In addition, the routing decisions are transferred to the physical network after the optimization is carried out.
2. *Simulation models*: The simulation models are used 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 i.e., network incidents, road closures, changes in demand etc.
3. *Simulation-based cost evaluation*: This part is used to estimate the intermodal route state and cost information which is required by the service graph optimization algorithm. 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 part controls the whole optimization process. The optimization algorithm searches 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 solution consisting of the decision in the service graph as well as the

dynamic assignment and dispatching results in the simulation-based cost evaluation layer are sent to the users of the actual transportation network.

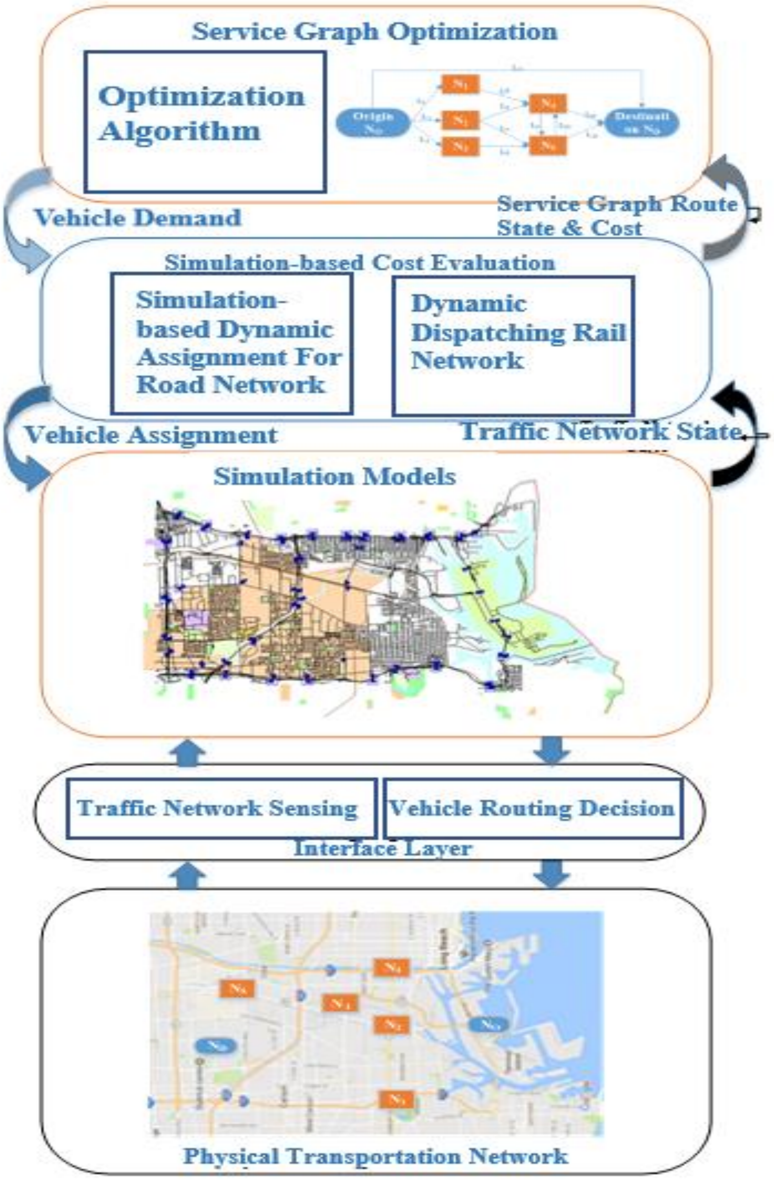

Figure 2. Structure of proposed freight load balancing system

In order to design, analyze and evaluate the proposed freight load balancing system we need a simulation test bed based on an actual transportation network which can be used to derive the simulation models for the approach as well as demonstrate its performance under different scenarios. The testbed is based on a regional transportation network which covers the LA/LB Ports and surrounding area. The simulation models used in the proposed Co-SiMulation Optimization (COSMO) freight load balancing approach consist of a macroscopic traffic road network model and a rail simulation model. We use the macroscopic traffic simulator VISUM

[47] to simulate the road network as it provides computationally fast predictions of the network states. The simulator parameters include lane number, length, speed limit and road capacity etc. configured based on a practical transportation network and available real traffic data. The model inputs include passenger and freight traffic for the road network expressed as the number of trips between zones in terms of origins to destinations pairs within the road network. We assume that the trucks can only carry one container so the number of truck trips between each OD pair is 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. Since the data is only available for a portion of the arcs in the selected region, dynamic traffic assignment is used to estimate volumes for the other network arcs.

For the rail simulator, we use the railway simulation system of Lu et al. in [48] 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 based on these segments. The inputs for the rail simulator are the passenger and freight train schedules including their planned departure times, origin stations, and destinations. 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 OD demands and simulation outputs. The road network simulator generates the freight traffic that destined for rail transshipment to the rail simulator. The rail simulator creates the freight train schedule based on the train capacity and simulates the train movements that include planned passenger trains and outputs the predicted train arrival times. After receiving the outputs of the rail simulator, the road network simulator generates the necessary truck flows to dispatch containers from the rail stations to their final destinations. Both the simulation models and optimization program are run on a desktop computer with 3.10GHz CPU and 8.0G memory.

We demonstrated the freight load balancing system presented above for a multimodal environment involving trains and diesel trucks. We evaluated the routing between six main destinations (D1 – D6) and three terminals (A, B, C) in the region with different demands in an area that includes the two major ports of Long Beach and Los Angeles as shown in Figure 3. The average weight of all the containers is assumed to be 25 tons and the transportation cost per unit (price/ton-mile) is assumed to be 8 cents for the road network and 3 cents for the railway network [49]. Three shippers communicate their demand to a coordinator who runs the proposed load balancing approach to generate individual routes by minimizing the overall cost that is defined by the transportation cost plus the travel time cost. The baseline number of delivery demand for each shipper is 1020 containers. The demands of the six destinations are shown in Table 1. We assume that the freight trains have a capacity of 50 containers and the port terminals and two rail stations are located near the destinations. We assume a single time window for all users.

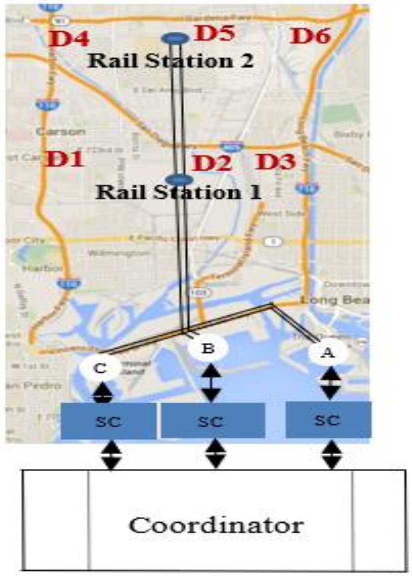

Figure 3. Region of study

Table 1. 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

The numbers of available freight trains from the port terminals to the two rail stations in the assumed scenarios are:

- Terminal A to station 1: 6 trains;
- Terminal B to station 1: 2 trains;
- Terminal C to station 1: 4 trains;
- Station 1 to station 2: 10 trains;

Four step sizes for the optimization algorithm are compared:

1) Enumeration method in which the step size is the most conservative;
2) Method of Successive Average (MSA) with priority in which the step size is computed;
3) Optimal step size selection;
4) A proposed new algorithm – optimal step size selection with priority;

Figure 4 shows a plot of the Central Processing Unit (CPU) time in unit of seconds of one load balancing step of the enumeration method as a function of the demand size. The x-axis is the multiplicative factor of the default demand load and the y-axis is the CPU time in unit of seconds for load balancing to compute the marginal costs of the used routes in equilibrium. As shown in Figure 4, the CPU time keeps increasing with respect to the demand. As a result, the load balancing based on the enumeration method is very slow for solving problems with hard vehicle constraints and high demands. We evaluated the CPU time for cases with hard vehicle constraints under normal traffic conditions. When the demand loads are 1.0 and 2.0 times the default values convergence is achieved in more than 13 and 22 CPU hours respectively. When the demand load is 2.5 times the default values, the enumeration method is not able to converge to a solution within one day.

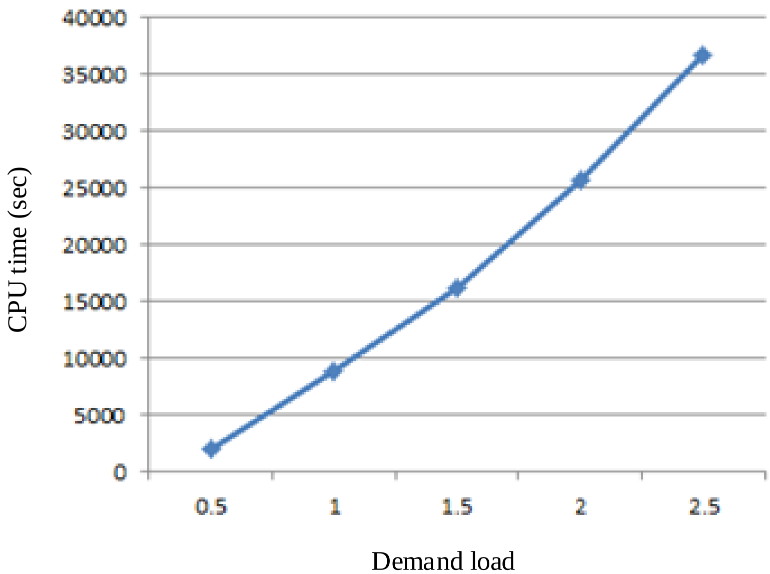

Figure 4. Load balancing time (unit: sec) increasing of enumeration method under fixed penalty factors

Table 2 compares the performances of the step size selection algorithms of the different demand loads (0.5, 1.0, 2.0, and 2.5 times the baseline demand) under normal traffic conditions. As the demand load increases, the average delivery cost increases because the more freight load in the transportation network, the higher the travel time for all the vehicles. In addition, the size of the problem is higher requiring more CPU computation time.

Table 2. 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	43.4	19415	43.4	508	43.6	162
1.0	48.3	28810	48.0	4051	48.4	1827
2.0	60.2	41568	61.2	9931	61.1	4187
2.5	68.3	90465	69.0	13045	68.7	11690

In Table 3, 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 volume;
2) Widely congested traffic in which the road network 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 Figure 5a);
4) Traffic under incidents in which 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 half as in Figure 5b);

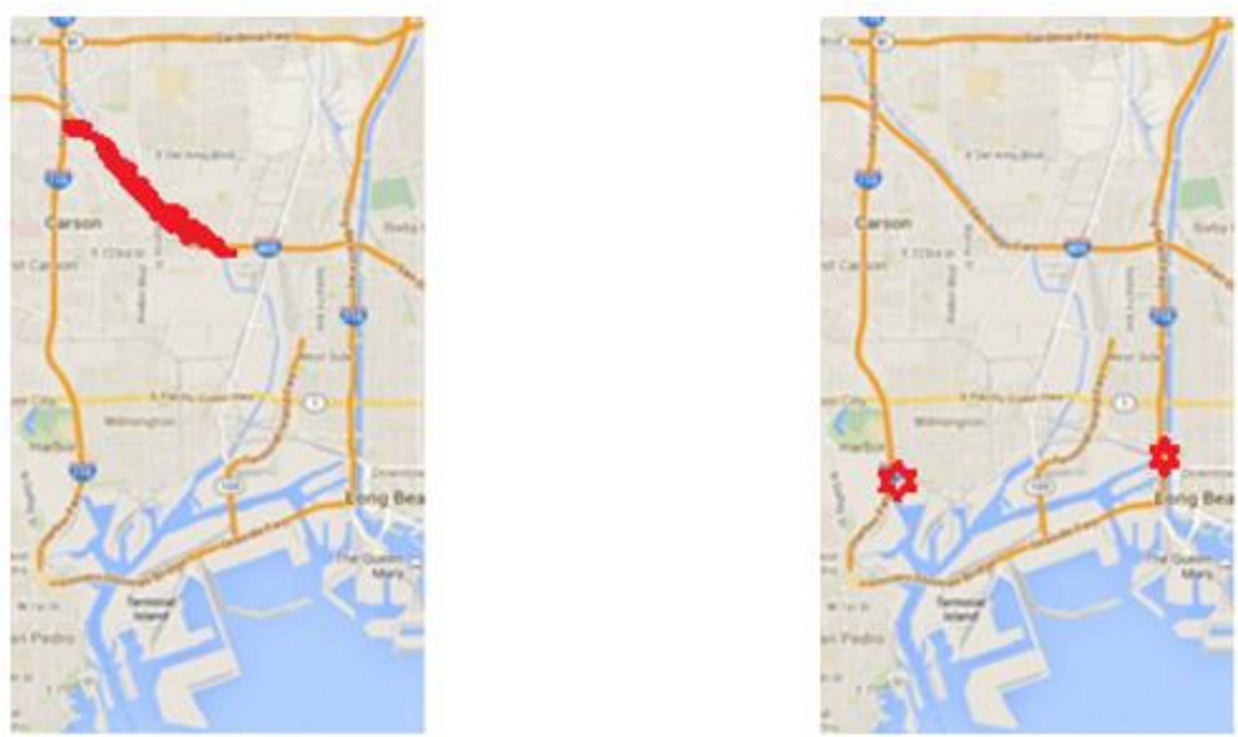

Figure 5. Traffic conditions a) I405 freeway congestion and b) freeway capacity reduction due to lane closure

Table 3. 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	48.0	4051	48.4	1827
Congested Traffic	65.61	50571	66.3	8647	66.4	5214
I405 Congested	48.62	38651	48.4	2345	48.6	1824
Lane Closures	66.20	39900	67.0	6305	67.1	5441

As shown in Table 2 and 3, although in most cases the load balancing algorithm with the MSA method generates a slightly better routing solution with respect to reducing the total cost, its CPU time is much higher, which limits its practical application. The load balancing algorithm with the optimal step size selection has a much faster convergence than the MSA method. Compared to the optimal step size method without priority, the proposed load balancing algorithm that combines the optimal step size selection and shipper priority can save from 10% to 68% on the CPU time. In summary, the proposed optimal step with priority algorithm provides the best convergence performance in reducing the computation time while providing nearly the same total costs compared to the other methods.

Figure 6 shows the average cost of transshipping each container using the load balancing approach and without load balancing under the three different traffic network status.

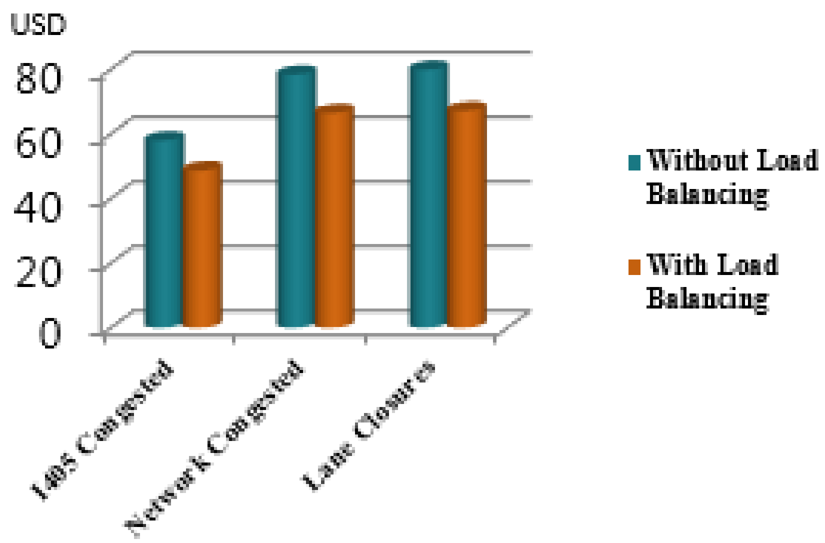

Figure 6. Load Balancing Results

It is clear from Figure 6 that the proposed load balancing approach provides consistent improvements in the total cost of routing freight when compared with current practices where decisions are made individually without the use of a coordinator. The study of the load balancing approach involving only diesel trucks also showed that the most appropriate optimization algorithm for the approach is the one that uses the optimal step size with priority which can be exploited further for lower computational times in decentralized load balancing approaches in future projects. Even though the above tests involve a rather simplistic demand compared to practice it is a starting point for evaluation of more complex scenarios as well as formulate the problem of load balancing for mixed fleets of vehicles that is addressed in the next subsection.

