Freight Routing for System Efficiency and Sustainability

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***Abstract*—The efficient supply of goods and transport of materials are important factors for sustainability in any urban environment where traffic and environmental issues also need to be addressed. In this paper we developed a centrally coordinated approach for routing freight in urban environments where traffic loads are unbalanced in time and space in an effort to improve mobility and reduce cost. We assume that freight is moved by trucks using the road network and truck fleets consist of a mix of diesel and electric trucks. We formulated the routing problem as an optimization problem with several constraints and we use a co-simulation load balancing approach to generate routes for trucks that reduce the overall cost. We use a simulation test of a road network in the Los Angeles/Long Beach Metropolitan areas that includes two major ports to demonstrate the results.**

***Index Terms*—Load Balancing System, Co-Simulation, Mixed Freight, Electric Truck, Routing**

I. Introduction

The efficient movement of goods is a critical factor for the sustainability and well-being of the whole society. Due to the increasing volume of goods to be transported and distributed as well as increases in travel demand by passenger vehicles make traffic congestion worse with adverse effects on the environment. Congestion results in enormous costs to shippers, carriers and the economy. According to [1], in 2016 around 1.2 billion hours of delay is wasted across the US national highway system, which is equal to approximately $74.5 billion. Trucks account for a significant share of air toxics: about on-third of all nitrous oxides (NOX) and nearly 30% of all particulate matter of 10 microns or less (PM10) [2]. Trucks also account for a significant share of green house gas (GHG) emissions. The US port sector accounts for 28% of all GHG emissions. Medium and heavy duty trucks account for 27% of the transport share [2].

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The above statistics motivate the need for an intelligent routing system for vehicles, especially freight trucks that not only meets the individual user demand, but also addresses overall system performance and optimality. Numerous research efforts have been carried out in this area, especially in view of recent advances in electric vehicles and clean fuel technologies. According to [3], the penetration of electric trucks into the global medium and heavy duty market is projected to be 9.4% by 2030. In comparison with diesel trucks electric trucks add more constraints which are associated with charging times, location of charging stations, battery range and energy which need to be taken into account by any routing system. Research efforts for this problem under various constraints can be found in [4]–[12]. However, in these methods, the dynamics of the background traffic system are not taken into account, which means that the assumption that the behavior of background traffic will not be affected by the routing of trucks in the same network may not be always true. In reality, the background traffic will be affected if many trucks are routed along the same link due to their size and bigger impact on traffic than passenger vehicles.

The dynamics of the transportation system can be taken into account by formulating the problem as a variant of a traffic assignment problem (TAP), which was first formulated by Beckmann et al. [13]. It was first proposed to predict an optimum route distribution in terms of minimizing the total cost for transportation planning purpose. These ideas have been applied for passenger vehicles as well as freight trucks. For example, Guelat and Florian proposed a linear approximation algorithm to solve a multimodal and multiproduct freight TAP [14]. Castelli et al. used a Lagrangian-based heuristic procedure to solve the freight scheduling problem [15]. Ham, Kim and Boyce showed the application of Wilson's iterative balancing method in interregional multimodal shipment planning [16]. Zografos et al. developed a dynamic programming based algorithm for multimodal scheduling [17]. Moccia et al. solved a multimodal routing problem with timetables and time windows by integrating a heuristic methodology with the column generation algorithm [18]. Crainic et al. proposed meta-heuristic methods for freight demand distribution in congested urban areas in [19], [20]. The trend of integrating electric trucks routing with a TAP variant is forming with the development of new technologies. Nan et al. presented a mathematical programming model and solution method for the path-constrained traffic assignment problem for electric vehicles in congested networks [21]. Bahrami et al. proposed a complementarity equilibrium model for electric vehicles without violating driving range constraints [22]. Based on the assumption of large adoption of electric vehicles, Faridimehr et al. [23] 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.

