Mixed Freight Dynamic Routing Using a Co-Simulation Optimization Approach

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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 may become congested. In this paper we show how a centrally coordinated load balancing system that considers all vehicles to be diesel can take into account electric trucks as mixed fleets. The electric trucks impose additional constraints due to the limitation of range, charging time of batteries as well as the dependency of the battery charge on traffic conditions. The use of a co-simulation approach as part of the system accounts for these nonlinear dependencies and provides more realistic cost estimates for the optimization part. Traffic simulation results using a realistic road network reveal the benefits of applying load balancing and show that as the number of electric trucks increases, the emissions reduce; however, due to the cost of charging, their operational costs are not necessarily less than those of the corresponding diesel trucks. For the electric trucks to compete with diesel, charging should occur when drivers are off duty since the cost of charging includes the labor cost of the waiting driver. It is also shown that a centrally coordinated truck routing system that considers the characteristics of electric trucks in mixed fleets can reduce the operational cost of trucks and encourage the deployment of electric trucks in order to reduce emissions and improve air quality.

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 world's population especially in urban areas. Worldwide container trade is expected to grow at a 4.3% annual rate [1]. Current forecasts expect US commodity trade to approximately double by 2030 [2]. With the rising volume of containers processed in ports, especially in some of the largest ports such as New York and Los Angeles, congestion and air pollution are significantly exacerbated. According to [3], there will be significant increases in highway congestion around US ports, air cargo, and border crossing nodes in the future. Congestion results in enormous costs to shippers, carriers and the economy. According to [4], the total cost of truck congestion amounted to approximately $74.5 billion in 2016 across the US national highway system

with the delay of 1.2 billion hours. Freight transport is also a significant contributor of $NO_x, CO_2, PM10$ and other pollutants. Of the Greenhouse Gases (GHG) emissions coming from transportation related sources, freight movement (trucks, ships, trains, airplanes and pipelines) account for 29% of the total; trucks are responsible for emitting 68% of GHG from these freight sources [5]. According to a report from the European Union [6], about 26% of the CO_2 emissions are due to heavy-duty vehicles.

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. One such trend is the use of electric trucks. It is forecasted that the penetration of electric trucks into the global medium and heavy duty market to be 9.4% [7]. During recent years researchers studied the deployment of electric trucks from the point of view of policy [8], [9], strategy [10] and operation [11]–[15]. Ambrose and Jaller examined the result of electric drayage trucks at the Port of Los Angeles and assessed emission reductions with increased electrification of port truck operations [16]. Related research efforts can be found in [17]–[25]. The use of electric trucks brings up the constraints of available charging stations and charging times which will affect optimum routing decisions. Since electric trucks are expected to be put in use gradually the problem of traffic assignment of mixed fleet of trucks with different characteristics and constraints is at important area of study. Numerous research efforts have addressed this problem under various constraints [26]–[34]. However, the dynamics of the background traffic system is not taken into account in these approaches, which means the decisions are made with the assumption that the behavior of background traffic in the same transportation system will not change. But in reality, the background traffic will be affected when trucks are added to the flow due to the size and dynamical characteristics of trucks and of course depending on their number. The absence of the interactions with background traffic may result in an non-optimal or even non-feasible solution when used in a realistic practical scenario. To include the dynamics of the transportation system, the problem should be formulated as a variant of a traffic assignment problem (TAP), which was first formulated by Beckmann et al. [35] and widely used in transportation planning to predict an optimal route distribution in terms of minimizing the total cost, e.g. travel time spent by all users in the network. In some cases, TAP is formulated to capture desirable properties such that the solution in the form of traffic flow pattern spreading across the network is consistent with actual traffic behavior. These properties include queue spillback considered

in [36]–[38], first-in-first-out (FIFO) in [39], [40] and nonvehicle holding in [41], [42]. On the other hand, TAP is also formulated to develop meaningful operational strategies for the goods movement industry, especially on the intelligent assignment of multimodal freight. For example, Guelat and Florian proposed a linear approximation algorithm to solve a multimodal and multiproduct freight TAP [43]. Castelli et al. used a Lagrangian-based heuristic procedure to solve the freight scheduling problem [44]. Ham, Kim and Boyce showed the application of Wilson's iterative balancing method in interregional multimodal shipment planning [45]. Zografos et al. developed a dynamic programming based algorithm for multimodal scheduling [46]. Moccia et al. solved a multimodal routing problem with timetables and time windows by integrating a heuristic methodology with the column generation algorithm [47]. Crainic et al. proposed meta-heuristic methods for freight demand distribution in congested urban areas in [48], [49]. Additional work can be found in [50]–[53].

With respect to research on incorporating electric trucks into TAP, Nan et al. presented a mathematical programming model and solution method for the path-constrained traffic assignment problem for electric vehicles in congested networks [54]. Bahrami et al. proposed a complementarity equilibrium model for electric vehicles without violating driving range constraints [55]. Based on the assumption of large adoption of electric vehicles, Faridimehr et al. [56] 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. For a more detailed topic for electric vehicle traffic assignment, Yao et al. [57] compared the electric vehicle's energy consumption rate on different road types from the floating car data collected from road networks in Beijing.