2.2 Incorporation of ZEFV in the Load Balancing Models

In this subsection we modified the load balancing approach presented in subsection 2.1 for diesel trucks to also include ZEFV trucks which are mainly electric trucks. Due to the incorporation of ZEFV the following symbols and notation are used:

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, $l \in L$;

$\hat{R}_{i,j}$: The set of all feasible diesel intermodal routes from an origin i to a destination j;

$\tilde{R}_{i,j}$: The set of all feasible electric 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;

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

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

$\hat{x}_l(k)$: The number of containers on diesel freight vehicles using modal segment l at time k;

$\tilde{x}_l(k)$: The number of containers on electric freight vehicles using modal segment l at time k;

$\hat{u}_l(k)$: The vehicle availability in the number of diesel freight vehicles for modal segment l at time k;

$\tilde{u}_l(k)$: The vehicle availability in the number of electric freight vehicles for modal segment l at time k;

$\hat{v}_l(k)$: The vehicle capacity in units of containers per diesel freight vehicle for modal segment l at time k;

$\tilde{v}_l(k)$: The vehicle capacity in units of containers per electric freight vehicle for modal segment l at time k;

$\hat{S}^r_{i,j}(k)$: The average service cost per container on intermodal diesel route r from node i to node$j$ at time k consisting of the operating cost $\hat{C}^r_{i,j}(k)$, the cost of intermodal route travel time $\hat{T}^r_{i,j}(k)$ and the emission cost $\hat{E}^r_{i,j}(k)$;

$\tilde{S}^r_{i,j}(k)$: The average service cost per container on intermodal electric route r from node i to node$j$ at time k consisting of the operating cost $\tilde{C}^r_{i,j}(k)$ and the cost of intermodal route travel time $\tilde{T}^r_{i,j}(k)$;

P_l : The set of all feasible vehicle paths consisting of arcs of the same transport mode as modal segment l;

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

$c_l^p(k)$: 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 mixed freight vehicle availability and capacity constraints can be expressed as follows:

$$\min TC(X) = \sum_{k\in K}\sum_{i\in I}\sum_{j\in J}\left(\sum_{r\in\hat{R}_{i,j}} \hat{S}_{i,j}^r(k)\hat{X}_{i,j}^r(k) + \sum_{r\in\tilde{R}_{i,j}} \tilde{S}_{i,j}^r(k)\tilde{X}_{i,j}^r(k)\right)$$

$$= \sum_{k\in K}\sum_{i\in I}\sum_{j\in J}\left(\sum_{r\in\hat{R}_{i,j}} \left(\hat{C}_{i,j}^r(k) + \kappa_r\hat{T}_{i,j}^r(k) + \hat{E}_{i,j}^r(k)\right)\hat{X}_{i,j}^r(k) + \sum_{r\in\tilde{R}_{i,j}} \left(\tilde{C}_{i,j}^r(k) + \kappa_r\tilde{T}_{i,j}^r(k)\right)\tilde{X}_{i,j}^r(k)\right) \quad (17)$$

subject to the following constraints:

$$\sum_{k\in K}\left(\sum_{r\in\hat{R}_{i,j}} \hat{X}_{i,j}^r(k) + \sum_{r\in\tilde{R}_{i,j}} \tilde{X}_{i,j}^r(k)\right) = d_{i,j}, \forall\, i \in I, \forall j \in J \quad (18)$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{r\in\hat{R}_{i,j}}\sum_{\hat{\tau}\le k} \hat{X}_{i,j}^r(\hat{\tau})\delta_{l,r,\hat{\tau},k} = \hat{x}_l(k), \forall l \in L, \forall k \in K \quad (19)$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{r\in\tilde{R}_{i,j}}\sum_{\tilde{\tau}\le k} \tilde{X}_{i,j}^r(\tilde{\tau})\delta_{l,r,\tilde{\tau},k} = \tilde{x}_l(k), \forall l \in L, \forall k \in K \quad (20)$$

$$0 \le \hat{x}_l(k) \le \hat{u}_l(k)\hat{v}_l(k), \forall l \in L^{\hat{R}}, \forall k \in K \quad (21)$$

$$0 \le \tilde{x}_l(k) \le \tilde{u}_l(k)\tilde{v}_l(k), \forall l \in L^{\tilde{R}}, \forall k \in K \quad (22)$$

$$\hat{X}_{i,j}^r(k) \ge 0, \forall i \in I, \forall j \in J, \forall r \in \hat{R}_{i,j}, \forall k \in K \quad (23)$$

$$\tilde{X}_{i,j}^r(k) \ge 0, \forall i \in I, \forall j \in J, \forall r \in \tilde{R}_{i,j}, \forall k \in K \quad (24)$$

$$\text{given } d_{i,j}, \hat{u}_l(k), \hat{v}_l(k), \tilde{u}_l(k), \tilde{v}_l(k), \forall i \in I, \forall j \in J, \forall l \in L, \forall k \in K \quad (25)$$

Equation (17) 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 mixed freight demand on all possible intermodal routes in the service graph. κ_r is the value of travel time of intermodal route r. Equation (18) represents the demand conservation constraint: the total number of the demand fulfilled by each type of freight vehicle is equal to the number required. Equation (19) is the diesel modal segment demand model where $\delta_{l,r,\hat{\tau},k} = 1$ when the demand of intermodal route r with departure time $\hat{\tau}$ uses diesel modal segment l at time k. Otherwise, $\delta_{l,r,\hat{\tau},k} = 0$. Similarly, equation (20) is the electric modal segment demand model where $\delta_{l,r,\tilde{\tau},k} = 1$ when the demand of intermodal route r with departure time $\tilde{\tau}$ uses electric modal segment l at time k. Otherwise, $\delta_{l,r,\tilde{\tau},k} = 0$. Equations (21) and (22) are the vehicle availability and capacity constraints with respect to diesel and electric freight vehicles where $L^{\hat{R}}$ and $L^{\tilde{R}}$ represent the sets of modal segments respectively. Since the explicit forms of the cost functions in the problem objective are not available directly due to the nonlinearities and complex variable interactions, traffic network simulation models are used to estimate the service graph states and costs for more accurate routing decisions.

For a directed graph $G(N, A)$, the route set for diesel freight vehicles can be represented as a collection of paths. A path P is a sequence of nodes of length $p - 1$ from n_1 to n_n, such that n_i is adjacent to n_{i+1} for $1 \leq i \leq p$. A non-negative cost c_{ij} is associated with each arc $a = (i, j)\ i, j \in N$, which can be interpreted as travel time, emissions or other criteria of cost. Classic route planning algorithms such as Dijkstra's algorithm [50] and Bellman-Ford algorithm [51] can be easily modified to generate shortest paths to build the route set. However, in the case of electric freight vehicles, due to the limited driving range, relatively scarce charging stations and comparably long recharging times, to find a minimum cost route which satisfies battery constraints is non-trivial. Since electric vehicles can gain energy when travelling downhill and recharged at charging stations, the cost for each arc is no longer non-negative as classic routing planning problems often assume. The algorithm in [52] is used to take into account this property (recuperation).

To deal with the choice of charging stations, we propose a heuristic method that uses the SPR algorithm. The method starts by exercising the SPR algorithm. If the algorithm stalls at some node v, we use a recharging act at node v, set v as the starting node and perform SPR again; else the algorithm terminates with a feasible route from node s to node t.

With the route set for diesel freight vehicles $\hat{R}_{i,j}$ and electric ones $\tilde{R}_{i,j}$ configured, we proceed to explain our method for solving the optimization problem (17)-(25). By defining $\hat{\phi}_l$ and $\hat{\sigma}_l$ as penalty function and penalty factor for diesel modal segment and $\tilde{\phi}_l$ and $\tilde{\sigma}_l$ as penalty function and penalty factor for electric modal segment, we can relax the optimization problem as follows:

$$\min J(X) = TC + \sum_{k\in K}\sum_{l\in L^{\hat{R}}} \hat{\sigma}_l \hat{\phi}_l(\hat{x}_l(k), \hat{u}_l(k), \hat{v}_l(k)) + \sum_{k\in K}\sum_{l\in L^{\tilde{R}}} \tilde{\sigma}_l \tilde{\phi}_l(\tilde{x}_l(k), \tilde{u}_l(k), \tilde{v}_l(k)) \tag{26}$$

The cost objective in (26) can at best reach the same minima as that of the original optimization problem if both $\hat{x}_l$ and $\tilde{x}_l$ from the optimal solution of (26) also satisfy the availability constraints (21) and (22). In such case $\hat{\phi}_l(\hat{x}_l(k), \hat{u}_l(k), \hat{v}_l(k))$ and $\tilde{\phi}_l(\tilde{x}_l(k), \tilde{u}_l(k), \tilde{v}_l(k))$ are both zero, which makes the minima of (26) equal to that of the original one. According to [53], the incremental penalty algorithm can be applied to solve this problem as follows:

Step 0: Choose initial penalty factors for diesel modal segment and electric modal segment: $\hat{\sigma}_l^0, \forall l \in L^{\hat{R}}$ and $\tilde{\sigma}_l^0, \forall l \in L^{\tilde{R}}$ then set master iteration round to n = 0;

Step 1: Find an optimal solution of the relaxed problem (26). The key element of this step is to update route sets $\hat{R}$ and $\tilde{R}$. We update the route set for diesel vehicles by augmenting $\hat{R}$ with shortest path found by Dijkstra's algorithm. The electric vehicle route set is updated with the heuristic method using SPR discussed above. Another key element is to estimate the marginal cost of the route. The marginal cost of a route is defined as partial derivative of $J(X)$ with respect to the load on this route. The explicit form of TC includes identifying a clear form of the travel time $t_l^p(k)$, which is difficult to get. So we use a transportation simulator to model the dynamic behavior of the transportation network, estimate the marginal cost on a service network basis and perform load balancing techniques with the estimated marginal cost, as shown in Figure 7.

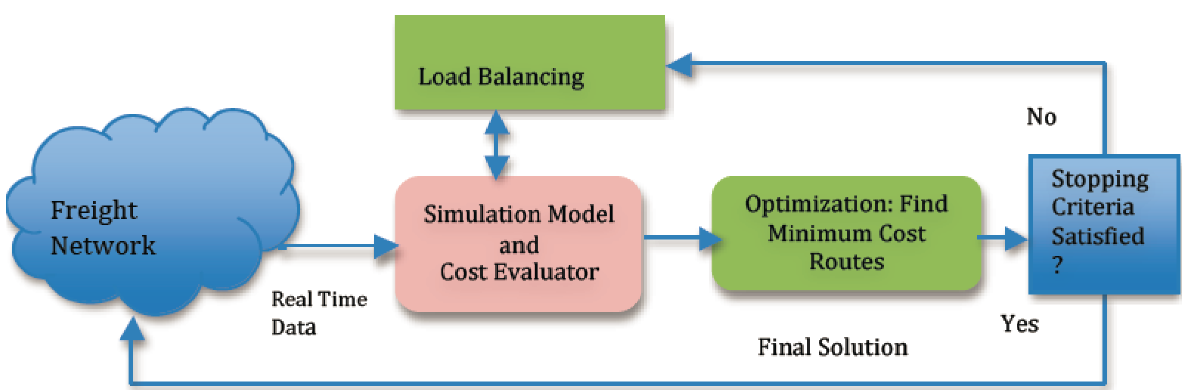

Figure 7. CoSiMulation Optimization method for routing

Step 2: Compute $\hat{\phi}_l^n(\hat{x}_l(k), \hat{u}_l(k), \hat{v}_l(k))$ and $\tilde{\phi}_l^n(\tilde{x}_l(k), \tilde{u}_l(k), \tilde{v}_l(k))$ in the current solution. If $\hat{\phi}_l^n(\hat{x}_l(k), \hat{u}_l(k), \hat{v}_l(k))$ and $\tilde{\phi}_l^n(\tilde{x}_l(k), \tilde{u}_l(k), \tilde{v}_l(k))$ are both zero, terminate the algorithm as the problem solution is found otherwise go to step 3.

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

$$\hat{\sigma}_l^{n+1} = \begin{cases} \hat{\sigma}_l^n + \widehat{\Delta}_l^n \hat{\phi}_l^n & \text{if } \hat{\phi}_l^n\big(\hat{x}_l(k), \hat{v}_l(k)\big) > 0 \\ \hat{\sigma}_l^n & \text{if } \hat{\phi}_l^n\big(\hat{x}_l(k), \hat{v}_l(k)\big) = 0 \end{cases}$$

$$\tilde{\sigma}_l^{n+1} = \begin{cases} \tilde{\sigma}_l^n + \widetilde{\Delta}_l^n \tilde{\phi}_l^n & \text{if } \tilde{\phi}_l^n\big(\tilde{x}_l(k), \tilde{v}_l(k)\big) > 0 \\ \tilde{\sigma}_l^n & \text{if } \tilde{\phi}_l^n\big(\tilde{x}_l(k), \tilde{v}_l(k)\big) > 0 \end{cases}$$

where $\widehat{\Delta}_l^n$ and $\widetilde{\Delta}_l^n$ are the increasing scalar to update the penalty factor at round n.

3. Simulation Experiment I

In this section we present the simulation scenarios and tests in order to evaluate the results of the load balancing approach that involves diesel and electric trucks. We simulate the traffic flow on the selected road network using the commercial software Visum [47]. The road network contains details including road attributes (name, category, number of lanes, speed limit, capacity, link performance function, etc.) and node attributes (name, incident links, traffic light control schedule, node impedance function, etc.). We assume that the trucks can only carry one container so the number of truck trips between each OD pair is equal to the number of containers to be delivered. The road traffic network used for testing covers a big part of the road network around the twin ports of Los Angeles/Long Beach and is shown in the following figures.

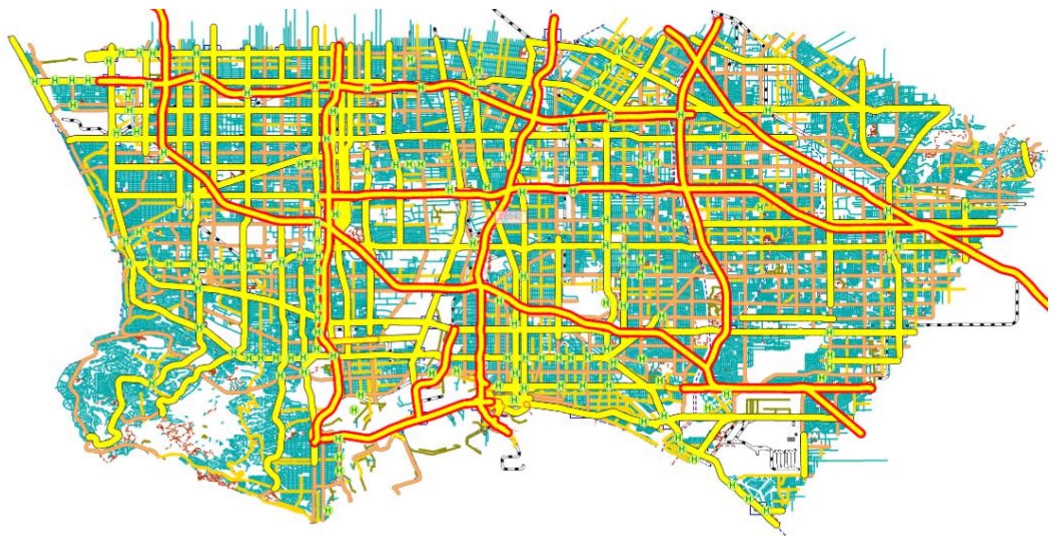

Figure 8. Area around Port of Long Beach/Los Angeles

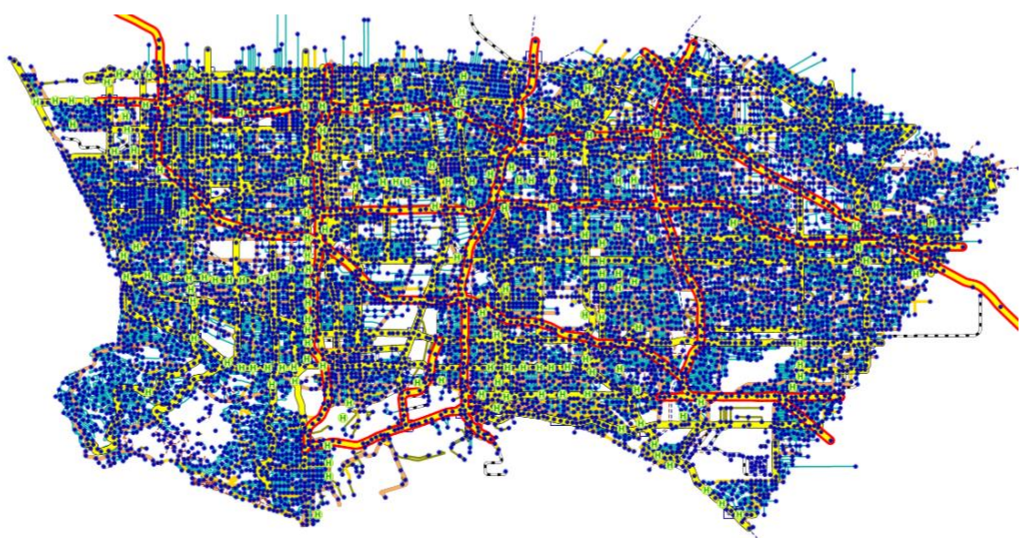

Figure 9. Area around Port of Long Beach/Los Angeles with nodes specified

In order to perform any testing, the characteristics of the various classes of trucks with different propulsion systems are reviewed and the results are summarized in Appendix 2. These results are used to choose realistic numbers for electric and diesel vehicles which are required by the load balancing approach.