Despite the amount of research in TAP, there are many issues that need to be addressed. First, the complexity of modeling the nonlinear behavior at the traffic flow level that caused by the non-homogeneous dynamics of different vehicle classes at the vehicle level is immerse. The complexity of the real system cannot be possibly captured by TAP mathematical models, especially with the integration of electric trucks. Second, 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 the model. The constraints introduced by electric trucks dealing with charging times, battery depletion behavior, etc. make the mathematical modeling even more complicated. These complications motivate the use of simulation models by taking into account the availability of fast computers and software tools. The simulation models can be used to predict the traffic states and this information can be used to optimize routes in a co-simulation approach. The challenge is how these simulation models can be integrated with optimization tools to generate more realistic outcomes. In this paper, we deal with how to route a mixed freight fleet conforming to a balanced assignment. The contribution of this paper is the development and evaluation of a centrally coordinated load balancing approach for a mixed fleet of trucks that is computationally feasible. Specifically, the contributions are:

- A centrally coordinated mixed freight dynamic routing system is formulated and constructed. The system achieves system-level minimal cost while considering the dynamics of background traffic and its interaction with the imposed truck load on the system at the same time.
- A co-simulation optimization method is proposed to solve the mixed freight routing problem. The method achieves load balancing across the road network.
- The system is tested using realistic scenarios under various percentages of penetrations of electric trucks in the whole mixed freight fleet and background traffic conditions.

The remainder of this paper is organized as follows. Section 2 deals with the problem formulation and solution methodology. Section 3 presents the numerical results of the proposed system. Finally, conclusions are presented in Section 4.

II. Problem and Methodology

In this section, the formulation of mixed freight fleet routing problem is presented and a centrally coordinated routing system with a co-simulation optimization method is proposed to address this problem. Specifically, this routing problem deals with drayage trucks transshipping containers and demand is expressed as containers to be transported from origin to destination. The aim for the routing problem is to provide each truck in the fleet with a route with minimal total cost that includes energy cost and time cost.

A. Formulation

We consider the road network to be a directed graph $G(E, V)$, where E is the set of all links and V is the set of all nodes. Among all the nodes, a subset of them are origin nodes, denoted as O, i.e. $O \subset V$. Another subset of nodes are destination nodes, denoted as D, i.e. $D \subset V$. For a certain pair of origin and destination nodes (i, j), $i \in O, j \in D$, the demand volume is $q_{i,j}$. All the truck types are included in a set U. To represent the distribution of trucks, we use m_i^u as the number of available trucks of type u at node i. To cope with the temporal dimension, we discretize the time horizon into $|K|$ time intervals and use K as the set of all the time intervals. The following notation is used in the formulation to follow:

- $R_{i,j}^u$: The set of routes for trucks of type u from i to j, $i \in O, j \in D$
- $X_{i,j,r,k}^u$: The number of trucks of type u from i to j, $i \in O, j \in D$, using route r in route set $R_{i,j}^u$ with a departure time k; The collection of $X_{i,j,r,k}^u$ is denoted as X.
- $S_{i,j,r,k}^u(X)$: The average service cost per container fulfilled by a truck of type u from i to j, $i \in O, j \in D$, using route r in route set $R_{i,j}^u$ with a departure time k;

Given the above notation we formulate the problem as follows:

$$\min_X \quad \sum_{k\in K}\sum_{i\in O}\sum_{j\in D}\sum_{u\in U}\sum_{r\in R_{i,j}^u} S_{i,j,r,k}^u(X) X_{i,j,r,k}^u \tag{1}$$

$$\sum_{k\in K}\sum_{u\in U}\sum_{r\in R_{i,j}^u} X_{i,j,r,k}^u = q_{i,j},\ \forall i \in O, j \in D \tag{2}$$

$$\sum_{k\in K}\sum_{j\in D}\sum_{r\in R_{i,j}^u} X_{i,j,r,k}^u \le m_i^u,\ \forall i \in O, u \in U \tag{3}$$

$$X_{i,j,r,k}^u \ge 0 \tag{4}$$

Equation (1) is the objective function, which aims to minimize the sum of the service cost of all the freight loads which are assumed to be containers. $S_{i,j,r,k}^u(X)$ is the unit service cost of transporting a container with a truck of type u using route r from i to j at time k given X. The cost $S_{i,j,r,k}^u(X)$ is given by

$$S_{i,j,r,k}^u(X) = C_{i,j,r,k}^u(X) + \eta T_{i,j,r,k}^u(X) \tag{5}$$

where $C_{i,j,r,k}^{u}(X)$ is the cost of the consumed energy, $T_{i,j,r,k}^{u}(X)$ is the travel time and η is the value of time. The energy and travel time cost depend on the dynamics of the traffic network. The dynamics of the traffic network can be expressed as nonlinear dynamic functions of all decision variables, denoted as X, and will be discussed in the following sections. Note here, the energy cost is calculated based on the dynamics of the traffic network [24]. More specifically, the energy cost coefficient of each truck type is formulated as a polynomial function of the speed of the road link, where the parameters of the function are estimated using regression over a set of testing data. Here we assume one truck can only load one container, so the total number of trucks for an O/D pair is equal to the demand of the O/D pair, as shown in equation (2). Equation (3) represents the constraints on availability of a certain type of truck at each node.