Despite the amount of research in TAP, there are many issues that need to be addressed and new techniques need to be developed in order to make full use of the emerging electric vehicle technologies in a way that benefit the overall system and the environment. The complexity of the traffic network is immense due to the non-homogeneous dynamics of different vehicle classes at the vehicle level to model nonlinear behavior at the traffic flow level. Mathematical models used by most TAP schemes cannot possibly capture the complexity of the real system in order to achieve the best possible outcome especially due to the added constraints of the electric trucks. A true optimum route for a truck for example may end up being 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 the model. The availability of fast computers and advanced software tools allows the development of traffic simulation models which can run in real time to provide the information and predicted states of the traffic network 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 to generate more realistic outcomes. In past work [53], [58],we considered the use of real time traffic simulators as part of a centrally coordinated multimodal freight load balancing system and 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 paper, we extend the work of [53], [58] which was focused on diesel trucks to include electric trucks in mixed fleets with diesel trucks. Electric trucks will be gradually entering the market due to efforts to reduce emissions and many 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. 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 and allows to increase the proportion of electric trucks from zero to 100%. Specifically, the contributions are:

- A centrally coordinated mixed freight dynamic routing system which takes into account background traffic interactions to achieve systematic minimal cost is formulated and constructed.
- A multi layer co-simulation optimization method to solve the central coordination problem for the mixed freight fleet that achieves load balancing across the road network by taking into account the impact of loads on travel time and cost is presented and analyzed.
- The diesel and electric truck energy consumption is accurately estimated with the integrated use of an estimated model with a traffic co-simulation that provides information such as link travel times.
- The central coordination system proposed experimentally shows that it can provide better arrangement in aspect of total cost for the mixed freight dynamic routing problem with background traffic interactions taken into account.
- The system is tested under scenarios under various percentages of electric trucks in the whole mixed freight fleet and background traffic conditions. The proposed co-simulation optimization method is experimentally shown to outperform a non-load balanced approach for these scenarios.

As the percentages of electric trucks in a mixed fleet increases from 0% to 100%, the results show that the proposed centrally coordinated routing system reduces the overall cost when compared without such coordination. With the EPA emission model MOVES, it also shows that as the percentage of electric trucks in the fleet increases the emissions reduce linearly as expected. The operational cost however does not reduce as the percentage of electric trucks increases due to the charging cost if we assume that the charging cost takes place while the driver is on duty. In order to see reduction in the operational cost with increasing number of electric trucks the charging of batteries should be done when the driver is off duty or in waiting mode for other than charging purposes.

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

Recent advances in battery technologies led to the development of electric trucks that offer strong potential of cutting operational costs and reducing pollution. Since their penetration will be gradual the question is how the centrally coordinated load balancing approach developed for diesel trucks [53] can be extended to deal with mixed fleets of trucks, diesel and electric. The problem is not straightforward because electric trucks have limited range, require longer charging times and the rate of depletion of battery life depends on traffic conditions. Our proposed method is described as follows: a central coordinator receives from individual users their origin/destination (O/D) demand and information about the mixed fleet of diesel and electric trucks and generates routes that minimize an overall system cost. The impact of the loads on each link is taken into account to achieve a load balance across the road network. The dynamic and predicted link cost information is generated by a traffic simulator that is part of the overall co-simulation optimization approach. The predicted link costs such as travel time is important in calculating battery life in the case of electric trucks.

A. Formulation

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:

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

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

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

$$X_{i,j,r,k}^u \ge 0 \quad (4)$$

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

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

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 calculation of the energy cost is different from the one used in the work of Zhao et al. [53], where it is treated as a constant. In our case, the energy cost depends on the dynamics of the traffic network. More specifically, we formulate the energy cost coefficient of each truck type 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 while in the work of [53] the use of trucks is assumed to be unlimited and one can only constrain the number of trucks indirectly by imposing the capacity on the service segment. Equation (3) can also be used to formulate the distribution of available mixed freight vehicles over the road network at the beginning of the time horizon.

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. As a result, the calculated optimum routes may not be optimum in a realistic situation. In our approach, we introduce the following changes that makes it more likely for a theoretical optimum to be closer to one in practice:

- Instead of using a simplified mathematical model to account for the complex traffic dynamics, we use a traffic simulation model in a co-simulation optimization approach. The simulation model provides a far more accurate description of the traffic dynamical characteristics to be used by the optimum route generator.
- To efficiently apply the simulation model, we construct a service network layer as a connection between the optimizer and the simulation model.
- To speed up the iterative algorithm process, we propose a way to intelligently choose the direction and step size at each iteration based on the knowledge of the marginal cost.

In the next subsection, we discuss the configuration of the service network and the changes it brings to the above formulation.