Based on the review of different truck technologies [78], we found out that the maximum class of electric freight vehicles allowed to operate in real life is class 8, which is characterized by four or fewer axles and single trailer. So, in our model, we assume both diesel and electric freight vehicles to be of class 8. The charging time is assumed to be in the range of 10 min to 2 hours and the maximum range of the electric truck is 100 miles [78]. The parameters used in the objective function that are related to electric and diesel engines, are calculated using analytical models of standard diesel truck and electric engines as shown in Appendix 1. The energy consumption of engines depends on road conditions such as road grade, vehicle speed, acceleration, weather etc. NREL provides a series of speed profiles under different road conditions that are used to evaluate the efficiencies and energy consumption of diesel and electric engines under different speed profiles. The details of this analysis are presented in Appendix 1. Based on the analysis of the energy consumed by the diesel and electric engine to complete drive cycles from NREL, we observed that electric engines for heavy-duty vehicles consume less energy than diesel engines in 4 out of 5 drive cycles by a factor of 23%-73%. The cycle that the electric engine performs much less efficiently than diesel (by about 400%) involves low speed that occur during traffic congestion. Based on the analysis in Appendix 1 we estimated that for an average weight of containers to be 25 tons the transportation costs per unit (price/ton-mile) is 8 cents for diesel freight vehicles and 6.16 cents for electric trucks. In addition to these costs the hourly wage of a truck driver is taken to be $21 as given in [14]. Since the goal of this project is not cost analysis but rather a demonstration that the load balancing approach could work for mixed fleet of vehicles these estimated costs are used for demonstration purposes. Further research involving real experiments may be needed to confirm such cost estimates generated by exercising mathematical models.

We present the location of origin and destination as well as the structure of the service network in Figure 10. Nodes in dark blue are the OD nodes for demand and nodes in red are charging stations. The demands require transferring a total of 26,000 containers, 2000 containers from node 1 to every node in the set {node 2, node 3, … node 14} whose location is shown in Figure 10. A series of scenarios are tested as shown below.

- ***Scenario 1****: Normal traffic; terminal (node 1); 13,000 diesel and 13,000 electric freight vehicles.*
- ***Scenario 2****: Normal traffic; terminal (node 1); 26,000 diesel and 0 electric freight vehicles.*
- ***Scenario 3****: Normal traffic; terminal (node 1); 8,000 diesel and 18,000 electric freight vehicles.*
- ***Scenario 4****: Normal traffic; terminal (node 1); 13,000 diesel and 13,000 electric freight vehicles without load balancing.*

Figure 10. Distribution of the service nodes

The results are presented in Table 4.

Table 4. Results of mixed freight load balancing

	Cost on diesel ($)	Cost on electric ($)	Total cost ($)
Scenario 1: 50% Diesel and 50% Electric	57,4795.9	1,080,565.0	1,655,361.0
Scenario 2: 100% Diesel	1,750,000.0	0.00	1,750,000.0
Scenario 3: 31% Diesel and 69% Electric	296,782.0	1,333,480.3	1,630,262.3
Scenario 4: 50% Diesel and 50% Electric with no Load Balancing.	592,610.6	1,149,923.4	1,742,534.0

As shown in Table 4, by performing load balancing for mixed freight assignment with 50/50 diesel and electric, the total cost is reduced by 5% when compared with the case of no-load balancing. It is also observed that by increasing the proportion of electric trucks the overall cost is reduced based on the costs estimates for diesel and electrine engines generated using mathematical models. As expected, the benefits of load balancing depend on the traffic situation. It is believed based on previous studies on load balancing that when the traffic situation becomes worse and unpredictable, the benefits of mixed freight load balancing will be even higher.

4. Simulation Experiments II

In this section, more detailed numerical experiments are performed that include:

1. Additional traffic conditions
2. Detailed range of ratios between diesel and electric vehicles in the freight fleet
3. Include charging cost
4. Evaluate emissions and fuel economy

The traffic network simulated in this section is shown in Figure 11. It covers the area from Los Angeles/ Long Beach terminal port area in the south side to I 105 freeway in the north side. The network is built close to the reality geographically and geometrically. For example, lane characteristics such as length, capacity, speed limit et al. are incorporated in the network. The freight vehicles from and to the terminal port area account for a large amount of traffic around the area and has a great impact on the environment.

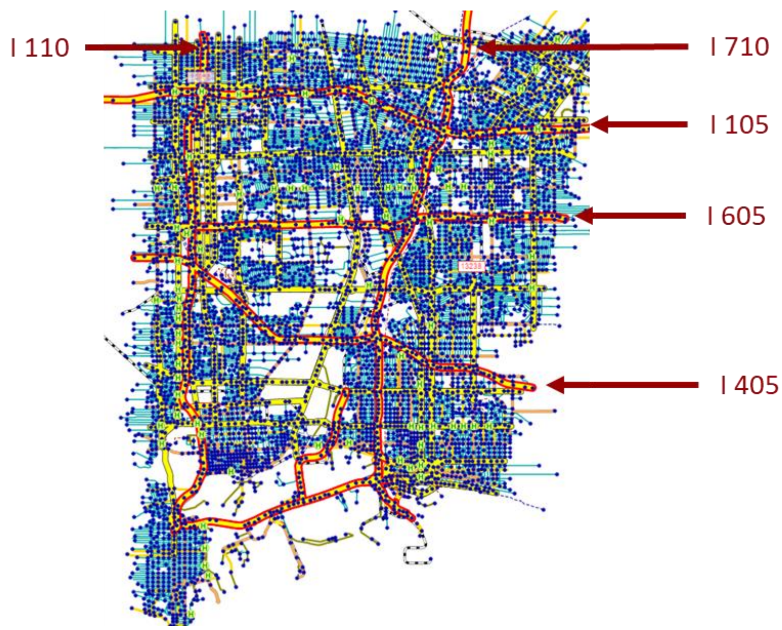

Figure 11. Road Network Overview

The input to the simulator is in the form of O/D matrix. There are two O/D matrices implemented: one for background traffic and one for mixed freight vehicles assignment. For the background O/D matrix, two data sources are used: freeway traffic data from PeMS [54] and arterial/local way traffic from Google Maps [55]. The traffic data are processed (formatted/truncated/aggregated) to interface with the simulator. The O/D matrix of mixed freight vehicles is generated by the optimizer. Figure 12 shows the overall structure of the mixed freight routing system.

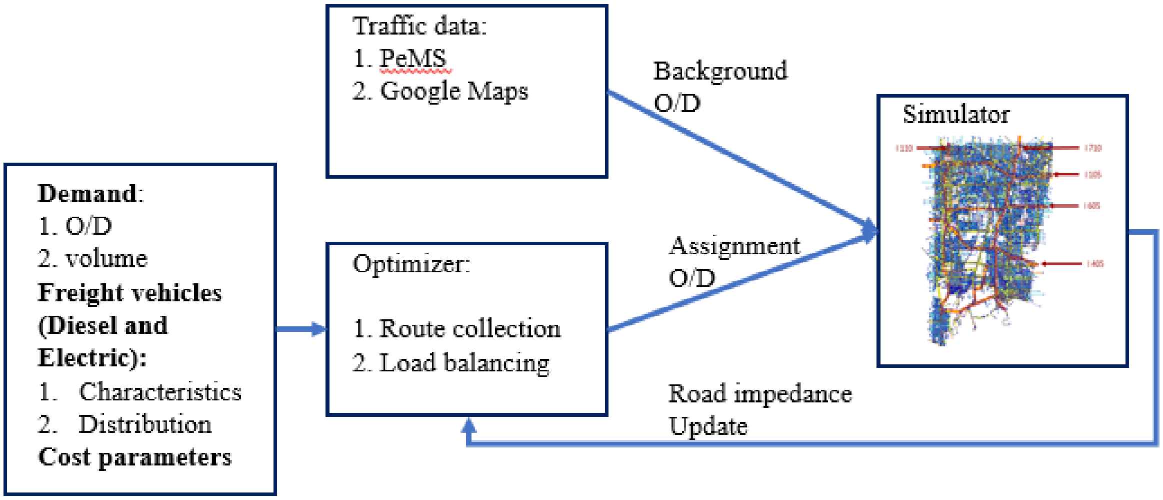

Figure 12. Mixed Freight Routing System Structure

The optimizer in the system plays the role of the coordinator, who collects information about demand, freight fleet, traffic network and generates optimal routes. The demand is presented in Table 5 and the location of origin/destination nodes of demands in Table 6. Table 5 shows in the first column the nodes of the origin and in first row the nodes of the destination. For example, there is a demand of 39 containers to move from node 14 to node 32.

Table 5. Demands by origin nodes (first column) and destination nodes (first row) (unit: number of container)

	Node 32	**Node 37**	**Node 26**	**Node 36**	**Node 25**	**Node 27**	**Node 33**	**Node 34**
Node 31	0	12	29	42	16	10	21	14
Node 14	39	0	10	16	43	16	15	50
Node 24	29	27	0	11	17	37	31	24
Node 12	29	36	22	0	26	30	38	39
Node 20	27	31	23	49	0	40	23	35
Node 16	12	26	37	35	26	0	41	22
Node 18	37	49	44	12	35	21	0	42
Node 10	16	32	29	17	31	11	39	0

Table 6 shows the exact location of the nodes with respect to longitude and latitude.

Table 6. Location of Demands Nodes

Node index	Longitude (°)	Latitude (°)
10	118.2807451 W	33.9286461 N
12	118.2843983 W	33.8561435 N
14	118.2612348 W	33.7482599 N
16	118.2081217 W	33.8269327 N
18	118.1809402 W	33.9125763 N
20	118.2284904 W	33.8255378 N
24	118.2383528 W	33.7586543 N
25	118.2325554 W	33.86890602 N
26	118.2182693 W	33.81382751 N
27	118.2526932 W	33.8570118 N
31	118.2901535 W	33.73358917 N
32	118.2971588 W	33.79803722 N
33	118.2912194 W	33.92329192 N
34	118.1603692 W	33.90347935 N
36	118.2157502 W	33.80452855 N
37	118.2758542 W	33.82437391 N

The freight vehicles in the experiments are assumed to be class 8. Table 7 shows the parameters used to model the energy (kWh) consumed based on analytical diesel and electric engine models [56], [57].

Table 7. Common Parameters for diesel and electric engine models

Weight	80,000 lbs
Frontal area	107.639 ft^2
Air density	0.076512 lb/ft^3
Los Angeles elevation	285 ft
Drag coefficient	0.78

According to [58], it is observed that the hourly value of time ranges from \$14.5 to \$70 in 1998 US dollar value. The equivalent rate in terms of 2020 US dollars is calculated to be \$23.1 to \$111.3 using the ratio provided by [59]. In this project, we chose the hourly time value to be \$60 in terms of year 2020 US Dollar value which is between the calculated range. The cost coefficient of distance is calculated based on [49], which is 8 cents per mile per ton in free flow traffic condition for diesel freight vehicles. With respect to charging cost we assume that a cost of \$60 per hour which is the same as the assumed time cost. In our simulation we assumed that it takes 4 hours for a full charge which is equivalent to \$240.

In our numerical experiments, two states of background traffic are implemented: off-peak traffic conditions (2 am to 6 am) and medium traffic conditions (12pm to 4pm). In each traffic condition, the percentage of electric vehicles in the fleet is varied from 0% to 100% in increments of 10%.

Using the demand, diesel/electric consumption models and cost measurements, the mixed freight routing is performed under two states of background traffic conditions. The results are shown in Table 8, 9 for off-peak traffic condition and Table 10, 11 for medium traffic condition. In the following, we will explain Table 8 and 9 column by column. The columns in Table 10 and 11 can be interpreted in the same way.

- Percentage of electric vehicles: this column specifies the percentage of electric freight vehicles in the whole freight fleet
- No. of Diesel used: this column specifies the number of diesel freights used in the assignment
- No. of Electric used: this column specifies the number of electric freights used in the assignment

Since the sum of all demand is 1715 according to demand matrix in Table 5, with the assumption that each freight can only load one container and the demand is considered to be fulfilled by a single-direction route with the number of containers required, the total number of freight vehicles is equal to 1715.

- Total Miles Diesel (miles): this column specifies the total miles traveled by diesel freights in the assignment. It is the sum of length of each diesel route multiplied by the number of diesel freights on that route.
- Total Miles Electric (miles): this column specifies the total miles traveled by electric freights in the assignment. It is the sum of length of each electric route multiplied by the number of electric freight vehicles on that route.
- Travel Time Cost (\$): this column specifies the total travel time cost, which is equal to the sum of travel time cost of each route multiplied by the number of freight vehicles. The route travel time cost is denoted as time value (60 \$/hour) by travel time of the route.
- Energy Cost (\$): this column specifies the total energy cost of all routes followed by freight vehicles. The energy cost of a route is determined by the energy consumption model in Appendix 1. From the energy consumption model, an energy consumption coefficient is first calculated based on the route type (diesel or electric) and speed. Then the energy cost of the route is calculated as the energy consumption coefficient multiplied by the number of freight vehicles on that route.
- Total Cost (\$): this column specifies the cost that includes travel time and energy cost of the assignment.
- Charging Time Cost (\$): this column specifies the total charging time cost, which is equal to the sum of charging time cost of each electric route multiplied by the number of electric vehicles on that route. The charging time cost is computed as the fraction of the battery used. For example, if 50% of the battery charged is used in an assigned route,

we take the charging cost for the route to be 50% of a full cycle charging time cost, which is $240.

- Total Cost including Charging Time Cost ($): this column gives the total cost that includes travel time, energy and charging time cost of the assignment.