The dynamics of a traffic network are highly nonlinear and exhibit the following temporal-spatial relations: traffic flow dynamics in a link and between links. The dynamics in a link describe how the traffic flow moves from the upstream end of a link to the downstream end, while the dynamics between links describe how the traffic flow propagates across the traffic network. In most of the literature of vehicle routing, the complex dynamics of the traffic network are overly simplified and the dynamics between links are ignored. The optimum routes from these methods may not be optimum in a realistic situation if the impact of routing on background traffic is ignored. In our approach, we introduce the following way to connect the traffic flow on each route with the number of trucks of a certain type on a road edge. First, a subset of nodes in the traffic network including all O/D nodes as well as the nodes necessary for the routing of freight vehicles are chosen. These nodes are called service nodes. Then a set of virtual service links connecting the service nodes are constructed. To differentiate the link in the road network, the virtual service links are called segments. Let $x_{l,k}^{u}$ be the number of trucks of type u passing through segment l at time k. Then the relations between routes and service segments can be shown as follows:

$$\sum_{i\in O}\sum_{j\in D}\sum_{u\in U}\sum_{r\in R_{i,j}^{u}}\sum_{\tau\leq k} X_{i,j,r,k}^{u}\delta_{l,r,\tau,k}^{u} = x_{l,k}^{u} \tag{6}$$

where $l \in L, k \in K$ and $\delta_{l,r,\tau,k}^{u} = 1$ when the truck of type u uses route r with departure time τ passing through segment l at time k, otherwise, $\delta_{l,r,\tau,k}^{u} = 0$. As for the relations between the service segment and traffic network links, we denote as $t_{l,k}^{p}$ the travel time on path p if a truck departs from the origin of segment l at time k. Assume links constituting path p to be $e_{p,1}, e_{p,2}, \dots, e_{p,N_p}$, where N_p is the total number of links on path p. We define $\xi_{e,k}$ as the entering time at link e of a truck with a departure time k from the origin of that path. With $w_{e,k}$ to be the travel time of link e at time k, we now write the travel time of a path as follows:

$$t_{l,k}^{p} = \sum_{n_p=1}^{N_p} w_{e_{p,n_p},\xi_{k,e_{p,n_p}}} \tag{7}$$

$$\xi_{k,e_{p,1}} = 1 \tag{8}$$

$$\xi_{k,e_{p,n_p+1}} = \xi_{k,e_{p,n_p}} + w_{e_{p,n_p},\xi_{k,e_{p,n_p}}} \tag{9}$$

where $n_p = 1, \dots, N_p - 1$. To make the notation simpler, we let $\hat{w}_{p,n_p,k} \equiv w_{e_{p,n_p},\xi_{k,e_{p,n_p}}}$ to denote the travel time of link e_{p,n_p} on path p with the path departure time being $\xi_{k,e_{p,n_p}}$. Then the mixed freight routing problem can be formulated in the form of service-road two-layer structure as:

$$\min_{y^u} TC = \sum_{k\in K}\sum_{l\in L}\sum_{p\in P_l}(c_{l,k}^{p,u} + \eta t_{l,k}^{p,u})y_{l,k}^{p,u} \tag{10}$$

where TC stands for the total cost of the assignment with mixed freight vehicles, which is a combined value of energy consumption cost and travel time cost. $c_{l,k}^{p,u}$ is the energy consumption coefficient for trucks of type u passing through path p of segment l at time k, $t_{l,k}^{p,u}$ is the travel time of path p in segment l that departs at time k, $y_{l,k}^{p,u}$ is the number of trucks of type u assigned to pass through path p of segment l at time k and η is the value of time. This objective function is constrained by equations (6)-(9) as well as the following equations:

$$\sum_{p\in P_l} y_{l,k}^{p,u} = x_{l,k}^{u},\ \forall l \in L, k \in K \tag{11}$$

$$y_{l,k}^{p,u} \geq 0,\ \forall l \in L, p \in P_l, k \in K \tag{12}$$

which represent the relation between variables from the service network and the simulated traffic network. In a summary, we introduce the following changes to make routing decisions close to a theoretical optimum:

- We use a traffic simulation model to capture the dynamics of the background traffic when it is loaded with trucks instead of using a simplified mathematical model. The simulation model provides a far more accurate description of the traffic dynamical characteristics to be used by the optimum route generator.
- We construct a service network layer to efficiently utilize the simulation model and apply the optimization algorithms.
- In the algorithm, the direction and step size are intelligently chosen based on the knowledge of the marginal cost.