B. Service Network

To differentiate the notation between the service network and the road traffic network, we use the following terminologies:

- Road network link: edge in the road network
- Path: a sequence of concatenated road network links
- Service segment: edge in the service network
- Route: a sequence of concatenated service segments

A service network can be configured based on a traffic network in the following steps:

- Collect 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 to form the service node set NS. These necessary nodes can be port terminals, truck depots, charging stations and so on.
- Construct a set of segments L connecting nodes in NS.

The service network can be seen as an abstracted upper layer of the traffic network. With the inclusion of the service network, the relations between routes and links can be divided into two parts: relations between routes and service segments and relations between service segments and traffic network links. 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:

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

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 $e_{p,1}, e_{p,2}, \ldots, e_{p,N_p}$, 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:

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

$$\xi_{k,e_{p,1}} = 1 \qquad (8)$$

$$\xi_{k,e_{p,n_p+1}} = \xi_{k,e_{p,n_p}} + w_{e_{p,n_p}, \xi_{k,e_{p,n_p}}} \qquad (9)$$

where $n_p = 1, \ldots, N_p - 1$. 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 $\xi_{k,e_{p,n_p}}$. Given the service segment volume $x_{l,k}^u$ and the path set of segment l, namely P_l, the vehicle dispatching problem in the traffic network can be expressed as follows:

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

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 the 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 as mentioned before. The total cost is represented by summing over the energy consumption cost and travel time cost of all the segments with respect to time and the objective is to find out an assignment for the mixed freight vehicles with minimum total cost. The constraints are defined by equations (6)-(9) generated from the service network as well as the complex dynamics from the simulated traffic network. In our method, the nonlinear dynamical functions for traffic networks are replaced by the real time traffic flow simulation model that generates the states of the network to be used in the optimization problem. Aside from equations (6)-(9), the following equations are used to represent the relation between variables from the service network and the simulated traffic network:

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

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

In this subsection, we discussed the inclusion of the service network and its relations between routes and traffic network links. In the next subsection, we present a co-simulation optimization method for solving the multi-layer routing problem.

C. Solution Methodology

In this subsection, we present the details of the proposed multi-layer co-simulation optimization method for solving the mixed freight dynamic routing problem stated previously. Figure 1 gives a general overview of the method. The service graph optimization plays a central role; in practice, it can be a central coordinator whose aim is to assign trucks to fulfill demands at minimal system cost. The input to the optimization are demands, truck types and their distribution, emission model and other predetermined parameters. Demands represent the number of containers to be transfered from origin to destination nodes. The truck types include the physical (weight, length, frontal area, et al.), dynamic (max speed, acceleration, et al.) and energy consumption (the amount of energy consumed based on the dynamic states) characteristics. 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. An emission model from National Renewal Energy Laboratory (NREL) is used to calculate the emissions. A real-time traffic simulator is used to capture the dynamical characteristics of traffic and provide traffic status 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 marginal cost of each service segment, which is used to

update the route cost. Based on the simulated route cost, the route collection for each O/D pair is updated as well. Then given the updated route collection, the assignment of diesel/electric trucks for each O/D pair is updated by solving an integer combinatorial programming problem using a properly selected efficient step size. The new assignment is then generated and passed to the next iteration. The traffic simulator uses two types of inputs: background traffic flow and assignment traffic flow. The background traffic flow is obtained from various sources, such as PeMS [59] and Google Maps [60]. The assignment traffic flow is generated by the optimizer. 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 assignment traffic flow 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 is equal to 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 $\hat{X}^n$.

$$\min_X \sum_{u \in U} \sum_{k \in K} \sum_{j \in D} \sum_{r \in R^u_{o,j}} MC^u_{o,j,r,k} X^u_{o,j,r,k} \quad (13)$$

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

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

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 [53].

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

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.

Rather than a single-type load balancing case in [53], this paper addresses the two-type vehicle load balancing case. Due to that, the type of steepest descent direction used in the work of [53] 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 at each node for each type of truck as shown in equations (13 - 15).

As mentioned in step 5 and step 6, the marginal cost plays an important role with respect to providing a feasible descent direction as well as an appropriate step size for the algorithm.

D. Marginal Cost

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, which can be calculated through the marginal cost of a path in the segment based on the traffic status from the traffic simulator. 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. It can be formulated as following:

$$\begin{aligned} MCP^{p',u'}_{l',k'} &= \frac{\partial TC}{\partial y^{p',u'}_{l',k'}} \\ &= \frac{\partial \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} (c^{p,u}_{l,k} + \eta t^{p,u}_{l,k}) y^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} \\ &= c^{p',u'}_{l',k'} + \eta t^{p',u'}_{l',k'} + \\ &\quad \eta \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} y^{p,u}_{l,k} \frac{\partial t^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} + \\ &\quad \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} y^{p,u}_{l,k} \frac{\partial c^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} \end{aligned} \quad (17)$$