The emissions are calculated by the modified EPA model MOVES [60] with speed as input and emissions in units of g/mile as output. The following emissions are measured:

- HC(g): total hydrocarbon emitted from the assignment
- CO(g): total carbon monoxide emitted from the assignment
- NOX(g): total nitrogen dioxide and nitric oxide emitted from the assignment
- CO_2(g): total carbon dioxide emitted from the assignment
- PM2.5 (g): total fine particles emitted from the assignment

Table 8. Cost results for off-peak traffic conditions

Percentage of electric vehicles	No. of Diesel used	No. of Electric used	Total Miles Diesel (miles)	Total Miles Electric (miles)	Total Cost ($)	Travel Time Cost ($)	Energy Cost ($)	Charging Time Cost ($)	Total Cost including Charging Time ($)
0%	1715	0	15829.2	0	172328.0	41610.5	130717.5	0	172328.0
10%	1544	171	14678.5	1633.0	169626.4	43395.8	126230.6	17891.4	187517.8
20%	1372	343	12873.4	3699.0	157701.0	44042.2	113658.8	40484.2	198185.2
30%	1201	514	12254.6	4588.5	139126.2	46521.2	92605.0	50019.4	189145.7
40%	1029	686	11257.5	5623.5	132024.5	46330.0	85694.5	61649.4	193674.0
50%	858	857	9522.0	6922.5	109350.8	44115.0	65235.78	75444.5	184795.3
60%	686	1029	8420.8	8318.6	96514.3	46641.4	49872.9	90717.7	187232.0
70%	515	1200	5499.5	10899.2	82749.3	46540.5	36208.8	118964.8	201714.1
80%	343	1372	4221.4	12511.6	70335.9	45665.6	24670.3	136214.8	206550.7
90%	172	1543	2429.0	14549.0	53943.8	46067.0	7876.8	158196.3	212140.1
100%	0	1715	0	16382.8	51405.2	43048.0	8357.2	178759.7	230164.9

Table 9. Cost results for off-peak traffic conditions

Percentage of electric vehicles	HC (g)	CO (g)	NOX (g)	CO_2 (g)	PM2.5 (g)
0%	326284.6	1774270.3	444067563	6.03E+09	108206.4
10%	271275.0	1486174.8	366701885	4.94E+08	89006.9
20%	236125.3	1294189.6	316497763	4.35E+09	77997.0
30%	230265.0	1262089.1	300813099	4.19E+09	75352.4
40%	212654.5	1167681.2	293741875	3.9E+09	69635.0
50%	150165.1	798596.3	203703351	2.71E+09	50062.0
60%	122467.2	668709.3	166317379	2.2E+09	38363.45
70%	87952.5	474060.6	122696480	1.64E+09	29915.5
80%	86909.8	461329.2	113047248	1.59E+09	27561.7
90%	36556.7	202137.7	50390039.8	6.69E+08	12183.8
100%	0	0	0	0	0

Table 10. Costs for medium traffic conditions

Percentage of electric vehicles	No. of Diesel used	No. of Electric used	Total Miles Diesel (miles)	Total Miles Electric (miles)	Total Cost ($)	Travel Time Cost ($)	Energy Cost ($)	Charging Time Cost ($)	Total Cost including Charging Time ($)
0%	1715	0	17394.1	0	202314.9	49784.6	152530.3	0	202314.9
10%	1544	171	16035.0	1726.2	202257.9	50551.9	151706.0	22455.9	224713.8
20%	1372	343	13851.8	3997.7	185173.1	51756.6	133416.5	52041.9	237215.0
30%	1201	514	13131.7	4855.6	172387.8	56049.8	116338.1	63655.7	236043.5
40%	1029	686	11881.2	6035.6	158458.0	57274.4	101183.6	79039.6	237497.6
50%	858	857	10367.0	7360.0	135261.6	54574.2	80687.4	95693.0	230954.6
60%	686	1029	8879.6	8818.0	117093.0	56673.3	60419.7	115317.8	232410.9
70%	515	1200	5914.6	11577.4	99657.3	57358.3	42298.9	151112.1	250769.3
80%	343	1372	4434.3	13330.6	91432.2	57211.1	34221.0	173422.1	264854.2
90%	172	1543	2664.7	15526.9	69514.3	59821.2	9693.0	203455.0	272969.2
100%	0	1715	0	17674.0	69351.9	59001.4	10350.5	231771.9	301123.8

Table 11. Costs for medium traffic conditions

Percentage of electric vehicles	HC (g)	CO (g)	NOX (g)	CO_2 (g)	PM2.5 (g)
0%	366287.4	1956335.3	502375854	6.84E+09	120242.6
10%	306923.8	1661840.7	409782756	5.66E+08	98088.9
20%	260615.2	1453708.8	362692510	4.83E+09	88390.5
30%	254809.3	1409050.5	351107313	4.7E+09	85270.5
40%	245926.2	1363943.8	333818313	4.64E+09	80821.8
50%	176205.1	958313.2	237495700	3.21E+09	59813.8
60%	143238.0	801409.3	197728578	2.58E+09	45688.1
70%	105238.2	551661.5	141823757	1.94E+09	35764.8
80%	103339.7	536964.3	134787121	1.92E+09	33910.7
90%	44689.6	248909.1	62425549.7	8.2E+08	14642.3
100%	0	0	0	0	0

By observing the results of mixed freight routing assignment in light and medium traffic conditions, the following conclusions can be made:

- The total energy cost without including charging cost decreases as the number of electric vehicles increases. However, this does not imply that for a specific route the use of electric vehicle is less costly than that of a diesel vehicle due to the complex influence from the surrounding traffic flow.
- The total cost that also includes the charging cost tends to increase in general with increasing number of electric vehicles in the fleet. The assumption made is that the charging cost includes the labor cost of the driver waiting for the vehicle to charge. If charging is done off-duty this cost can be reduced considerably.
- As expected, the emissions go down drastically as the number of electric vehicles increases in the fleet.

5. Empty Container Reuse as Load Balancing

Empty container reuse through an exchange of information system between users can cut the distance of empty trips considerably and such an approach falls under the load balancing concept which is the subject of this project. The use of electric trucks mixed with diesel trucks to carry out operations that involve loaded and empty containers raises interesting allocation questions. The range limitation of electric trucks may encourage allocation of more electric than diesel trucks for transporting empty containers. In this section we show how the load balancing approach can be used to incorporate the empty container reuse concept.

Empty container movements are important for all levels of operational and logistic planning. It is generally agreed that the inefficiency of empty vehicles is enormous. According to the U.S. rail system, about 40% of the time of the car cycle, the car is empty [61]. The taxonomy of problems related to empty containers can be divided into two [62]:

a. Policy models that are planning oriented, long-range or regional, dealing with long term effect.
b. Operational models that focus on short term effect, short-range.

In this project, we consider empty container movements within a region rather than multiple regions. Dejax and Crainic [62], mentions that the work on developing models related to container transportation problems is very limited. In their seminal paper, Crainic et al.[63] proposed dynamic and stochastic models for empty container allocation in a transportation system. The work did not address empty container exchange, nor did it develop any optimization technique for handling empties. The empty container allocation problem was considered by Cheung and Chen [64], where the authors formulated the dynamic container allocation problem as a two-stage stochastic network model. The model is designed to assist liner operators to allocate empty containers and consequently reduce their leasing cost and inventory level at the ports. Koichi et al. [65], consider both ship routing and empty container management, modeled as a knapsack-like two-stage formulation and solved it with a genetic algorithm-based heuristics. In another related work, Choong et al. [66] address the effect of the length of the planning horizon on empty container management. Jula et al. [46] consider the impact of empty container traffic on traffic congestion in the Los Angeles and Long Beach port area and how it is reduced by the concept of empty container reuse.

The empty container movement generally can be divided into two major categories: import and export movements. As stated in the work of Jula et al. [46], the import container movements, shown in Figure 13, can be described as follows: a truck is dispatched to pick-up a loaded import container from the terminal (move 1); the truck then delivers the loaded container to its designated local consignee (move 2); if an empty container is available at the time of delivery, the truck takes it back to the terminal (move 5), and then goes to its trucking company or another assignment (move 6). If an empty container is not available, the truck goes back to its trucking company or to another assignment after delivering the loaded import container (move 3). When the emptied container becomes available at the local consignee, a truck is dispatched to take it back to the terminal (move 4).

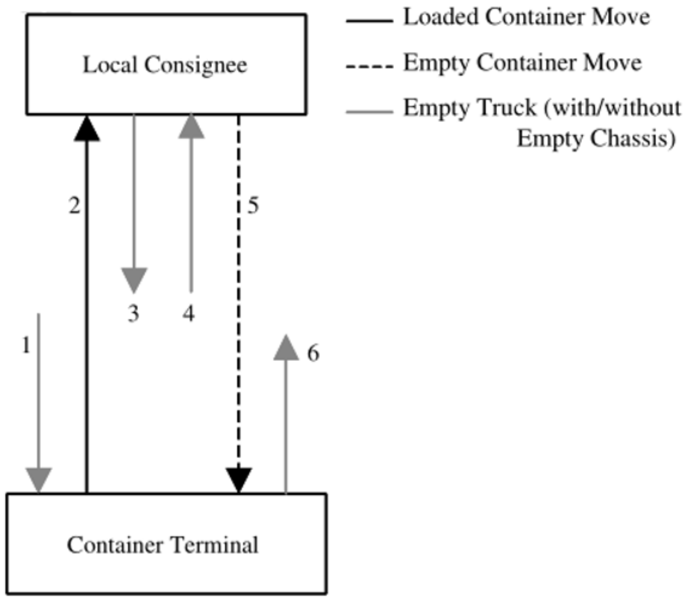

Figure 13. Import container movement

The export container movements, shown in Figure 14, are described as follows: a truck is dispatched to pick an empty container from the terminal (move 1); the empty container is trucked to a designated local shipper for loading (move 2); if a loaded container is available at the time of the empty delivery, the truck returns it to the terminal (move 5), and finally the truck goes back to its trucking company or another assignment (move 6). If the loaded container is not available, the truck goes back to its company or another assignment after delivering the empty container (move 3), and when the loaded container becomes available, a truck is dispatched to take it from the local shipper to the terminal (move 4).

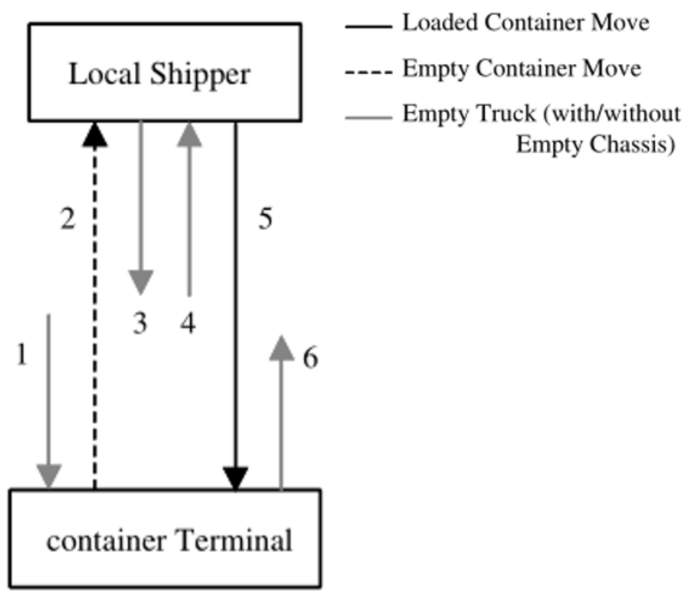

Figure 14. Export container movement

A study by Barber and Grobar [67] showed that 40% of the trucks visiting the LA/LB terminals are involved in more than 2 h waiting time. The traffic congestion around LA/LB terminal area also caused problems such as air pollution, energy waste, traffic collision, et al. By a smart repositioning of empty containers, the number of trips involving empty containers decreases so that the aforementioned problems are alleviated. The idea of repositioning empty containers can be fulfilled in two ways: *depot-direct* and *street-turn*, shown in Figure 15.

Depot-direct: Other than terminals, empty containers can be stored, maintained and interchanged at off-deck container depots. The depots can be used as a supply point for reusable empties for trucks to drop off or pick up empty containers when the terminals are not accessible at the time i.e., they are closed or congested.

Street-turn: The empty containers are moved directly from local consignees to local shippers.

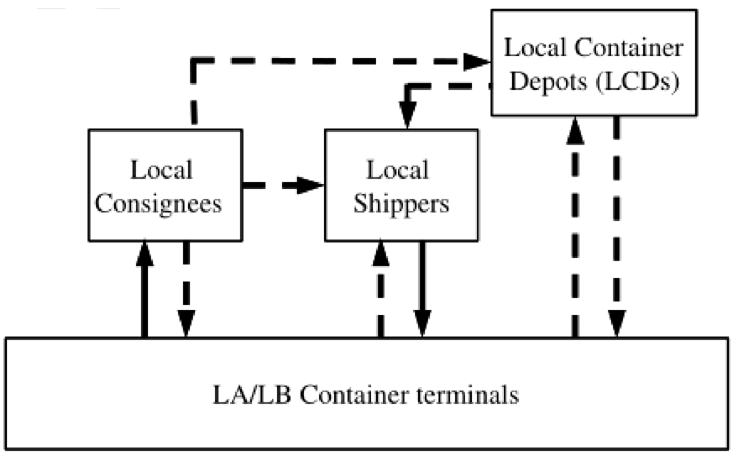

Figure 15. Local container flows: (—) loaded flows, (- - -) empty flows

In order to model the empty container reuse problem, let us first assume that all containers belong to a single class and all information regarding the location and the time of requests and supplies are known priori. The window of time under consideration is divided into $|K|$ periods. At each period k, $k = 1, \dots, |K|$, the locations of consignees are identified. In an area like LA/LB port area, a realistic assumption is made that all local empty container movements can be processed within $|K|$ periods. In our formulation, we adopt the following notation:

K : set of time periods in planning horizon

I : set of consignees with excess of empties in horizon $|K|$

P : set of shippers with requests for empties in horizon $|K|$

$x_{ij}^{kk'}$: number of empties moved from consignee $i \in I$ at time k to demand $j \in J$ to satisfy the demand at time k'

$c_{ij}^{kk'}$: cost of moving an empty container from consignee $i \in I$ at time k to demand $j \in J$ to satisfy the demand at time k'

t_{ij}^{k} : time needed to move an empty between consignee $i \in I$ and shipper $j \in J$ initiated at time k

x_{ip}^{k} : number of empties moved from consignee $i \in I$ at time k to depot $p \in P$

c_{ip}^{k} : cost of moving an empty container from consignee $i \in I$ at time k to depot $p \in P$

$x_{pj}^{k'}$: number of empties moved from depot $p \in P$ to shipper $j \in J$ to satisfy the demand at time k'

$c_{pj}^{k'}$: cost of moving an empty container from depot $p \in P$ to shipper $j \in J$ to satisfy the demand at time k'

$U\left(x_{ij}^{kk'}\right)$: index generator, $U\left(x_{ij}^{kk'}\right) = k$, returns the earliest pick-up time

$D\left(x_{ij}^{kk'}\right)$: index generator, $D\left(x_{ij}^{kk'}\right) = k'$, returns the latest delivery time

Based on the above notation, the dynamic single commodity empty container movement can be mathematically modeled as follows:

$$\min_{u} \sum_{k\in K} \Big(\sum_{k' \geq k, k\in K} \sum_{j\in J} \sum_{i\in I} c_{ij}^{kk'} x_{ij}^{kk'} + \sum_{p\in P} \sum_{i\in I} c_{ip}^{k} x_{ip}^{k} \Big) + \sum_{k' \geq k, k\in K} \sum_{p\in P} \sum_{j\in J} c_{pj}^{k'} x_{pj}^{k'}$$

$$\sum_{k' \geq k} \sum_{j\in J} x_{ij}^{kk'} + \sum_{p\in P} x_{ip}^{k} = s_{i}^{k}, \qquad \forall\, i \in I, \forall\, k \in K \tag{27}$$

$$\sum_{k' \geq k} \sum_{i\in I} x_{ij}^{kk'} + \sum_{p\in P} x_{pj}^{k} = d_{j}^{k}, \qquad \forall\, j \in J, \forall\, k \in K \tag{28}$$

$$x_{ij}^{kk'} \cdot \left(U\left(x_{ij}^{kk'}\right) + t_{ij}^{U\left(x_{ij}^{kk'}\right)} - D\left(x_{ij}^{kk'}\right) \right) \leq 0, \forall\, i \in I, \forall j \in J, \forall k, k' \in K \tag{29}$$

$$x_{ij}^{kk'}, x_{ip}^{k}, x_{pj}^{k} \geq 0 \text{ and integer } \forall\, i \in I, \forall j \in J, \forall p \in P, \forall k, k' \in K \tag{30}$$

The objective function is to find the best match for empty containers between the supply and demand in horizon T. Constraints (27) ensure that the total number of empties moved from a consignee at period k is equal to the number of supply of empties at that location at the same period. Constraints (28) guarantee that the number of empties arrived at a shipper by time k' is the same as the demand for empties at that location. Constraints (29) are time feasibility constraints. It should be noted that in (29) we assume that all empty moves to/from the port and depots are feasible in time; as a consequence, these moves are not included in (29). Finally, constraints (30) are the integer constraints.