In the next subsection, we present a co-simulation optimization method for solving the multi-layer routing problem.

B. Solution Methodology

Figure 1 gives a general overview of the method. The input to the routing system are demands, vehicle-related characteristics and other predetermined parameters. Demands represent the number of containers to be transfered from origin to destination nodes. The truck characteristics include the physical (weight, length, frontal area, et al.), dynamic (max speed, acceleration, et al.). The energy consumption (the amount of energy consumed based on the dynamic states) characteristics for each type of truck is included in the predetermined parameters. Based on the energy consumption characteristics of diesel/electric trucks, the cost coefficients on each segment of both types of trucks are calculated under different traffic conditions. We use an emission model from National Renewal Energy Laboratory (NREL) to calculate the emissions. In the routing system, two major components, the service graph and traffic simulator form a feedback loop that stops when certain criteria are satisfied. Like a central coordinator, the optimization of truck assignment is performed on the service graph aiming to fulfill demands at minimal system cost. A real-time traffic simulator is used to capture the dynamical characteristics of traffic and provide traffic state predictions such as travel times along the links and routes as well as estimates of the energy cost of diesel and electric trucks depending on the simulated traffic flow. The information from the simulator is used by the service graph optimization component to update the status, such as marginal cost of each service segment which is then used to update the route cost. Based on the simulated route cost, the route collection for each O/D pair is updated as well. The updates of route collection start by trying to find if there is a new minimum cost route. If there is, add the new route to the route collection; otherwise, do nothing. Then given the updated route collection, the assignment of diesel/electric trucks for each O/D pair is then updated by solving an integer combinatorial programming problem using a properly selected efficient step size. The new assignment is then generated in the form of route flow vector and passed to the traffic simulator for another iteration. Other than the route flow vector from the service graph, the background traffic data accounts for the other part in the road network. The background traffic flow data are obtained from various sources, such as PeMS [26] and Google Maps [27]. The assignment traffic flow is generated by the optimizer in the service graph. The co-simulation optimization procedure iterates in a feedback loop that involves the traffic simulator and service graph optimization. Through this procedure, the states of route flow vector and road network feedback are sequentially updated until both states converge. The difficulty in this procedure is to calculate the marginal cost of each route, which represents the change in the total cost as a result of adding one unit of demand on that route. Since the total cost TC of equation (10) is complex, the marginal cost with respect to a route cannot be calculated directly. One way to calculate the marginal cost is to use Monte Carlo to simulate the impact of one unit of demand on each route at each time. However, it is impractical to enumerate all routes due to the fact that the number of possible routes grows exponentially with respect to the service network size. Our proposed approach bypasses this issue and works as follows:

Step 1: Initialize cost coefficients based on the physical features such as speed limit for each segment l and iteration number $n = 0$. Initialize the diesel/electric route collections for each O/D pair based on the segment cost calculated with the cost coefficients. Establish the initial route flow vector $X^{(0)}$ by assigning the portion of demands in the origin node to electric trucks with the portion of demand to be equal to the portion of electric trucks in the mixed fleet.

Step 2: If $n > 1$, check if the objective function value of the current iteration converges, i.e., $|TC(X^{(n)}) - TC(X^{(n-1)})| < \varepsilon$; ε is set to be a small number. If it converges, then stop the procedure and return with route flow vector; otherwise, continue to the next step.

Step 3: Input the route flow vector $X^{(n)}$ into the traffic simulator and obtain the marginal cost of each segment.

Step 4: Update the marginal cost of each segment as well as diesel/electric routes for each O/D pair and check whether there is a new minimal marginal cost route. If there is, then add it into the route collection.