where the first two terms are the cost of the path and the third term describes the travel time cost change due to the impact
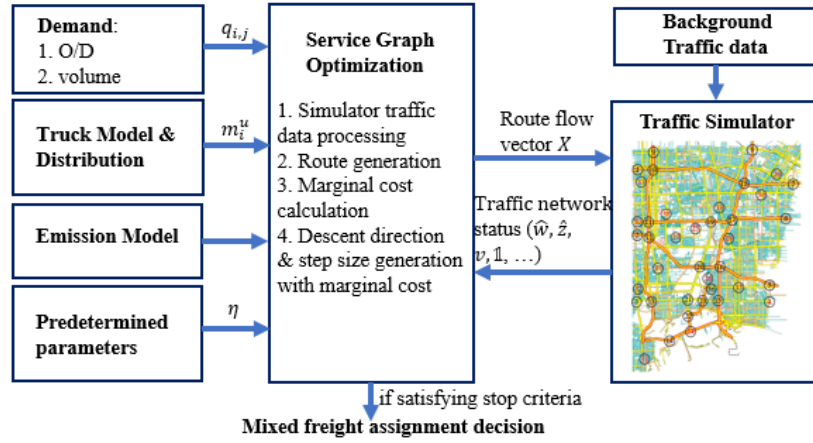
Fig. 1. Framework of proposed mixed freight dynamic routing system

on the link travel time based on the dynamics of the traffic system. The fourth term accounts for the change of energy cost associated with the changes in link volume and can be calculated approximately using the traffic network states from the simulator. A detailed derivation procedure is presented in appendix. The final form of marginal cost is:

$$MCP_{l',k'}^{p',u'} \approx c_{l',k'}^{p',u'} + \eta t_{l',k'}^{p',u'}$$

$$+ \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} \sum_{n_p=1}^{N_p} \mathbb{1}_{e'_{p,n_p}, \xi_{k'}, e'_{p,n_p}} (e_{p,n_p}, \xi_{k,e_{p,n_p}})$$

$$\cdot y_{l,k}^{p,u} \frac{1}{v_{p,n_p,k} \Delta t} (\eta + \frac{\partial h^u(v_{p,n_p,k})}{\partial \hat{w}_{p,n_p,k}} d_{p,n_p}) B_{p,n_p,k} \hat{z}_{p,n_p,k}^{\beta_{e_{p,n_p}}-1}$$

$$\forall l' \in L, p' \in P_{l'}, k' \in K, u' \in U \tag{18}$$

where $\frac{\partial h^u(v_{p,n_p,k})}{\partial \hat{w}_{p,n_p,k}}$ is obtained from equation (30). Since the first and second terms are decomposable with respect to the links, the marginal costs of the paths belonging to the same segment will be placed in equilibrium by running a dynamic assignment algorithm. Then the marginal cost for a segment $MC_{l',k'}^{u'}$ is approximated by its marginal cost of path $MCP_{l',k'}^{p',u'}$,

$$MC_{l',k'}^{u'} \approx MCP_{l',k'}^{p',u'}, \forall l' \in L, k' \in K, u \in U \tag{19}$$

From equation (31), we can see that to calculate the marginal cost of a segment requires the knowledge of the propagation of other segments ($\mathbb{1}_{e'_{p,n_p}, \xi_{k'}, e'_{p,n_p}} (e_{p,n_p}, \xi_{k,e_{p,n_p}})$), the basic traffic network status ($\hat{w}_{p,n_p,k}, \hat{z}_{p,n_p,k}, v_{p,n_p,k}, h^u(v_{p,n_p,k})$), as well as the aggregated segment-level information ($c_{l,k}^{p,u}, t_{l,k}^{p,u}, y_{l,k}^{p,u}$) from the simulator. With the marginal cost of each segment updated, route collections are updated by checking whether there are new lower marginal cost routes. Then the route flow vector X is updated to move along the descent direction with the step size described in the previous subsection with the knowledge of the updated marginal cost. The algorithm stops when no more improvement on the total cost can be gained. In the next section we implement the method and present some numerical results.

III. NUMERICAL EVALUATION

This section presents the evaluation of the proposed approach using a regional transportation network which covers the Los Angeles/Long Beach terminal port area from the south to I 105 freeway in the north. 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. The road traffic network is shown in Figure 2 and simulated using the macroscopic traffic simulator VISUM [61]. The background

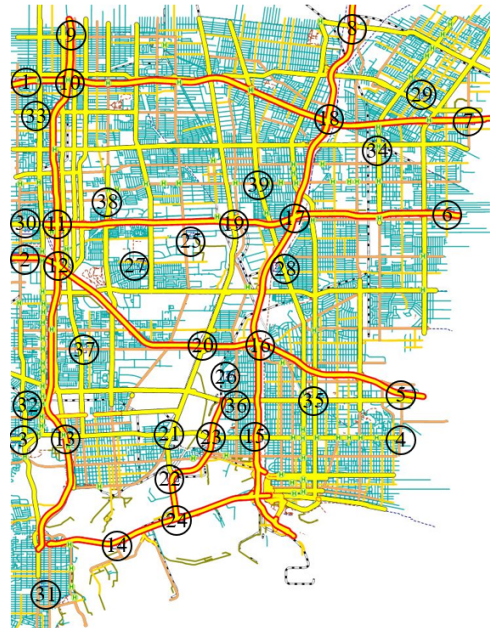Fig. 2. Road Network Overview

traffic is expressed as the number of trips between nodes that are origins and destinations. The historical freeway traffic flow data are obtained from PeMS [59] and Google Maps [60]. The raw traffic data are processed (formatted/truncated/aggregated) to fit the format of the traffic simulator. The traffic conditions used in the numerical evaluation are: off-peak (2am to 6am),