In our solution, the nonlinearity introduced by the time feasibility constraint (29) in the formulation is removed in phase I so that efficient linear optimization techniques can be used to solve a relaxed form of the problem in phase II. The approach is described as follows:

Phase I: Bipartite network generation.

Let I^k denote the set of consignees with supplies of empties at period k. I^k is defined as follows:

$$I^k = \{i^k | i \in I, s_i^k > 0\}, \forall\, k \in K$$

where i is the index of consignee and k is the index of time period.

We also denote $J^{k'}$ as the set of shippers with demands for empties at period k'. $J^{k'}$ is defined as follows:

$$J^{k'} = \{j^{k'} | j \in J, d_j^{k'} > 0\}, \forall\, k' \in K$$

where j is the index of shipper, and k' is the index of time period. Then we can define $\boldsymbol{I}$ and $\boldsymbol{J}$ as

$$\boldsymbol{I} = \{I^1, I^2, \ldots, I^{|K|}, P\}$$

$$\boldsymbol{J} = \{J^1, J^2, \ldots, J^{|K|}, P\}$$

The bipartite network $\boldsymbol{G}(\boldsymbol{N}, \boldsymbol{A})$ is then generated as follows: $\boldsymbol{N} = \boldsymbol{I} \cup \boldsymbol{J}$ is the node set, $\boldsymbol{A} = \{(v, w) | \boldsymbol{v} \in \boldsymbol{I}, w \in \boldsymbol{J}\}$ is the arc set, and c_{vw} is the cost associated with each arc $(v, w) \in \boldsymbol{A}$. c_{vw} can be calculated as follows, with period generators $\Pi : \boldsymbol{I} \rightarrow \{1, \ldots, |K|\}$ and $\Delta : \boldsymbol{J} \rightarrow \{1, \ldots, |K|\}$, node index generators $\sigma : \boldsymbol{I} \rightarrow \{I, P\}$ and $\delta : \boldsymbol{J} \rightarrow \{J, P\}$:

$$c_{vw} = \begin{cases} c_{\sigma(v)\delta(w)}^{\Pi(v)} & \text{if } \delta(w) \in P, \sigma(v) \notin P \\ c_{\sigma(v)\delta(w)}^{\Delta(w)} & \text{if } \sigma(v) \in P, \delta(w) \notin P \\ c_{\sigma(v)\delta(w)}^{\Pi(v)\Delta(w)} & \text{if } \Pi(v) + t_{\sigma(v)\delta(w)}^{\Pi(v)} \leq \Delta(w), \sigma(v) \notin P, \delta(w) \notin P \\ M & \text{otherwise} \end{cases}$$

where M is a big number. We then prune the network $\boldsymbol{G}$ by eliminating arcs (v, w) with $c_{vw} = M$.

Phase II: With the bipartite network, we can relax the original problem to the following form:

$$\min_{\mathrm{x}} \sum_{v \in \boldsymbol{I}} \sum_{w \in \boldsymbol{J}} c_{vw} x_{vw} \tag{31}$$

$$\sum_{w \in \boldsymbol{J}} x_{vw} = \boldsymbol{s}_v \,, \forall v \in \boldsymbol{I}$$

$$\sum_{v \in \boldsymbol{I}} x_{vw} = \boldsymbol{d_w}, \forall w \in \boldsymbol{J} \tag{32}$$

$$x_{vw} \geq 0 \text{ and integer } \forall \mathrm{v} \in \boldsymbol{I}, \mathrm{w} \in \boldsymbol{J} \tag{33}$$

Here $\boldsymbol{s_v} = s_{\sigma(v)}^{\Pi(v)}$ and $\boldsymbol{d_w} = d_{\delta(w)}^{\Delta(w)}$. Since all supply of empties at consignees and all demands at the shippers are integer values, the relaxed problem is an integer transportation problem, which can be optimally solved using linear programming.

The area we used to test our method is the LA/LB port area together with the area bounded from the West by I-110, from the East by freeway I-710 and from the North by I-105. The location of consignees, shippers and depot are shown in Figure 16.

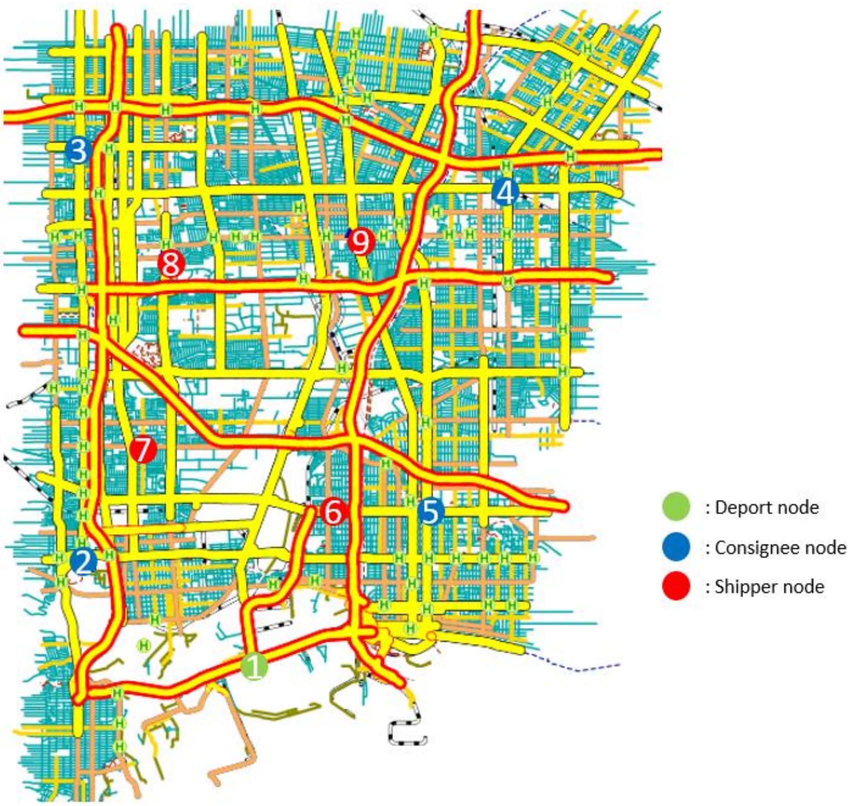

Figure 16. Locations of consignees, shippers and depots

The supply and demand numbers used are based on an estimated number of empty container demand and supply for 2020. It is anticipated that by 2020, the number of export and import loads in the LA/LB port area will increase by 3.4% and 4.0% respectively compared to 2000, which is about 908 in supply and 2188 in demand. We assume active level i.e., there are available empty containers to be processed by the consignees and shippers. For consignees, we assume the active level of node 2,3,4,5 to follow the ratio of 4:3:2:1, which means that node 2 has a supply 872 empty containers, node 3 has 654, node 4 has 436 and node 5 has 226.

Likewise, by assuming the active level for node 6,9,8,7 to follow the ratio 4:3:2:1 for the demand is 360, 270, 180, 98 empty containers respectively.

Scenario 1: There is a supply of empties at the consignees location but no exchange of empties between consignees and shippers is in place. In this case the only option is for the shippers to pick up the empties from the depot. As a result, the O/D pairs are unique and described in the following table:

Table 12. Movement of empties for Scenario 1

From	To	No. of empties
Node 1 (depot)	Node 6	360
Node 1 (depot)	Node 9	270
Node 1 (depot)	Node 8	180
Node 1 (depot)	Node 7	98

Scenario 2: There is a supply of empties at the consignees location and there is an exchange system in place. In this case our algorithm generated the following optimum O/D pairs:

Table 13. Optimal movement of empties for Scenario 2

From	To	No. of empties
Node 2	Node 7	98
Node 3	Node 8	180
Node 4	Node 9	270
Node 5	Node 6	226
Depot	Node 6	134

Scenario 2 demonstrates how empty container exchange can help avoid trips to the depot by doing exchanges at nearby nodes which according to [46] can reduce the number of empty trips to a depot by 40%. In scenario 2 the same number of containers are handled as in scenario 1 where exchanges were not allowed. Scenario 2 also shows that the depot provided the remaining empties that the consignees did not have available. Table 14 shows the O/D pairs that result from the optimum empty container exchange. How they will be routed in the network by following minimum time routes is the part that the load balancing will generate. Therefore, the O/D pairs from the empty reuse problem is a natural input to the load balancing system as shown in Figure 17.

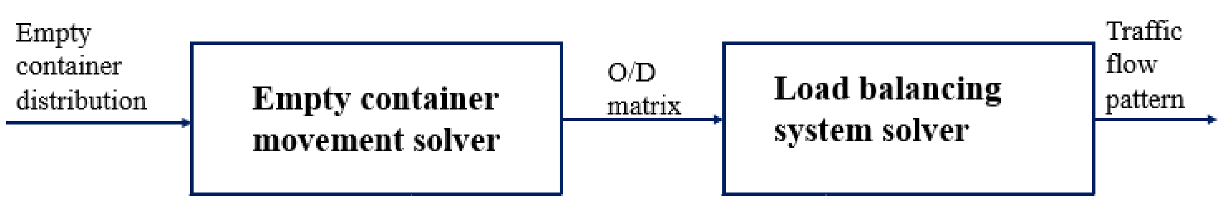

Figure 17. incorporation of empty container and load balancing

The optimal movement of the empty containers is achieved by a 2-phase method: in Phase I, a bipartite network is generated; in Phase II, a relaxed integer transportation problem is solved. We implemented a sample test on the combination of optimal empty container move and load balancing transportation network, which achieves 2 benefits: the empty container is moved optimally and all the freight vehicles that transship the empty containers are assigned to optimal routes so that the total cost of the transshipment is minimized.

We carried out simulation tests of the load balancing model for the LA/LB port area with empty container reuse based on *Scenario 2*. The results are shown in *Figure 18* and Table 14. The notation used in Table 14 is the following*:*

Orig. Zone No: index of the origin node;

Dest. Zone No: index of the destination node

Index: Index of the route in the route collection between origin and destination node

tCur: Vehicle travel time on the route;

vCur: Average speed of the route

Vol: The number of demands assigned on the route

Distance: The length of the route

Figure 16 shows the region considered and the selected routes are indicated in dark red color. Based on scenario 2, 180 empty containers had to be transshipped from the 2nd consignee at the 1st interval to the 3rd shipper at the 2nd interval of time. The 2nd consignee in the network is labeled as zone 3 and the 3rd shipper is labeled as zone 8. There are two routes from zone 3 to zone 8 shown in Table 14, with 80 containers on the first route and 100 containers on the second route. The length of these two routes are 6.239 km and 6.408 km respectively. The travel time on both routes is 5 minutes and 55 seconds which demonstrates that the loads are balanced between the two routes. The same is true for the two routes from zone 4 to 9. The travel time in this case is also equal between the two routes demonstrating the balancing of the loads.

Table 14. Result of Scenario 2

Orig. Zone No	Dest. Zone No	Index	Vol No.	tCur	vCur	Distance
1	6	1	134	4min 23s	91.3km/h	6.7km
2	7	1	98	5min 18s	64.5km/h	5.7km
3	8	1	80	5min 55s	63.2km/h	6.2km
3	8	2	100	5min 55s	64.9km/h	6.4km
4	9	1	211	5min 44s	63.6km/h	6.1km
4	9	2	60	5min 44s	63.6km/h	6.1km
5	6	1	226	3min 16s	56.4km/h	3.1km

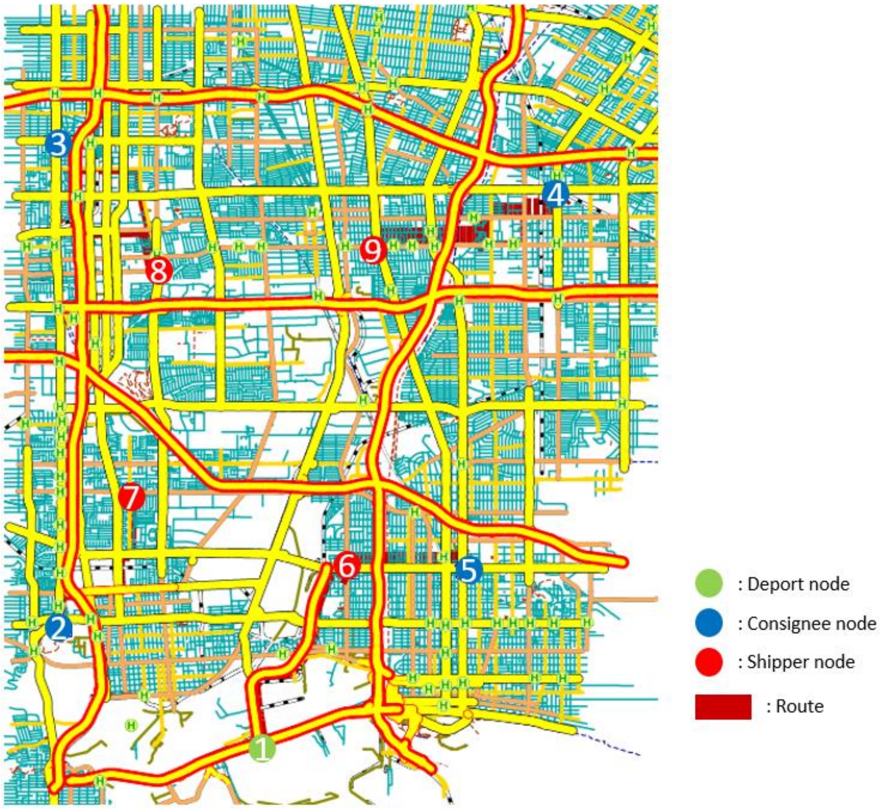

Figure 18. Load balancing result of Scenario 2

6. Implementation Issues

Implementation of a load balancing system would require that shippers, cargo owners and freight transporters share information and defer to a system manager to establish route assignments across time, routes and modes. Participants would have to be willing to change current operational practices.

To understand limitations and concerns of the load balancing system on shippers and transportation providers, in-depth interviews were conducted with six (6) individuals with responsibility for trucking operations in the Los Angeles region. All trucking companies are either drayage operations (hauling freight to and from the ports or intermodal facilities) or short-haul operators that move goods between manufacturers, distribution center, and retail facilities. The list of firms and titles of those interviewed is shown in Table 15 below.

Table 15. List of companies interviewed

Title	Company	Date
Ops Manager	States Logistics Services, Inc.	Thursday, Oct 31, 1:00pm
Executive	Ability Tri-modal	Thursday, Oct 31, 2:30pm
Ops Manager	Total Transportation Service (TTSI)	Thursday, Oct 31, 10:00am
Executive	L.A. Grain	Friday, November 22, 8:30am
Executive	Ventura Transfer	Monday, November 25, 2:00pm
Executive	Southern Counties Express	Friday, December 6, 9:30am

The interview questionnaire is presented in Appendix 2. Although the sample size is small, the firms interviewed vary greatly in size, complexity, and operations. A summary of key operational profiles is included in *Table XVI*. The companies range from a national firm with thousands of trucks to smaller firms with only 23 trucks. Some lease their equipment while others own, and a few both lease and own trucks. Some have 1 shift while others work 3 shifts 24-hours a day. Although operationally different, trends emerge in the responses to load balancing questions especially in the areas of challenges. No statistical conclusions can be made that these trends are representative of all drayage/short-haul trucking companies due to the sample size. However, in speaking informally with a local trade association and other carriers in the region, the responses are consistent and provide a starting point for further research efforts.