Step 5: Solve the following optimization problem for each origin node o to obtain a feasible route flow vector $\hat{X}^n$.

$$\min_{X} \sum_{u\in U}\sum_{k\in K}\sum_{j\in D}\sum_{r\in R^u_{o,j}} MC^u_{o,j,r,k}X^u_{o,j,r,k} \tag{13}$$

$$\sum_{u\in U}\sum_{k\in K}\sum_{r\in R^u_{o,j,k}} X^u_{o,j,r,k} = q_{o,j},\ \forall j\in D \tag{14}$$

$$\sum_{k\in K}\sum_{j\in D}\sum_{r\in R^u_{o,j,k}} X^u_{o,j,r,k} \le m^u_o,\ \forall u\in U \tag{15}$$

where $MC^u_{o,j,r,k}$ is the marginal cost of route r from o to j with a truck of type u departing at time k. The marginal cost of a route is the sum of the marginal costs of the segments along it. The computation of the marginal cost of a segment will be addressed in the next subsection.

Step 6: Set the route flow vector for the next iteration as $X^{(n+1)} = X^{(n)} + \lambda^{(n)}\cdot(\hat{X}^n - X^{(n)})$, where $\lambda^{(n)}$ is the step size at the nth iteration, and go back to step 2. The step size $\lambda^{(n)}$ at the nth iteration is selected as in [25].

$$\begin{aligned} &X^{(n+1)} = X^{(n)} + \lambda^{(n)}\cdot(\hat{X}^n - X^{(n)})\\ &\lambda^n_{i,j} = \min\{\lambda_{max},\\ &\sum_{i\in O}\sum_{j\in D}\lambda^{n-1}_{i,j}\cdot\frac{\sigma(q_{i,j})}{\sum_{i\in O}\sum_{j\in D}\sigma(q_{i,j})}\} \end{aligned} \tag{16}$$

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

Different from the load-balancing cases with single-type vehicles, we address the problem with two types of trucks, diesel and electric trucks. Due to that, the type of steepest descent direction used in the work of [25] may not be feasible for the mixed freight case. The update of each iteration should consider not only the marginal cost of a certain route but also the availability of each type of truck at a certain node. In step 5, a linear programming subproblem is formulated by explicitly imposing the availability constraints for each type

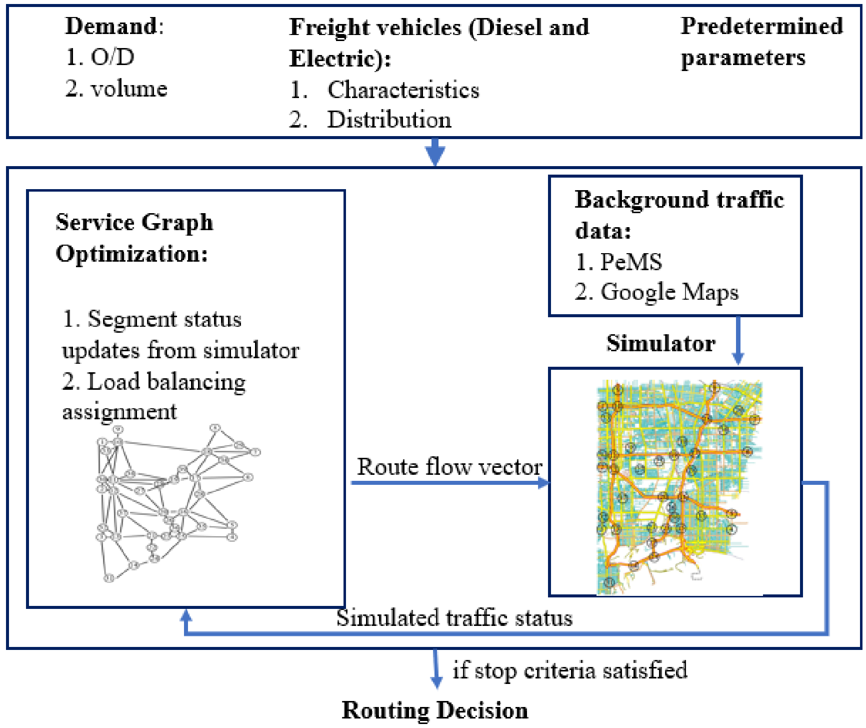

Fig. 1. Framework of proposed mixed freight dynamic routing system

of truck as shown in equations (13 - 15).