medium (12pm to 4pm), peak (7am to 11am). The demand for the O/D matrix is shown in Table I. The total number of all demands is 1715 containers according to the demand matrix in Table I, with the assumption that each truck can only load one container and the demand is considered to be fulfilled by a single-direction route. As a result, the total number of freight vehicles is equal to 1715. The locations of service network nodes are presented in numbers with circle around in Figure 2. The service network nodes are composed of O/D nodes as well as intersections of freeways and major arterial ways. The service nodes also play roles of 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. The length of each interval is 30 minutes.

The advantage of the optimized load balancing co-simulation method proposed in this paper is summarized as follows: It minimizes the total route assignment cost by balancing the load in each route based on the information generated by the dynamic traffic simulator. We demonstrate the benefits of the proposed method by comparing it with the following two methods. In method one we simply use the simulator to carry out the assignment of routes as follows: we assume that for each pair of O/Ds we use the traffic simulator to determine the minimum cost route to be followed by each diesel/electric truck without performing any load balancing optimization. In the second method we do not use the traffic simulator to provide traffic information but instead use historical traffic data to provide traffic information along the routes. The historical information is used to carry out the load balancing optimization. In all cases we assume that the percentage of electric trucks changes from 0 to 100%. The results are shown in Figure 3. In method one, due to the lack of optimized load balancing, all trucks are routed along the same route which appears to be the minimum cost one initially however it gets congested due to the added loads. The lack of optimized load balancing does not provided any anticipation and correction that if all trucks are routed along any minimum cost route the route may no longer be the minimum cost route due to the added loads. According to Figure 3, method one increases the cost by 24.8% when compared with the cost of the proposed optimized load balancing with co-simulation. In method two the optimized load balancing uses historical traffic information rather than the dynamic ones generated by the traffic simulator. Since historical data do not capture the effects of added loads to the routes, method two increases the cost by 15% when compared with the proposed approach of optimized load balancing with co simulation. In the case of optimized load balancing co-simulation method, the changes in traffic flow characteristics on a certain route as well as the reactions of background traffic are reflected in the marginal cost so that the freight vehicles assigned on one route may be shifted to another route with lower marginal cost. In this way, the total cost of the assignment of mixed freight is reduced.

We next test the system under different scenarios of various percentages of electric vehicles. The experimental scenarios are constructed in the following manner: under each traffic
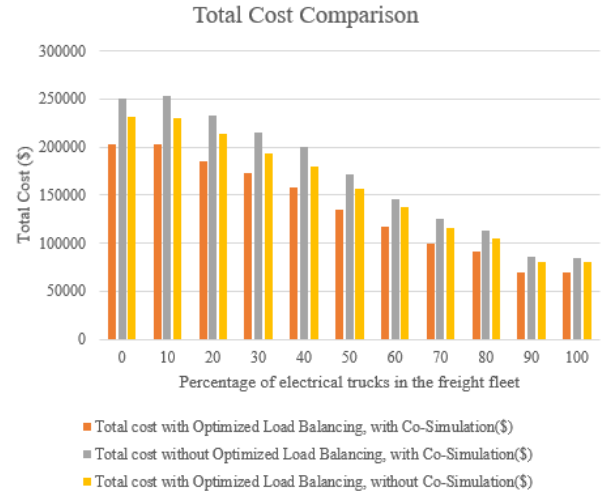

Fig. 3. Total cost comparison between assignment with/without optimized load balancing and with/without co-simulation

condition, the percentage of electric vehicles in the fleet is varied from 0% to 100% in increments of 10%. To obtain the accurate energy consumption of both types under various working conditions, we implement analytical models of diesel/electric engines, which give the power consumed under the different traffic situations. The diesel truck engine model used is based on [62] and the electric truck engine model is based on the work of [63]. Table II summarizes the vehicle characteristics and parameters used in these models. The energy consumption coefficient function $h(v)$ in units of US dollar per mile per ton is obtained using the following procedure:

1: Test the engine models under different drive cycles.
2: Average the total energy consumption for each drive cycle by the length. We use EC as energy consumption per mile.
3: For each drive cycle, transfer the energy consumption per mile to US dollars based on [64]. A sequence of feature pair (v, C) is obtained for every drive cycle. v is the average speed and C is the US dollar per mile per ton.
4: Use regression to to calculate the polynomial coefficients of $h(v)$ given by equation (29) based on the (v, C) sequence.