Table 16. Summary of firm operational characteristics

Operational Questions	Responses (6 firms)
Number of trucks operating	46.2 (w/o large firm of 500+)
Use of truck	Drayage, short haul
Own or lease trucks	3 lease, 5 own, 1 use owner operator (OO) trucks
Location of hubs (So CA)	South Bay, Inland Empire, Orange County
Type of goods transport	Various
Number of shifts/day for a truck	1 shift: 2, 2 shifts: 3, 3 shifts: 1
Operate on weekends? (currently)	3 yes, 3 no
Number of customers/tour	1 to 8
Type of driver used	2 emp only, 1 OO, 3 mix
Number of drivers	Range 23 to 500+
Miles driven/shift/truck	15 to 120
Turns per shift	1 to 8
Route planner	1 driver, 4 dispatcher, 1 mix
Trucks assigned to specific driver	5 yes, 1 no
Trucks driven a regular route	4 yes, 2 no
Customer concerns about shipment	Timely, quality
% time spent waiting	20 to 75%
Used PierPass of-peak < 11/2018	5 yes, 1 no
Did discontinuation of free off peak PierPass change your behavior	1 yes, 4 no

Of particular interest is the type of drivers that are employed, since this had an impact on results on the load balancing questions. There are two classifications of drivers: employees and owner operators/independent contractors. The latter is paid by load or other contract method; independent truck drivers have autonomy for the most part deciding how and when to move cargo within the constraints of service agreement. In this survey group, one firm used independent contractors exclusively, two had all driver employees, and three had a both employee and independent drivers. In our experience, most companies do employ some or all independent contractors for this type of work. These independent drivers may or may not utilize their own trucks. However, the introduction of Bill AB-5 which is slated to start on January 1, 2020 may have an impact on status for independent drivers. This California legislation states that:

> "a person providing labor or services for remuneration shall be considered an employee rather than an independent contractor unless the hiring entity demonstrates that the person is free from the control and direction of the hiring entity in connection with the

> performance of the work, the person performs work that is outside the usual course of the hiring entity's business, and the person is customarily engaged in an independently established trade, occupation, or business." [68].

A second area with impact on load balancing is the number of shifts. Of the companies interviewed, one firm works 3 shifts, three work two shifts, and two worked one shift. Travel per 24-hour day for these drayage/short-haul operators varies between 80 and 240 miles/day/truck; the average miles per day is 138 for one truck. Any changes in delivery times outside the normal work shift would have consequences for the firm, as well as, routes that could add mileage. Range is especially important for firms rolling out new battery electric and other lower range technologies, so adding miles to reroute a trip could be a problem.

Customer satisfaction is a direct correlation of timely deliveries. Second to this is quality of shipments. Being able to deliver goods in the time window required is paramount. Having a disruption in delivery times can be quite sensitive to smaller firms who have no external storage on site; the only option is to dock for loading/unloading. Larger firms typically have a yard, so earlier/later deliveries are not as time sensitive since containers can be dropped in the yard. All but one firm has sensitive pick-up and/or deliveries time slots for customers. A common theme is that different customers have different requirements. Time-window sensitivity is as small as 30 minutes, with half having a time-window of 2 hours. Only one firm has no time window limitations, but this is due to the nature of the business which delivers products to the port for export from internally controlled warehouse facilities.

The questions about load balancing resulted in quite different answers. After explaining the scheme as proposed, the question "Do you think a load balancing system could be implemented?" resulted in two responses of yes, two responses of no, and two responses of maybe. The main concern expressed about load balancing was regarding driver hours since daily work hours/breaks are tightly regulated. This is tracked and reported, with violations having stiff penalties due to safety regulations. Load balancing shipment delays could infringe on the work time window available. Regarding customer satisfaction, any load balancing scheme which resulted in early or late customer shipments (for those with tight time windows) would be unacceptable.

Allowing an outside entity to control routes and/or time windows would be problematic for all but one firm. Making sure that such a scheme could deliver the promises of overall benefits to the firm would help to waylay some fears. All but one of the firms said they would try the scheme if the benefits were clear. Interesting enough, whether or not other firms benefited too was not a concern for half of the firms. Self-interest was the driving factor in a decision to consider participating.

One point stressed by most respondents is that the load balancing scheme would reduce the competitive advantage of one firm over another, which was considered a mandatory differentiator in a service marketplace. Other points included that 1) tens of thousands of service points and thousands of goods movement companies would need to be coordinated creating a hugely complex system, and 2) each firm wants to manage their business as they see fit for efficiency and profit maximization. Comments included that the scheme would "take away control from the firm." Unpredictable wait times (especially at the port) would be challenging. But the main point reiterated by every firm was that customers required deliveries in a certain time frame. Without buy-in from these parties, the program will be difficult, if not impossible, to achieve.

Implementing a load balancing scheme could be accomplished in an iterative fashion first targeting trucking companies who already work collaboratively in associations and vertical markets. These clusters of firms have built working relationships, engage in communication, and have trust between members at the offset. Positive results will entice others to join.

Please note that firms have asked to not be identified specifically; there is no correlation to firm order in Table 15.

Conclusions from interviews: The firms interviewed are very eager to resolve congestion-related problems in the Los Angeles region. All agree that congestion issues are bad for business efficiency and predictability. How to resolve is unknown, but most regard more off-peak road use a viable approach. Half believe that route changes in themselves will not have much of an impact since this approach is being used with real-time GPA monitoring of freeway congestion. For the most part, firms would be willing to try a load balancing scheme if results could be proven to them beforehand. There is a major regulatory hurdle to overcome with limits on driver work times. Independent drivers schedule their own work; dictating exact directions on where and how to do their work could impact employment status. (AB-5 may clarify this further). The number #1 issue is customer service. On-time deliveries (as perceived by the customer) is mandatory. A system that does not include customers will be unlikely to succeed. In addition, a cultural shift from independent decision making to a more collective collaboration mentality must be addressed. As in most things, behavioral changes of the firm and individuals may be the hardest to change.

7. Conclusions

In this project, we developed a methodology to reduce inefficiencies due to lack of coordination across the supply chain by introducing a centrally coordinated load balancing system. New technologies of improving air quality and environment such as ZEFV are investigated in depth in a way that compares the physical characteristics between electric engines and diesel engines. A set of tests is done for the comparison, which provides crucial parameters for the load balancing models. A set of more detailed experiments are implemented, which proves the benefits of deploying electric freight vehicles as part of freight fleet in the aspect of environment and the need for an intelligent recharging coordination. We developed a solution procedure that accounted for the exponentially increasing complexity introduced by the range limitation of electric vehicles. The charging cost of electric vehicles adds to the overall cost in a way that as the percentage of electric vehicles in a mixed fleet with diesel vehicles increases the overall cost also tends to increase in general. The charging cost includes the labor cost of the driver during charging and can be reduced if charging is done off duty hours.

We discussed the relation between load balancing system and empty container operation in a general supply chain system where exchange of containers between users can be optimized to reduce empty trips. We showed that the empty container operations can be used as an input to the load balancing system. A close loop system containing empty container operations and load balancing system is needed if the objective is to optimally operate the empty containers.

We interviewed six individuals with responsibility for trucking operations in the Los Angeles region to better understand the implementation issues of a load balancing system. All the interviewed trucking companies are either drayage operations (hauling freight to and from the ports or intermodal facilities) or short-haul operators that move goods between manufacturers, distribution center, and retail facilities. The answer for load balancing system varies between interviewees and we recommend an iterative fashion first targeting trucking companies who already work collaboratively in associations and vertical markets. These clusters of firms have built working relationships, engage in communication, and have trust between members at the offset. Positive results will entice others to join.

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Data Management

Products of Research

In this project, the freeway traffic flow data are collected from Freeway Performance Measurement System (PeMS) (C. Chen, “Freeway performance measurement system (PeMS),” 2003) that is publicly available at http://pems.dot.ca.gov. The traffic flow data on arterial ways are collected from Google Maps publicly available at https://www.google.com/maps.

Data regarding diesel/electric engine models and cycles and characteristics are collected from the National Renewable Energy Laboratory (NREL) website at: https://www.nrel.gov/transportation/drive-cycle-tool.

Data collected from interviews regarding current practices are included in the final report.

Data Format and Content

The format and content are available to the public through the links provided for the publicly available data. The data collected from interviews are presented in tables in this report and can be easily accessed.

Data Access and Sharing

For PeMS data: the public can access the data through http://pems.dot.ca.gov

For Google Maps data: the public can access the data through https://www.google.com/maps

For NREL drive cycle data: the public can access the data through https://www.nrel.gov/transportation/drive-cycle-tool/

Interview Data: see tables in this Final Report.

Reuse and Redistribution

The data are publicly available and can be reused and redistributed freely to the public.

Appendix 1

A1.1 Testing Electric and Diesel engines

Fuel Consumption model for diesel engine

The analytic model used to describe the diesel engine is taken from [56]. This is a fuel consumption model for a heavy-duty diesel truck (HDDT) and is described below:

Resistance force module: The resistance force is represented as a combination of aerodynamic, rolling, and grade resistance forces:

$$R(t) = \frac{\rho_a}{25.92} C_d C_h A_f v(t)^2 + 9.8066m \frac{C_r}{1000}(c_1 v(t) + c_2) + 9.8066mG(t)$$

where

$R(t)$: vehicle resistance force (N)

ρ_a : air density at sea level at a temperature of $15°\text{C}$ $(59°\text{F})$, which is $1.2256\ kg/m^3$

C_d : drag coefficient, usually is 0.78 [69]

C_h : correction factor for altitude, which is $1 - 0.085H$, H is the altitude in km

A_f : frontal area of trucks (m^2)

$v(t)$: velocity in km/h

m : vehicle mass in kg

C_r, c_1 and c_2 : rolling resistance parameters [69]

$G(t)$: instantaneous road grade

Vehicle power module: The power at any instant t is formulated in [70] as:

$$P(t) = \frac{R(t) + (1 + \lambda + 0.0025\xi v(t)^2)ma(t)}{3600\eta} v(t)$$

where

$P(t)$: vehicle power (kW)

λ : mass factor accounting for rotational masses, usually is 0.1 [71]

ξ : gear ratio

$a(t)$: instantaneous acceleration (m/s^2)

η : driveline efficiency

Fuel consumption model: Based on the resistance force and vehicle power module, the fuel consumption model for HDDT is described by a second-order polynomial function of vehicle power as follows:

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2, \forall P(t) \geq 0 \\ \alpha_0 \ , \forall P(t) < 0 \end{cases}$$

where

$$\alpha_0 = \frac{P_{fmp}\omega_{idle}d}{22164(HV)N}$$

$$\alpha_2 = \frac{\left(F_{city} - F_{hwy}\frac{P_{city}}{P_{hwy}}\right) - \left(T_{city} - T_{hwy}\frac{P_{city}}{P_{hwy}}\right)\alpha_0}{P_{city}^2 - P_{hwy}^2\frac{P_{city}}{P_{hwy}}}$$

$$\alpha_1 = \frac{F_{hwy} - T_{hwy}\alpha_0 - P_{hwy}^2\alpha_2}{P_{hwy}}$$

P_{fmp} : Idling fuel mean pressure ($400{,}000\ Pa$)

d : Engine displacement ($liters$)

HV : Conventional diesel fuel lower heating value ($43{,}200{,}000\ J/kg$)

N : Number of engine cylinders

ω_{idle} : Engine idling speed (rpm)

F_{city} , F_{hwy} : Fuel consumed for SPA city and highway drive cycles ($liters$)

$P_{city}, P_{city}^2, P_{hwy}, P_{hwy}^2$: The sum of the power and power squared over EPA city- and highway- cycle respectively

T_{city}, T_{hwy} : Duration of EPA city and highway drive cycle (s)

After calculation, $\alpha_0 = 1.02E-03$, $\alpha_2 = -9.28E-08$, $\alpha_1 = 1.06E-04$

Energy consumption model for electric engine

For electric freight vehicles, we use the computationally efficient model from [57] to estimate the energy consumption. In addition to the resistive forces, motor drive characteristics, regenerative braking and battery are also taken into account by the model. Among those factors, regenerative braking is one of the key advantages that can make electric freight vehicles outperform diesel ones, with respect to both economy and environment.

Traction power at wheels: The traction force at wheels is modeled as a combination of aerodynamic, rolling resistance, hill climbing, linear acceleration and the inertia forces by:

$$F_{te} = F_{ad} + F_{rr} + F_{hc} + F_{la} + F_{\omega\alpha}$$

where

$F_{ad} = \frac{1}{2}\rho A C_d u^2$ represents the aerodynamic force, where

ρ : air density (kg/m^3)

A : frontal vehicle area (m^2)

C_d : aerodynamic drag coefficient

u : velocity of vehicle

$F_{rr} = \mu_{rr} mg \cos \phi$ represents the rolling resistance force, where

μ_{rr} : tolling coefficient

m : vehicle mass (kg)

ϕ : angle of the incline (rad)

$F_{hc} = mg \sin \phi$ represents the component of the gravity force

$F_{\omega\alpha} = C_i m\alpha$ represents the inertia force, usually C_i is assumed to be 5%. [72]

Then the traction power is formulated as:

$$P_{te} = F_{te} u$$

Note the total tractive force F_{te} is positive when the battery provides power to the motor and negative if the motor works as a generator.

Transmission system: The motor torque is transferred to the wheels via the transmission system and a gear ratio g_{ratio} leading to the following equation between the angular speed of the wheels and that of the motor.

$$\omega_{motor} = g_{ratio}\omega_{wheels} = g_{ratio}\frac{u}{r}$$

where r is the radius of the wheel. The relation between the power of the motor and traction power on wheels is given by:

$$P_{motorout} = \begin{cases} P_{te} n_{gear}, P_{te} < 0 \\ P_{te}/n_{gear}, P_{te} \geq 0 \end{cases}$$

where n_{gear} is the gear efficiency of the transmission system. The torque from the motor is given by:

$$T_{motorout} = \frac{P_{motorout}}{\omega_{motor}}$$

Motor module: The efficiency of the motor is formulated in [57] as a function of loads on the engine.

$$efficiency(x) = \begin{cases} \dfrac{cout1 * x + cout2}{x + cout3}, 0 \le x < 0.25 \\ dout1 * x + dout2, 0.25 \le x < 0.75 \\ eout1 * x + eout2, \qquad x \ge 0.75 \end{cases}$$

where x is proportional to the ratio of mechanical power of the motor $P_{motorout}$ (W) over its rated power $P_{motorrated}$ (kW),

$$x = 0.001|P_{motorout}|/P_{motorrated}$$

$cout1, cout2, cout3, dout1, dout2, eout1, eout2$ are constant parameters. Using two sets of data from [76] the values of these parameters are estimated to be as described in the following table.

	cout1	cout2	cout3	dout1	dout2	eout1	eout2
Motor Mode	0.924300	0.000127	0.012730	0.080000	0.860000	-0.073600	0.975200
Generator Mode	0.925473	0.000148	0.014849	0.075312	0.858605	-0.062602	0.971034

Another major factor that influences the efficiency of a motor is the motor size [73]. A normalization factor $normfactor$ that takes into account the motor size is introduced into the model by [74] as:

$$P_{motorin} = \begin{cases} P_{motorout} n_{gen} normfactor, P_{te} < 0 \\ \dfrac{P_{motorout}}{n_{mot} normfactor}, P_{te} \ge 0 \end{cases}$$

where

n_{gen} : is the efficiency of the electric machine when operating as generator

n_{mot} : is the efficiency of the electric machine when operating as motor

Regenerative braking: A key feature of an electric vehicle is its ability to recuperate energy in a way that the motor operates as a generator by converting kinetic energy to electric energy. To describe such feature, according to [75], a speed-dependent regeneration factor $regenfactor(u)$ should be taken into account as follows:

$$P_{motorin} = \begin{cases} P_{motorout} * regenfactor(u) n_{gen} * normfactor, if\ P_{te} < 0 \\ \dfrac{P_{motorout}}{n_{mot} normfactor},\ if\ P_{te} \ge 0 \end{cases}$$

Charging and discharging efficiency: The energy losses during battery discharging and charging are taken into account by including in the model the battery round trip efficiency coefficient RTE as follows:

$$P_{total} = \begin{cases} P_{batteryout} * \sqrt{RTE},\ if\ \ battery\ charging\ (P_{batteryout} < 0) \\ \frac{P_{batteryout}}{\sqrt{RTE}},\ \ if\ \ battery\ discharging\ (P_{batteryout} \geq 0) \end{cases}$$

Combined with the power for accessories P_{ac}, the power flow is described by:

$$P_{batteryout} = P_{motorin} + P_{ac}$$

The cumulative energy consumption $E(t)$ (kW) at each time instance t is calculated by:

$$E(t) = E(t-1) + \int_{t-1}^{t} Ptotal(\tau)d\tau$$

Using the above equations, we can divide the representation of energy consumption of an electric engine into three sub-functions: the first sub-function is when the regenerated energy exceeds the consumption of the accessories and the excess energy is stored into the battery; the second one is the case when the regenerative energy is not sufficient to cover the consumption of the accessories; and the third case is when battery provides the energy to cover kinetic energy as well as the energy needed by accessories as described by the following equation:

$$E(t) = \begin{cases} E(t-1) + \left[P_{te}(t)n_{gear}n_{gen}\frac{0.001|P_{motorout}(t)|}{P_{motorrated}}regenfactor(u(t))normfactor + P_{ac}\right]\Delta t\sqrt{RTE}, P_{te} < 0\ and\ P_{batteryout} < 0 \\ E(t-1) + \frac{\left[P_{te}(t)n_{gear}n_{gen}\frac{0.001|P_{motorout}(t)|}{P_{motorrated}}regenfactor(u(t))normfactor + P_{ac}\right]\Delta t}{\sqrt{RTE}}, P_{te} < 0\ and \geq 0 \\ E(t-1) + \frac{\left[\frac{P_{te}(t)}{n_{gear}n_{gen}\frac{0.001|P_{motorout}(t)|}{P_{motorrated}}regenfactor(u(t))normfactor} + P_{ac}\right]\Delta t}{\sqrt{RTE}}, P_{te} \geq 0 \end{cases}$$

Numerical Tests

We created a scenario that compares energy consumed by an electric freight vehicle with that of a diesel freight vehicle of the same weight travelling a straight route of 10% grade and 10$\mathbf{km}$ length. A velocity profile that specifies the velocity of vehicles second by second is created given the entering and exiting vehicle speed, as well as the length of the route. The result shows that the electric vehicle consumes 24.413072$\mathbf{kWh}$ and the diesel vehicle consumes 15.040805$\mathbf{kW} = \mathbf{15.040805} * \mathbf{35.9mJ} = \mathbf{15.040805} * \mathbf{10.0}\boldsymbol{kWh}$ [76]. Based on this scenario the electric vehicle consumes much less energy than the diesel one.