The marginal cost of a service segment represents the change in the total cost if one unit of demand/container is changed on the segment. Let $MCP^{p,u}_{l,k}$ be the marginal cost of path p of segment l with departure time k for the trucks of type u. The final form of marginal cost is:

$$\begin{aligned} &MCP^{p',u'}_{l',k'} \approx c^{p',u'}_{l',k'} + \eta t^{p',u'}_{l',k'} \\ &+ \sum_{k\in K}\sum_{l\in L}\sum_{p\in P_l}\sum_{n_p=1}^{N_p} 1_{e'_{p,n_p},\xi_{k',e'_{p,n_p}}}(e_{p,n_p},\xi_{k,e_{p,n_p}}) \\ &\cdot y^{p,u}_{l,k}\frac{1}{v_{p,n_p,k}\Delta t}\left(\eta + \frac{\partial h^u(v_{p,n_p,k})}{\partial \hat{w}_{p,n_p,k}} d_{p,n_p}\right) B_{p,n_p,k}\hat{z}^{\beta_{e_{p,n_p}}-1}_{p,n_p,k} \\ &\qquad \forall l' \in L, p' \in P_{l'}, k' \in K, u' \in U \end{aligned} \tag{17}$$

The derivation details of marginal cost can be found in [24], [25].

III. Numerical Evaluation

The evaluation of the proposed approach is performed using a regional transportation network covering the road network from the Los Angeles/Long Beach terminal ports to I-105 freeway. A commercial traffic simulator VISUM [28] is used to configure the digital twin of the road network. Road network features such as such as lane length, capacity, speed limit et al. are configured in the traffic simulator. The road network in the traffic simulator is shown in Figure 2. The road network is on the right and its service network is on the left. The circles with number in them are the service nodes. The service network nodes are composed of O/D nodes as well as intersections of freeways and major arterial ways. The service nodes also include charging stations. To make sure the routes of electric trucks are feasible, we assume every charging station has enough capacity for charging and electric trucks always get charged the amount of electricity they consumed on the previous segment along the route.

Other than the lane features, background traffic also needs to be configured in the traffic simulator. We use freeway traffic flow data from PeMS [26] and arterial way data from Google Maps [27]. Background traffic data in three time periods are extracted from the raw data: from 2am to 6am representing a light background traffic condition, from 12pm to 4pm representing a medium background traffic condition and from 7am to 11am representing a heavy background traffic condition. The extracted traffic data are then processed (formatted/truncated/aggregated) to fit the format of the traffic simulator. The total number of demands is 3430. The hourly time value is set to be \$60 in terms of year 2020 US Dollar value [29]. We assume the charging cost to be the same with time cost at \$60 per hour. In our simulation we assume that it takes 4 hours for a full charge which is equivalent to \$240.

The routing system is tested under different scenarios of various percentages of electric vehicles. The experimental scenarios are constructed in the following manner: 3 background traffic conditions (light, medium and heavy) are constructed and under each background traffic condition, the percentage of electric vehicles in the fleet is varied from 0% to 100% in increments of 10%. Let v be the speed of the truck, according to [24], the energy cost coefficient function

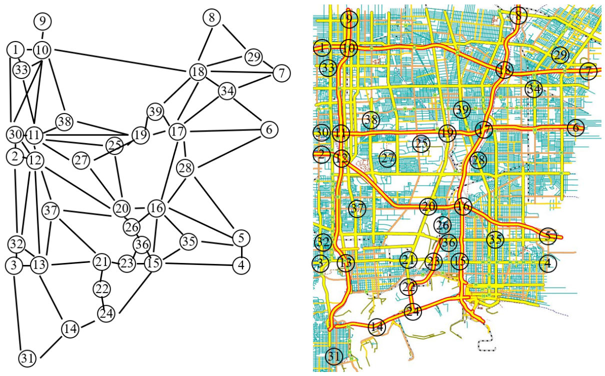

Fig. 2. Road Network and Service Network Overview

for diesel trucks is:

$$h^d(v) \;=\; 11.327 \,-\, 0.649v \,+\, 0.045v^2 \,-\, 0.001v^3 \quad (18)$$

For electric trucks, it is:

$$h^e(v) \;=\; 66.552 \,-\, 7.670v \,+\, 0.291v^2 \,-\, 0.004v^3 \quad (19)$$

The experiments are performed on a desktop computer configured with 4.2GHz CPU and 16G memory. The results include total costs in unit of dollar of the assignment (with and with out charging time cost), the weight in unit of gram of several emissions (CO, NOX, CO2, PM25) as well as fuel consumed in unit of kg. A modified EPA model MOVES [30] is used to calculate the emissions. Figures 3 - 5 show the results under medium background traffic condition. Similar results patterns are observed under light and heavy traffic conditions, which are not included in this paper due to space limit. We can see that by increasing the % of electric trucks the overall cost without charging time cost is decreasing. But the total cost with the inclusion of charging time cost does not decrease since the cost of charging time becomes more and more dominant as the % of electric trucks increases. Another observation is that by increasing the % of electric trucks, all types of emissions are decreasing.