To test the engine models, we use the following drive cycles provided by NREL [65]:

- 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 energy consumption for each drive cycle by diesel/electric trucks is obtained and shown in Table III. The energy cost

TABLE I
DEMAND MATRIX BY ORIGINS (1st COLUMN) AND DESTINATIONS (1st ROW) (UNIT: NUMBER OF CONTAINERS)

	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 II
PREDETERMINED PARAMETERS

Truck weight	80,000 lbs
Frontal area	107.639 ft^2
Air density	0.076512 lb/ft^2
Los Angeles elevation	285 ft
Drag coefficient	0.78
Road grade	0

TABLE III
AMOUNT OF ENERGY CONSUMED (KWH)

Drive Cycle	suburban	transient	cruise	creep	composite
Diesel Engine	650.71	277.50	2257.19	15.14	2558.53
Electric Engine	500.04	187.09	574.10	79.18	840.38

coefficient function for diesel trucks is found to be:

$$h^d(v) \;=\; 11.327 - 0.649v + 0.045v^2 - 0.001v^3 \quad (20)$$

For electric trucks, it is found to be:

$$h^e(v) \;=\; 66.552 - 7.670v + 0.291v^2 - 0.004v^3 \quad (21)$$

According to [66], 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 [67]. In this paper, we chose the hourly time value to be $60 in terms of year 2020 US Dollar value which is between the calculated range. With respect to charging cost we assume the cost of $60 per hour which is the same as the assumed time cost. In our simulation we assume that it takes 4 hours for a full charge which is equivalent to $240. Using the demand, diesel/electric consumption models and cost measurements, the mixed freight dynamic routing is performed under three states of background traffic conditions. The computational time varies from 6 to 15 CPU hours running on a desktop computer 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. The emissions are calculated by the modified EPA model MOVES [68] with speed as input and emissions in units of g/mile as output. We present the results under light, medium and heavy traffic

condition in Table IV, V and VI. Similar result patterns are observed under light, medium and heavy traffic conditions. We can see that by increasing the % of electric trucks, all types of emissions are decreasing. Another observation is that by increasing the % of electric trucks the overall cost does not decrease. The cost of charging time becomes more and more dominant as the % of electric trucks increases.

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

- The proposed system provides an improvement on average of 24% reduction in total cost when compared with one without optimized load balancing and on average of 15% reduction with one without co-simulation.
- The computational time of the system increases with the number of service nodes in the service network.
- The total cost without including charging cost decreases as the % of electric vehicles increases. However, this does not imply that for a specific route the use of an electric truck is less costly than that of a diesel truck 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 % of electric trucks in the fleet. The assumption made is that the charging cost includes the labor cost of the driver waiting for the truck to charge. By comparing the total cost including/excluding charging time in the results, we can observe that if charging is done off-duty the total cost can be reduced considerably.
- As expected the emissions go down as the number of electric vehicles increases in the fleet.
- With the background traffic becoming denser, the total cost of the mixed freight load balancing assignment increases in both with and without charging time cases. The emissions also increase when more background traffic volumes are introduced.

IV. CONCLUSION

In this paper, we have proposed a mixed fleet freight centrally coordinated dynamic routing system based on a multi-layer co-simulation optimization method to achieve freight load balance across the road network. The interactions with background traffic have been considered in the problem and as well as inclusions of electric trucks with their penetration

TABLE IV
SYSTEM PERFORMANCE UNDER LIGHT TRAFFIC CONDITION

% of electric trucks	Total Cost excluding Charging Time ($)	Total Cost including Charging Time ($)	Fuel Consumption (kg)	HC (g)	CO (g)	NOX (g)	CO2 (g)	PM25 (g)
0	172328	172328	48795	326285	1774270	4.44E+08	6.029E+09	108206
10	169626	187518	40152	271275	1486175	3.67E+08	4.939E+09	89007
20	157701	198185	35268	236125	1294190	3.16E+08	4.348E+09	77997
30	139126	189146	34524	230265	1262089	3.01E+08	4.192E+09	75352
40	132025	193674	32126	212654	1167681	2.94E+08	3.905E+09	69635
50	109351	184795	23027	150165	798596	2.04E+08	2.712E+09	50062
60	96514	187232	18709	122467	668709	1.66E+08	2.2E+09	38363
70	82749	201714	13627	87953	474061	1.23E+08	1.635E+09	29916
80	70336	206551	12803	86910	461329	1.13E+08	1.586E+09	27562
90	53944	212140	5535	36557	202138	5.04E+07	6.69E+08	12184
100	51405	230165	0	0	0	0	0	0

TABLE V
SYSTEM PERFORMANCE UNDER MEDIUM TRAFFIC CONDITION

% of electric trucks	Total Cost excluding Charging Time ($)	Total Cost including Charging Time ($)	Fuel Consumption (kg)	HC (g)	CO (g)	NOX (g)	CO2 (g)	PM25 (g)
0	202314	202314	54463	366287	1956335	5.02E+08	6.84E+09	120242
10	202257	224713	45569	306923	1661841	4.1E+08	5.66E+09	98088
20	185173	237215	38827	260615	1453709	3.63E+08	4.83E+09	88390
30	172387	236043	38419	254809	1409051	3.51E+08	4.7E+09	85270
40	158458	237497	38221	245926	1363944	3.34E+08	4.64E+09	80821
50	135261	230954	27039	176205	958313	2.37E+08	3.21E+09	59813
60	117093	232410	22068	143238	801409	1.98E+08	2.58E+09	45688
70	99657	250769	16198	105238	551661	1.42E+08	1.94E+09	35764
80	91432	264854	15530	103339	536964	1.35E+08	1.92E+09	33910
90	69514	272969	6841	44689	248909	6.24E+07	8.2E+08	14642
100	69351	301123	0	0	0	0	0	0