In addition to the above scenario we performed a series of tests on both energy consumption models based on the drive cycle data from NREL. A drive cycle is a form of data that describes the speed of a vehicle versus time. In this project, we use the following typical drive cycles provided by NREL [77]:

- California Air Resources Board (CARB) Heavy Heavy-Duty Diesel Truck (HHDDT) Composite Cycle

- CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Creep Segment
- CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Cruise Segment
- CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Transient Segment
- City Suburban Heavy Vehicle Cycle (CSHVC)

The following Figures present the speed profiles of these cycles. The composite drive cycle is the combination of HHDDT creep segment, transient segment and cruise segment. It is used to test the general performance of an engine. Figure 19 shows the details of this drive cycle.

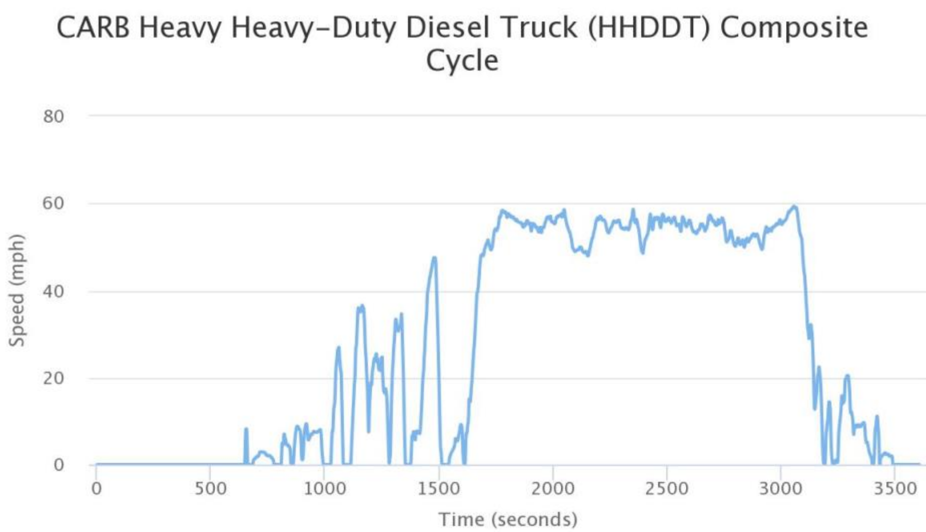


Figure 19. CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Composite Cycle

The creep segment drive cycle is used to test the performance of an engine during traffic congestion speeds. Figure 20 shows the details of the drive cycle.

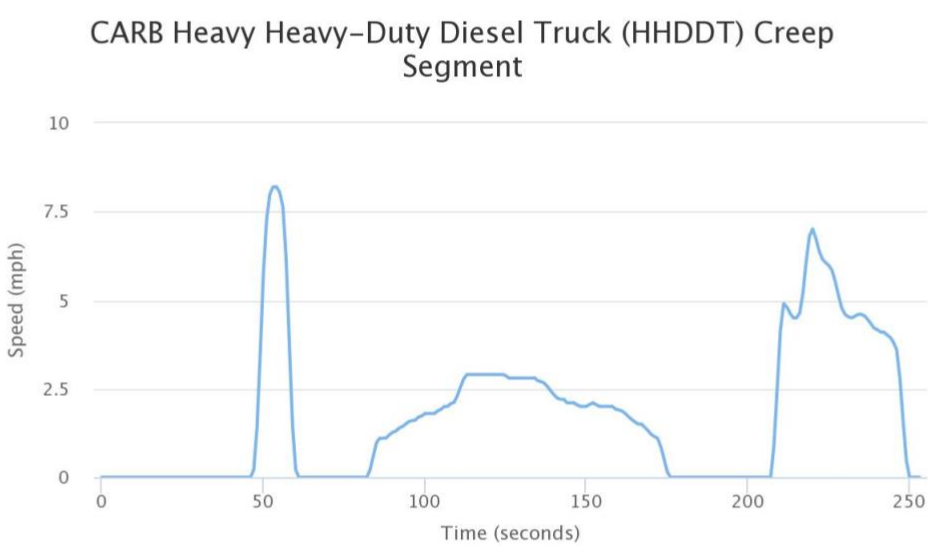


Figure 20. CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Creep Segment

The cruise segment drive cycle is set to test the engine's performance when the vehicle is cruising on a freeway with high average. Figure 21 shows the details of this drive cycle.

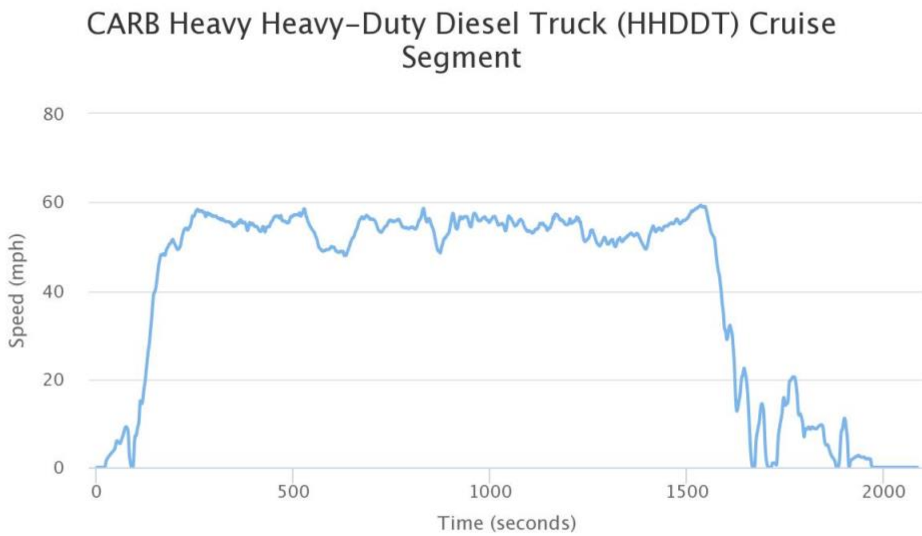


Figure 21. CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Cruise Segment

The transient segment is used to test the performance of an engine of constant speed changes typical of on-road driving. Figure 22 shows the details of this drive cycle.

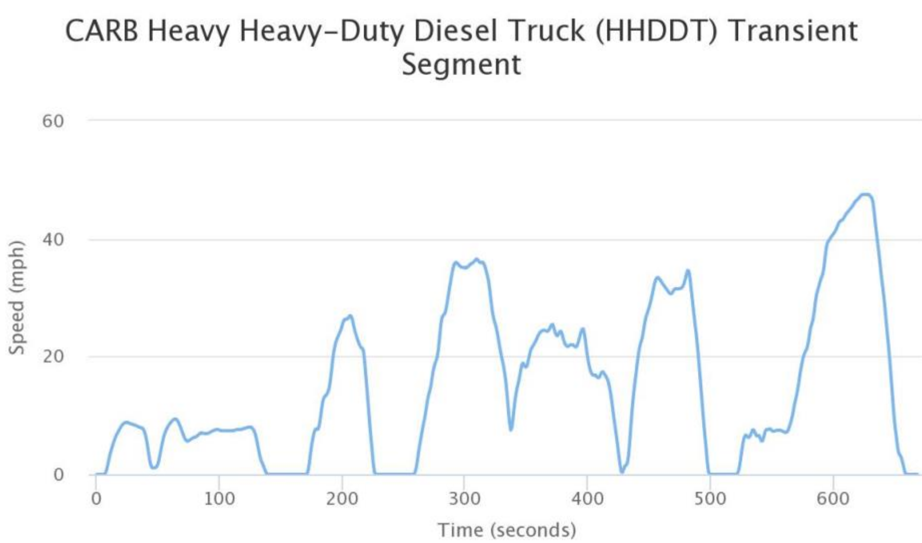


Figure 22. CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Transient Segment

The City Suburban Heavy Vehicle Cycle (CSHVC) is developed by West Virginia University using operating data from trucks in Richmond, Virginia, and Akron, Ohio [79]. Figure 23 shows its details.

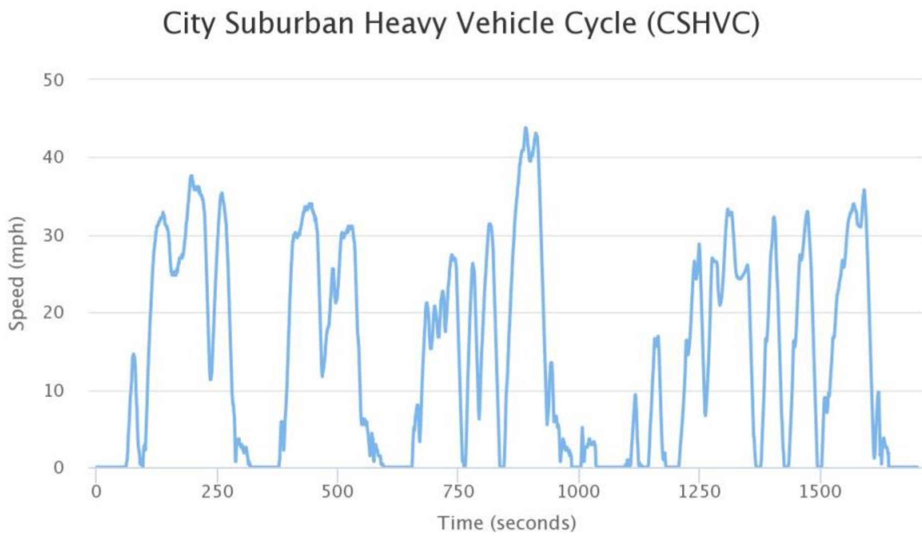


Figure 23. **City Suburban Heavy Vehicle Cycle (CSHVC)**

Table 17 specifies the key factors of the aforementioned drive cycles, including time (minutes), distance (mi), max speed (mph), average speed (mph), average driving speed (mph), acceleration (ft/sec^2) and the number of stops.

Table 17. Drive cycle specifications

Cycle	Time (minutes)	Distance (mi)	Max Speed (mph)	Avg Speed (mph)	Avg Driving Speed (mph)	PKE (ft/sec2)	KI (1/mi)	Stops (#)
Suburban Cycle	28.3	6.7	43.8	14.1	18.4	1.1	1.8	13
Transient Segment	11.1	2.9	47.5	15.4	18.2	1.0	1.4	4
Cruise Segment	34.7	23.1	59.3	39.9	43.2	0.3	0.1	6
Creep Segment	4.2	0.1	8.2	1.8	3	0.4	24.9	3
Composite Cycle	60.1	26.1	59.3	26.0	35.6	0.4	0.2	13

We tested the electric engine model of [57] with the drive cycles from NREL. The results are shown in Table 18.

Table 18. Amount of energy consumed (kWh) by the electric engine

suburban	transient	cruise	creep	composite
500.0	187.1	574.1	79.2	840.4

We tested the diesel engine model from [56] with the drive cycles from NREL. The results are shown in Table 19.

Table 19. Amount of energy consumed (kWh) by the diesel engine

suburban	transient	cruise	creep	composite
650.7	277.5	2257.2	15.1	2558.5

Based on the above tests the % energy improvement produced by the electric engine when compared with the diesel on are summarized as follows:

- % Energy improvement by electric during suburban cycle: 23%
- % Energy improvement by electric during transient cycle: 32%
- % Energy improvement by electric during cruise cycle: 75%
- % Energy improvement by electric during creep cycle: -423%
- % Energy improvement by electric during composite cycle: 67%

It is clear but not surprising that during traffic congestion where speeds are very low the electric engine is very inferior to the diesel engine with respect to energy consumption. In all other cycles the electric engine has consistent and significant advantages over the diesel engine. This information is important in routing mixed fleets of vehicles with the objective of minimizing energy consumption. A quick conclusion is to avoid using electric trucks during congestion times if diesel vehicles are available.

A1.2 Interview Questionnaire

Trucking Company Questionnaire

Operations

1. *Are you a?*
    a. *Owner-Operator*
        i. *If yes: How many trucks do you own?*
    b. *Fleet Manager*
        i. *If yes: How many trucks do you operate?*
    c. *Trucking Company Owner/Principle*
        i. *If yes: How many trucks do you operate?*
    d. *Other*
        i. *Please specify ___________*
        ii. *How many trucks do you operate?*

2. *What do you mostly use your truck for?*
    a. *Drayage (port only)*
    b. *Short-Haul*

c. *Long-Haul*

3. *Where is operation located (city/cities)? Do you have more than one "home-base?"*

4. *What type of goods do you transport? (choose all that apply)*
   a. *Perishables*
   b. *Non-perishables*
   c. *Clothing*
   d. *Food*
   e. *Bulk*
   f. *Parcel*
   g. *Non-alcoholic beverages*
   h. *Alcoholic beverages*
   i. *Grocery*
   j. *Furniture*
   k. *Electronics*
   l. *Office Supplies*
   m. *Chemicals*
   n. *Other (specify) _________*

5. *Which of those goods do you transport most often? (specify a-n above)*

6. *On a typical day, how many shifts do you operate each truck?* *(1,2,3)*

7. *Do you operate on weekends?* *(Y/N)*

8. *On average, how many customers do you serve on a tour? What type of drivers do you use? (employees, independent operators, mix) Number of drivers?*

9. *During your most common type of shift, how many miles is the truck driven?*
   a. *0-40*
   b. *40-80*
   c. *80-120*
   d. *120 or more*

10. *How many turns per shift are typically completed?*

11. *Who plans the routes and sequences of stops for each shift?*
    a. *Driver*
    b. *Dispatcher*
    c. *Other _____________*

12. *Other open-ended questions to understand more about their operation:*
    a. *Are trucks assigned to a specific driver? (not for owner operators, of course – Y/N) Slip-seated to keep them on the road? (Y/N)*
    b. *When is vehicle maintenance performed? Where? Do you employ people for maintenance?*
    c. *When do you refuel? Where?*
    d. *Is there anything like a "regular" route that some trucks take on a routine basis? For example, are trips like clockwork or is everyday a blank page?*
    e. *What type of concerns do your customers have about their shipments?*
    f. *How much of the trip time is spent waiting (at the port, at a customer, in traffic)?*
    g. *Did you use PierPass off-peak prior to Nov 2018? Why/why not? Has the change in cost impacted your decision to keep this schedule? Why/why not?*

Time-windows/load balancing

13. What are the biggest concerns your company is facing right now? Looking out 5 years? What strategies are you using to address?