In summary, the following observations can be made from the experiments:

- The total cost without including charging cost decreases as the % of electric vehicles increases.
- The total cost that also includes the charging cost tends to increase in general since the cost of charging time becomes more and more dominant with increasing % of electric trucks in the fleet.
- The difference between the total cost including and excluding charging time is the charging time, which we assume that the time of driver waiting for charging is included in. Due to that, we can observe that if charging is done off-duty the total cost can be reduced considerably.
- The emissions go down as the number of electric vehicles increases in the fleet.

IV. Conclusion

In this paper, we have proposed a mixed freight routing system with central coordination. A multi-layer co-simulation optimization method to achieve freight load balancing across the road network is proposed and tested under a realistic regional road network. The method considers the inclusion of electric trucks with their penetration varying from 0% to 100% and manages to optimally route a mixed freight fleet with the complexity of the traffic network dynamics and constraints imposed from the electric trucks such as charging time and energy depletion. The multi-layer co-simulation optimization method consists of one layer for the traffic simulator and another layer for service network. The traffic simulator is used to accurately predict the states of the transportation system and the service network to generate the optimum routes. Numerical experiments are performed using a realistic traffic network in the Los Angeles/Long Beach area that includes the two ports to evaluate the approach with a mixed freight fleet. The results show that the use of electric trucks can notably reduce the emissions and total cost when the charging time cost is not included. If charging is done during working hours then the driver cost should be included and this will make the operational cost of electric trucks to be comparable or even higher than those of diesel trucks. As a result scheduling the charging of trucks when the driver is off or resting should be taken into account in scheduling and routing electric trucks.

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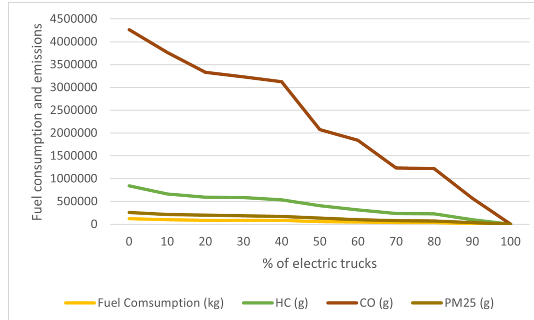

Fig. 3. Fuel consumption, HC, CO, PM25 emission versus percentage of electric trucks under medium traffic condition

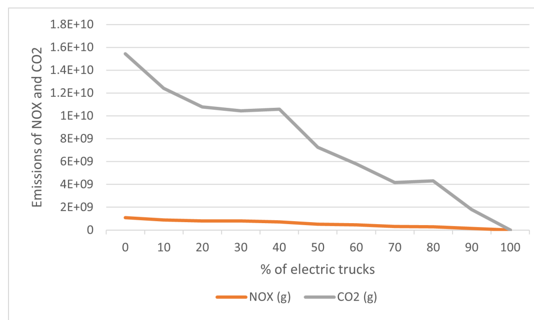

Fig. 4. NOX, CO2 emission versus percentage of electric trucks under medium traffic condition

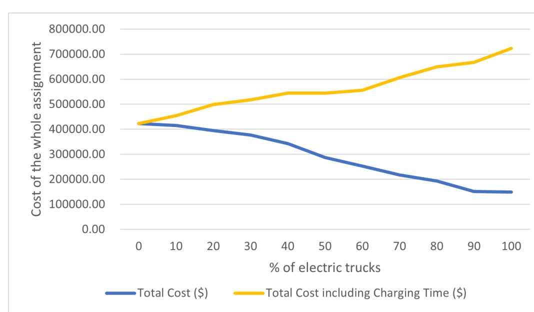

Fig. 5. total cost with/without charging time cost versus percentage of electric trucks under medium traffic condition