TABLE VI
SYSTEM PERFORMANCE UNDER HEAVY TRAFFIC CONDITION

% of electric trucks	Total Cost excluding Charging Time ($)	Total Cost including Charging Time ($)	Fuel Consumption (kg)	HC (g)	CO (g)	NOX (g)	CO2 (g)	PM25 (g)
0	337883	328357	92368	662831	3084400	8.28E+08	1.07E+10	203417
10	365334	362831	68173	574148	2641681	7.08E+08	8.85E+09	180032
20	281215	410149	67346	461815	2471731	6E+08	8.13E+09	154795
30	293060	447340	72393	443857	2409706	5.89E+08	7.32E+09	152612
40	273118	341798	60493	378233	2088242	5.37E+08	7.02E+09	131985
50	209046	342228	50254	268813	1494408	3.65E+08	4.85E+09	98162
60	201568	357070	33464	267528	1380235	3.62E+08	4.63E+09	72735
70	151413	473325	27546	184257	888319	2.6E+08	3.34E+09	64057
80	138993	399298	22313	178121	777054	2E+08	2.8E+09	48933
90	127869	461474	11457	64982	462265	1.07E+08	1.48E+09	24746
100	106205	533655	0	0	0	0	0	0

varying from 0% to 100%. The electric trucks have additional constraints that include limited range, longer refueling (charging) times and in addition the depletion rate of the battery life depends on traffic conditions. These characteristics introduce additional constraints that need to be taken into account in finding optimum routes that lead to freight load balance across the road network. We have solved the problem by using a multi-layer optimization method; one layer for the traffic simulator to accurately predict the states of the transportation system and another layer of service network to generate the optimum routes. A realistic traffic network in the Los Angeles/Long Beach area that includes the two ports has been used to evaluate the approach and the impact of electric trucks in a mixed fleet. The proposed optimized load balancing with co-simulation leads to an average 24% reduction in total cost when compared with the method of no load balancing optimization and using co-simulation in the assignment of routes. In addition the proposed method leads to an average 15% reduction in total cost when compared with a method of optimized load balancing based on historical traffic data instead of those generated by the co-simulator. Another result reveals that although the use of electric trucks can notably reduce the emissions, the charging time cost makes the operational cost of electric trucks comparable or higher than diesel trucks. It is assumed that charging is done during working hours and includes the driver cost. One future direction to make the operational cost of electric trucks lower than those of diesel trucks is to schedule charging during driver off hours or during times that the driver is idle for job purposes.

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APPENDIX
DERIVATION OF MARGINAL COST

The marginal cost represents the change in the total cost if one unit of demand/container is changed on the path and is formulated as following:

$$
\begin{aligned}
MCP_{l',k'}^{p',u'} &= \frac{\partial TC}{\partial y_{l',k'}^{p',u'}} \\
&= \frac{\partial \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} (c_{l,k}^{p,u} + \eta t_{l,k}^{p,u}) y_{l,k}^{p,u}}{\partial y_{l',k'}^{p',u'}} \\
&= c_{l',k'}^{p',u'} + \eta t_{l',k'}^{p',u'} + \eta \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} y_{l,k}^{p,u} \frac{\partial t_{l,k}^{p,u}}{\partial y_{l',k'}^{p',u'}} + \\
&\quad \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} y_{l,k}^{p,u} \frac{\partial c_{l,k}^{p,u}}{\partial y_{l',k'}^{p',u'}}
\end{aligned}
\tag{22}
$$

where the first two terms are the cost of the path and the third term describes the travel time cost change due to the impact on the link travel time based on the dynamics of the traffic system. The fourth term accounts for the change of energy cost associated with the changes in link volume and can

be calculated approximately using the traffic network states from the simulator. According to the derivative chain rule and equation (7),

$$\frac{\partial t^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} = \sum_{n_p=1}^{N_p} \frac{\partial \hat{w}_{p,n_p,k}}{\partial y^{p',u'}_{l',k'}} = \sum_{n_p=1}^{N_p} \frac{\partial \hat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}} \frac{\partial \hat{z}_{p,n_p,k}}{\partial y^{p',u'}_{l',k'}} \quad (23)$$

where $\hat{z}_{p,n_p,k}$ is the traffic volume of the link e_{p,n_p} on path p with the path departure time being $\xi_{k,e_{p,n_p}}$. The term $\frac{\partial \hat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}}$ represents the travel time change in link e_{p,n_p} at time $\xi_{k,e_{p,n_p}}$ caused by changing the link volume by one unit. One of the most commonly used relationships between link volume and travel time is the Bureau of Public Roads (BPR) function [69]:

$$w_e = t_f(1 + \alpha_e(\frac{z_e}{\text{cap}_e})^{\beta_e}) \quad (24)$$

where w_e is the link travel time, t_f is the link free-flow travel time, z_e is the vehicle volume on link e and cap_e is the road link capacity. α_e and β_e are parameters for the model and can be estimated through historical traffic data. Then the link travel time derivative $\frac{\partial \hat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}}$ based on equation (24) can be written as follows:

$$\frac{\partial \hat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}} = \frac{\alpha_{e_{p,n_p}} \beta_{e_{p,n_p}} t_f \hat{z}^{\beta_{e_{p,n_p}}-1}_{p,n_p,k}}{\text{cap}_{e_{p,n_p}}} \equiv B_{p,n_p,k} \hat{z}^{\beta_{e_{p,n_p}}-1}_{p,n_p,k} \quad (25)$$

The calculation of the term $\frac{\partial \hat{z}_{p,n_p,k}}{\partial y^{p',u'}_{l',k'}}$, in the view of the service network level, can be estimated in an aggregated way. We introduce $\mathbb{1}_{e',t'}(e,t)$ be the indicator equal to 1 when $e = e'$ and $t = t'$, and 0 otherwise. Using $v_{p,n_p,k}$ to represent the speed of the n_p-th link in path p at time $\xi_{k,e_{p,n_p}}$, we get

$$\frac{\partial \hat{z}_{p,n_p,k}}{\partial y^{p',u'}_{l',k'}} \approx \mathbb{1}_{e'_{p,n_p},\xi_{k',e'_{p,n_p}}}(e_{p,n_p}, \xi_{k,e_{p,n_p}}) \frac{1}{v_{p,n_p,k}\Delta t} \quad (26)$$

where $e'_{p,n_p} \equiv e_{p',n_{p'}}$. With equations (23)-(26) we get

$$\frac{\partial t^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} \approx \sum_{n_p=1}^{N_p} \frac{\mathbb{1}_{e'_{p,n_p},\xi_{k',e'_{p,n_p}}}(e_{p,n_p}, \xi_{k,e_{p,n_p}})}{v_{p,n_p,k}\Delta t} \frac{\partial \hat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}} \quad (27)$$

The term $\frac{\partial c^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}}$ is obtained by applying the chain rule as:

$$\frac{\partial c^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} = \sum_{n_p=1}^{N_p} \frac{\partial h^u(v_{p,n_p,k})}{\partial v_{p,n_p,k}} \cdot \frac{\partial v_{p,n_p,k}}{\partial \hat{w}_{p,n_p,k}} \frac{\partial \hat{w}_{p,n_p,k}}{\partial y^{p',u'}_{l',k'}} d_{p,n_p} \quad (28)$$

where $h^u(v)$ is the energy consumption coefficient function for the trucks of type u and d_{p,n_p} is the length of link e_{p,n_p}. In this paper, we assume that the energy consumption coefficient $h^u(v)$ satisfies a cubic polynomial function of the speed v:

$$h^u(v) = b^u_0 + b^u_1 v + b^u_2 v^2 + b^u_3 v^3 \quad (29)$$

where the parameters of the polynomial are estimated for both electric and diesel trucks using off-line experiments demonstrated in the numerical evaluation section . The relationship

between speed v and its travel time w is simply $v = \frac{d}{w}$, where d is the length of a road link. Then we obtain

$$\frac{\partial h^u(v_{p,n_p,k})}{\partial \hat{w}_{p,n_p,k}} = \frac{\partial h^u(v_{p,n_p,k})}{\partial v_{p,n_p,k}} \frac{\partial v_{p,n_p,k}}{\partial \hat{w}_{p,n_p,k}}$$
$$= -\frac{(b^u_1 + 2b^u_2 v_{p,n_p,k} + 3b^u_3 v^2_{p,n_p,k})d_{p,n_p}}{\hat{w}^2_{p,n_p,k}} \quad (30)$$

By combining equations (22) - (30), the marginal cost of a path in a segment can be approximately calculated by,

$$MCP^{p',u'}_{l',k'} \approx c^{p',u'}_{l',k'} + \eta t^{p',u'}_{l',k'}$$
$$+ \sum_{k \in K} \sum_{l \in L} \sum_{p \in P_l} \sum_{n_p=1}^{N_p} \mathbb{1}_{e'_{p,n_p},\xi_{k',e'_{p,n_p}}}(e_{p,n_p}, \xi_{k,e_{p,n_p}})$$
$$\cdot y^{p,u}_{l,k} \frac{1}{v_{p,n_p,k}\Delta t}(\eta + \frac{\partial h^u(v_{p,n_p,k})}{\partial \hat{w}_{p,n_p,k}} d_{p,n_p}) B_{p,n_p,k} \hat{z}^{\beta_{e_{p,n_p}}-1}_{p,n_p,k}$$
$$\forall l' \in L, p' \in P_{l'}, k' \in K, u' \in U \quad (31)$$

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