14. Since freight is expected to continue growing, with all things being equal, congestion should increase in the region. What do you see as a potential for reducing congestion without slowing down the economy? (multiple answers allowed)
    a. changing routes
    b. changing time of day
    c. changing access right through congestion pricing (for certain areas of the city)
    d. other?

15. Are your pick-up/deliveries time sensitive and require strict adherence to a schedule?
    a. Y - do these pick-ups/deliveries have specific time-windows? (Y/N)
    b. N

16. What is the time-window for truck arrival at your customers locations? (E.g., how narrow is the window?)
    a. Need to arrive at a specific time (no flexibility)
    b. Arrival can vary by 2 hrs. without problem
    c. Arrival can vary by 4 hrs. without problem
    d. Arrival can vary by 8 hrs. without problem
    e. Arrival can vary by 12 hrs. without problem
    f. Arrival can vary by 1 day without problem

g. Totally flexibility; we can arrive whenever

17. If applicable, are time-windows determined by customer contracts or operational considerations?
    a. Contract
    b. Operations
    c. Other (please specify) _________________

18. Do you collaborate with other carriers or delivery services to determine schedules? (Y/N)

19. Do you collaborate with other carriers or delivery services to coordinate deliveries? (Y/N)

20. Would you consider coordinating your schedule and deliveries with other carriers if there is a clear benefit for doing so? (Y/N)

21. In our research, one strategy is to assign routes to trucks so that the demand is more balanced across the available highway facilities. How do you think a load balancing system could be implemented?

22. Do you think that trucking firms would be willing to use an outside entity (say a quasi-public transportation manager) for assigning routes? Do you think that truck drivers would be willing to adjust routes "on the fly" to avoid congestion?

23. Under what circumstances would you participate? (check all that apply)
    a. Clear benefit to my company
    b. If benefits all delivery companies in area
    c. If my operations do not substantially change
    d. It benefits the region from reduced congestion
    e. None of the above

24. Another strategy is to assign trips to time windows so that demand is more balanced across the day. Do you think that trucking firms would be willing to use an outside entity (say a quasi-public transportation manager) for assigning trips to time windows? What are some of the challenges of assigning time windows? Are there constraints on the delivery or destination time that would affect the timing of deliveries?

25. Imagine a case where all trucking firms, say for example all drayage trucking firms, are managed by the same transportation manager. The transportation manager may now be able to allocate trips to routes and time windows so as to minimize the total congestion cost. In order to do so, some drivers may have to make trips at less desired times or routes. However, over a period of time, all drivers would be better

off because of the savings in travel time. What are your thoughts on firms being willing to cooperate in this way? What do you see as major challenges?

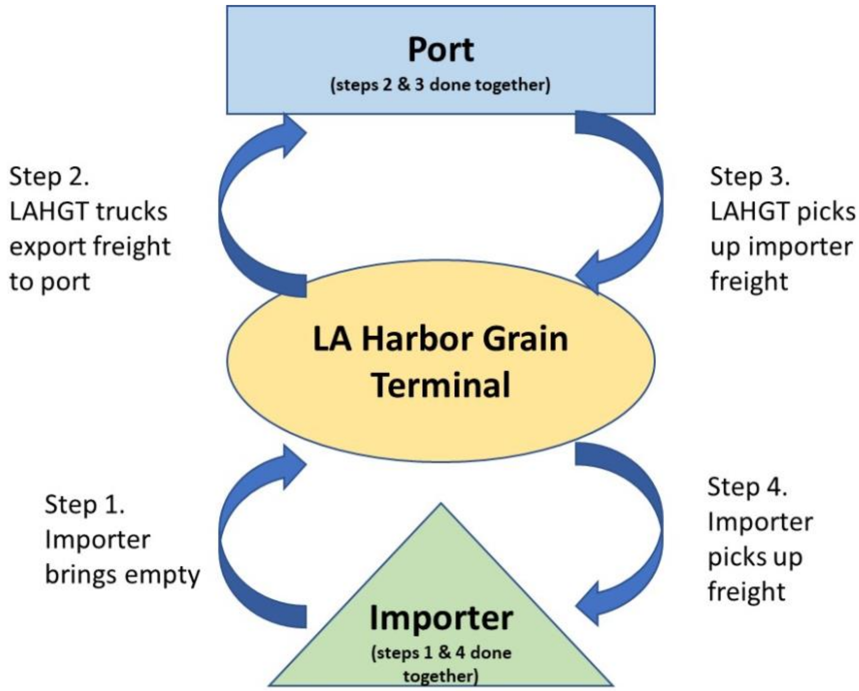
26. Now consider the case of zero emission heavy duty trucks. The only available zero emission trucks are battery electric or hydrogen fuel cell. Only a few fuel cell prototypes are in existence, hence the current demos are with BETs. BETs have a shorter range and longer refueling time relative to conventional diesel trucks. Do you see any challenges in optimizing routes and/or time windows using a mixed fleet?
27. Would you consider participating if this system of routing and time window management if built? Yes/no

28. 28. Some days your trucks would be assigned a different schedule than they are now. Would you participate if this happens? Yes/no

A1.3 Interview with Mr. Dwight Robinson, SCAQMD Board Member

Attendees: Dwight Robinson, Petros Ioannou, Pengfei Chen, Aristotelis Papadopoulos, Sue Dexter

- Dwight Robinson is the VP and GM of LA Harbor Grain Terminal and a board member of the SCAQMD. He is also a Council Member in Lake Forest.
- Firm operational summary
    - Exporter, 23 trucks drayage operation
    - Owns all chassis; cost per move $130 ($260 RT)
    - Very short trips (3-5 miles) on the 710/405 freeways to port
    - His operation does 3.5 round trips in an 8- to 9-hour time period (port to destination and back); operates 2 shifts
    - Located very close to port (near 405/710 interchange); 3-5 miles from port complex
    - Used to have independent truckers, but the Clean Truck Program at the ports required newer trucks. Hired all his own drivers. 100% of drivers are employees now.
    - Moved 7k containers last year
    - Is a proponent of eliminating moving empty containers ("moving air") for emission reduction
    - To avoid "moving air," he coordinates with an importer to bring empties to his warehouse (step 1). He then loads with his export product and takes to the port (step 2). While at the port he picks up the importer's freight and brings to his warehouse facility (step 3). The importer picks up their freight from his facility (step 4). In this manner, the truck shuttles freight both in and out of the port eliminating trips and congestion at the port complex. The importer does not need to go to the port at all. A diagram to explain:



- Because of being able to partner with importer, his cost per move is $130 in one direction.
- In operation for 4 years
- This has meant a savings of $100k (from original cost of $900k); decrease of cost by 11%

- **Question:** What do you think of the idea of platooning trucks?
    - **Answer**: Think this is in the distant future since the challenges are similar to autonomous trucks – moral decision for accidents. Software will need to be programmed to determine does the truck save the most lives, the truck, etc.

- **Question:** What strategies could be employed for reducing congestion from heavy-duty trucks?
    - **Answer**: Shift to off-peak. Utilize trucks 24 hours a day since PierPass allows for nighttime port access.
        - Now he has two shifts (8am-4pm, 6pm – 2am). This corresponds to the port which is closed from 2:15am-7am.
        - He wishes the port was open 24 hrs. day/7 days a week
        - 23 trucks are driven by 40 drivers across these 2 shifts
        - PierPass last November started charging for nighttime access after 13 years of being free
        - Certain segment accepts and appreciates night operations due to lower congestion; some drivers (approx. 40%) would rather work night

        - Pay is 10% more for night work (he considers very little as a supplement)

    - **Answer:** Optimizing schedules. His small business is not able to do this on its own.
        - He would be amicable to be a test subject for future work in optimizing routes.

    - **Answer:** Expansion of short-haul intermodal rail (from seaport to inland port)
        - Alameda corridor is not at 100% capacity
        - Plus have rail to Moreno Valley (new hot spot for warehousing). But rail companies not keen on this – too little money.

    - **Answer:** State/region allow for increased weight limits (less trips). Consider 82K, 84K lbs.

    - **Answer:** "Peel-off" yards
        - Terminals move product off precious port real estate to another yard nearby, but not at port complex.
        - Because truckers come to port and then must wait for extended times to get to the container they are coming for.
        - Must move many containers to get to "the one"
        - Concept: driver goes to port and picks up any container (FIFO), take to off-site location; so just pick up and go. At off-site location, get container they are after. May mean more moves, but less time. Idling is reduced.
        - This is a problem since no connection to how ship is loaded and instructions/timing for pick-up. Data flow/apps could help to provide links and information across the supply chain.
        - Port executive directors are wanting to optimize these things.

    - **Discussion:** Biggest challenge of reducing logistics emissions lies in State government
        - Optimization and automation versus labor and jobs
            - Cost of automation must be justified by lower labor costs
            - Labor is against this
            - Long Beach zero emission goals means more automation
            - Ports of Singapore moving towards automation; Rotterdam very successful in this area

- **Question:** What is your experience/knowledge of heavy-duty zero emission trucks?
    - **Answer**: His firm is not a part of any demonstrations. However, he does have knowledge of them, specifically TTSI.

        - Tesla has not shared any data with AQMD. Remains to be seen if can actually reach range promised (300 or 500 miles).
        - On hybrids – manufacturers say that two systems are just too costly
        - Short haul is the right business for these short-range trucks, but going to Moreno Valley would require charging after 1 trip
        - CARB is pushing, but market is not ready
        - TESLA in EV, Nikola hydrogen – but these are not major players. Nikola has a 7 year wait list now. Not until the heavy hitters have offers will the market be warm to the products (Daimler/Volvo for EV, Toyota for hydrogen)

- **Question**: What are your thoughts on a transportation manager/coordinator to optimize routes for multiple trucking companies? Would companies sign on to this scheme? Would truckers follow routes?
    - **Answer**: He thinks companies would welcome it. Way for industry to improve operations. Predictive analytics have proven benefits.
        - Drivers today use tried and true routes. They travel to/from same routes daily. Do not use WAYS or Google Maps. Drivers share info on route conditions/terminal congestion with others
        - Need a common appointment system across all terminals and between LA/Long Beach
        - Should not put truck in long lines
        - Truck drivers would follow routes if it could be proven that this is a better way but only on nonregular routes; regular routes – they know the way

- **Question:** What are your thoughts on a transportation manager/coordinator to assign time windows for delivery/pick-up? Would companies sign on to this scheme?
    - **Answer:** There are two different trip types: live load and drop/pick.
        - Live loads are very time sensitive and dictated by the customer. Space constraint is the whole issue. Drayage is very time sensitive.
        - This would be difficult.
        - Now, if a specific time is specified (appointment), drivers come early (maybe 2 hrs. early) and wait on a street since need to make sure they make it on time and do not know how long it will take to get there. If hot, they are running AC, etc.

- **Question:** How narrow of a time window?
    - **Answer**: The further away, the wider the time window.
        - If close by, would be less than 2 hours.
        - If long (like LA to NY), then 8 hours would be okay.
        - The problem is that there is no communication when coming, no visibility.

        - His operation is vertically integrated (warehouse + trucking) which gives him visibility

- **Question:** In the scheme where a transportation manager/coordinator coordinates routes/time windows, some firms/drivers will be better off sometimes and worse off other times. Overall (in the long run) firms would be better off. Would companies sign on to this scheme?
    - **Answer:** This is so highly model dependent.
        - For example, he has 23 trucks over his 2 shifts. But if was told could only run 20 during one shift, the other 3 pushing back, then would need to purchase an additional 3 trucks since would need now 26. + capital investment for this push
        - (He did not really answer this, but feeling was "no.")

- **Other discussion**: Regulation mandate versus voluntary adoption
    - Mandates have push-back
    - Tech option would be wide-spread adoption

Appendix 2

Table 20. Characteristics of different types of commercial vehicles

Truck Type	Class	Description	Example	Applications
Light Commercial Vehicles (LCV)	3	One- and two- axle, four-tire trucks	Heavy duty pick-up, walk-in van, minibus, box truck	Local pick-up and delivery; heavy duty pickup trucks, vans, minibuses
Medium Commercial Vehicles (MCV)	4	Two- and three- axle buses	Large walk-in van, city delivery truck	Parcel delivery, short distance
	5	Two-axle, six-tire, single-unit trucks	Bucket truck, large walk-in van, city delivery truck	
	6	Three-axle single-unit trucks	Beverage truck, school bus, rack truck	
Heavy Commercial Vehicles (HCV)	7	Four or more axles single-unit trucks	Refuse, city transit bus, medium semi-tractor, tow truck	Long haul truckload or less than truckload cargo (containers)
	8	Four or fewer axle single-trailer trucks	Cement mixer, heavy semi-tractor, dump truck, sleeper cab, fire truck, refrigerator van, tour bus	
	9	Five-axle single-trailer trucks	2 units: heavy semi-tractor with trailer	
	10	Six or more axle single-trailer trucks	2 units: heavy semi-tractor with trailer	
	11	Five or fewer axle multi-trailer trucks	3 units: heavy semi-tractor with 2 trailers	
	12	Six-axle multi-trailer trucks	3 units: heavy semi-tractor with 2 trailers	
	13	Seven or more axle multi-trailer trucks	3 units: heavy semi-tractor with 2 trailers	

Table 21. Fuel economy of ZEV, near-ZEV and diesel heavy- and medium-duty vehicles (DGE: diesel gallon equivalent)

Demonstration project	Class	Fuel	Vehicles	Fuel economy (miles/DGE)
Port of LA trucks	8	Electric	7	10.8
Foothill bus comparative study	8	Electric	12	17.5
		CNG	8	4.5
Transpower yard tractor, IKEA in-use, comparison drawn from CARB study	8	Electric	Not given	0.45 DGE/hr
		Diesel	Not given	2.4 G/hr
Transpower yard tractor, Port of LA in-use comparison drawn from CARB study	8	Electric	Not given	0.3 DGE/hr
		Diesel	Not given	2.4 G/hr
Altoona bus Commuter test cycle, comparison drawn from CARB study	8	Electric	Not given	26.0
		Diesel	Not given	7.5
Altoona bus CBD test cycle, comparison drawn from CARB study	8	Electric	Not given	18.3
		Diesel	Not given	2.6
Frito-Lay delivery truck comparative study	6	Electric	10	24.1
		Diesel	9	7.6
Smith Newton trucks	6	Electric	259	24.9
CalHEAT step van, comparison drawn from CARB study	5	Electric	Not given	56.2
		Diesel	Not given	11.7
SD Airport V6 shuttle can in use comparison drawn from CARB study	3	Electric	Not give	80.6
		Diesel	Not given	17.9
CalHEAT step van (in-use), comparison drawn from CARB study	3	Electric	Not given	76.8
		Diesel	Not given	11.2
Navistar eStar trucks	3	Electric	101	46.1

Table 22. Demonstration project Class Fuel Refueling time, Refueling conditions, Fuel capacity, Range (miles)

Demonstration project	Class	Fuel	Refueling time	Refueling conditions	Fuel capacity	Range (miles)
Navistar eStar delivery vans	3	Electric	Average charge duration 3.5 hours	Predominantly charged in the night/evening	80kWh battery	100 (av. Daily use 20)
Smith Newton delivery vans	6	Electric	Average charge duration 6.4 hours	Predominantly charged in the night/evening	80kWh battery	100 (av. Daily use 25)
Port of LA	8	Electric	4 hours with single 70 kW charger from 20% charge	Dedicated infrastructure	Not given	70-100 at av. load (65,000 lbs)
Frito-Lay delivery truck	6	Electric	Average 6.1 hours to recharge from 42% (post-loading) to 100%	Recharged at depot, recharging occurs in two steps (separated by loading)	80 kWh battery	Drove 32 miles/day on average after full charge
Foothill bus	8	Electric	Reaching full charger with overhead charges <10 mins	On-route fast-charge station at mid-way point in route. Bus charged through overhead charger	88kWh battery	Not given
ZEBA bus	8	Fuel cell	30 kg of H_2 in 6 mins	Central station with H_2 produced on-site	40 kg H_2	235
Sunline bus	8	Fuel cell	Not given	Fueled at least once daily at station	50 kg H_2 & 11 kWh battery	270
Coca Cola	8	Diesel hybrid	Not given	Not given	56 gallon diesel tank and 1.8 kWh battery	Not given
Odyne trucks	6-8	Diesel hybrid	Not given	Not given	28.4 kWh battery (and diesel tank, size not given)	Not given