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16. ABSTRACT

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 such as the integration of battery electric trucks (BEHTs) and techniques of truck platooning, offer a strong potential for dramatic improvements in balancing freight loads in multimodal networks. However, the electric trucks impose additional constraints due to the limitation of range and charging time of batteries; the different forms of truck platooning also require analysis with the combination of a coordinated routing system.

In this project, the design and evaluation of a freight load balancing system are addressed 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

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Executive Summary

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 such as the integration of battery electric trucks (BEHTs) and techniques of truck platooning, offer a strong potential for dramatic improvements in balancing freight loads in multimodal networks. However, the electric trucks impose additional constraints due to the limitation of range and charging time of batteries; the different forms of truck platooning also require analysis with the combination of a coordinated routing system.

In this project, the design and evaluation of a freight load balancing system are addressed 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 and space. The load balancing system is developed for two type of trucks, diesel and battery electric. Battery electric trucks are assumed to be those that qualify as a zero emission freight vehicle (ZEFV) under current California law and 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 BEHTs have a higher capital cost, shorter range, and longer refueling time than diesel trucks. The benefits of optimized load balancing with co-simulation for a mixed freight routing system are compared with alternative approaches of routing based on a co-simulator with no optimized load balancing over time and with optimized load balancing using historical traffic data instead of the data generated by the co-simulator. In both cases the proposed load balancing approach with co-simulation provides significant reduction in total cost. The effect of the percentage of electric trucks in the mixed fleet of vehicles on the total cost is also investigated.

Due to the complexities of traffic road network and the need to apply the coordinated routing system on a large-scale network, a distributed version of the optimized load balancing co-simulation method is proposed. The performance of various partitioning techniques with respect to number of subnetworks, boundary nodes and demands under different penetration of electric trucks is experimented.

Finally, the concept of truck platooning has been incorporated into the proposed mixed freight load balancing system. Truck platooning is defined as a string of vehicle driving along the same lane as if it was one long vehicle. Truck platooning seeks to reduce the energy consumption via the reduction of air drag force on the vehicles. The purpose of incorporating truck platooning into the 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 as well as the Los Angeles Metropolitan area are used for evaluation. The main outcomes of these evaluations are listed as follows:

- *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.*
- *The scalability issue can be solved by using a distributed load balancing method.*
- *For the Long Beach network, the distributed load balancing is tested based on different number of subnetworks, demands and boundary nodes. By increasing the number of boundary nodes, we can achieve better assignment with more computational time. By increasing the number of subnetworks, we can achieve a large amount of computational time with a relatively small loss on optimality. However, a proper decomposition is needed since if the network is decomposed too much, the interactions between subnetworks will compromise the computational time gained from decomposition.*
- *For Los Angeles Metropolitan network, similar relation between performance and number of subnetworks is revealed.*
- *The proposed method is compatible with different truck platooning techniques and presents advantages with respect to total cost by utilizing truck platooning.*

We have to emphasize that the research performed is a preliminary step toward a 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 coordinated freight load balancing system by solving some challenging problems whose solutions point the directions for future research.

Table of Contents

1. 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 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]. 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. Containers in the ports are distributed through various of transportation mode, such as truck and rail freight. 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 [2]. 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% [2]. Trucks dominate due to shipment size, trip length, and ubiquity of the road network, [3]–[6]. 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. According to [7], due to the increase of container movement, 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 [8], 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 [9]. According to a report from the European Union [10], about 26% of the CO_2 emissions are due to heavy-duty vehicles. In European Union the impact of trucks on CO2 emissions is also significant relative to that of other vehicle classes as according to [10] 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 [10] 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 [11]. 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) [12]. 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 [12]. 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% [12]. 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 [13]. Nevertheless the industry is moving ahead with companies like Volvo and Tesla producing electric trucks [14] 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 [15], as a generalization of the Traveling Salesman Problem (TSP) presented by Flood [16]. 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. [17], Cordeau et al. [18], Laporte [19], [20], and Toth and Vigo [21]. 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 [22], [23]; and stochastic demands [24]–[28]. 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 [24]–[28]. Additional work on shortest route problems which cover the four categories mentioned can be found in [29]–[37] which also include work on multimodal routing and planning.

With respect to electric vehicle routing, Ambrose and Jaller [38] 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 [39]. Bahrami et al. proposed a complementarity equilibrium model for electric vehicles without violating driving range constraints [40]. Based on the assumption of large adoption of electric vehicles, Faridimehr et al. [41] 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. [42] 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.

Along the pursuit for energy saving, researchers in the area of truck automation came up with the idea of platooning, where a string of vehicles drive along the same trajectory with only a short gap in between, since the emerging of automated driving for passenger vehicles from the 1950s [43]. Driving experiments on testing the performance of different form of truck platooning are conducted around the world [44]–[50]. Gehring and Fritz [44]conducted experiments on a platoon of three heavy-duty trucks along the Brenner Pass through the Alps between Austria and Italy with a longitudinal control with vehicle to vehicle communication. Lu and Shladover [47], [51] applied Dedicated Short Range Communication (DSRC) radio sets with an automatic longitudinal control on a platoon of three Class 8 trucks and showed an average 4.3% energy saving from the lead truck, 10% from the second truck and 14% from the third truck. Kunze et al. [48] developed a platoon system of four heavy duty trucks, constituted with a lead truck driven by a human driver and three following trucks by automated driving system. Tsugawa [49] developed a automated control system with lateral control and longitudinal control for a platoon of three trucks and showed the saving on fuel consumption is 15% in simulation. However, based on the knowledge of authors, researches and analysis on the routing system that cover platooning techniques are still left to be fully studied. In one section of this report, we integrated the characteristics of truck platooning into the routing system for heavy-duty trucks and studied the impact of it.

In our past work [37], [52] 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 [37], [52] 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. The idea of truck platooning was integrated into the system and experiments on the impacts from different platooning techniques were also examined. Also, as a solution for the computation complexity induced by the scalability of network, a distributed version of the dynamic routing system is proposed and tested as a section of this report.

The report is organized as follows. Section 2 deals with the main project content. Respectively Section 2.1 presents the literatures of dynamic models for truck platoons. Section 2.2 presents the traffic simulator built for the real-time traffic prediction with a commercial transportation software. Section 2.3 presents the formulation of the optimization models for the mixed freight load balancing system and the optimization algorithm. Section 2.4 presents the key elements for the optimization algorithm as well as the emission model to assess the emission from the whole assignment procedure. Section 2.5 presents the partitioning techniques for distributed routing generation and in Section 2.6 we present the simulation results that demonstrate the consistency of performance. Finally, conclusions are presented in Section 3 and appendices can be found in section 4.

2. Project Contents

2.1 Dynamic models of truck platoons

In this section, we performed an extensive literature review on characteristics of different types of commercial vehicles, fuel economy and refueling conditions of trucks that already in service. The studies reviewed are: Port of LA interim electric drayage report [53], Foothill bus comparative study [54], studies from California Air Resources Board (CARB) [55], Frito-Lay delivery truck comparative study [56], Smith Newton trucks [57], Navistar eStar [57] as well as a market survey developed by Giuliano et al [58]. The characteristics of different types of commercial vehicles, fuel economy and refueling time are presented in Table I, II and III.

Table I: 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 II: 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	17.48
		CNG	8	4.51
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	0.345 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	24.09
		Diesel	9	7.63
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 given	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 III: 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)
Firto-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

More acceleration behaviors are presented in Table IV from [59].

Table IIV: Acceleration behavior

Type	**Sample Size**	**Piecewise-constant average acceleration rates (ft/s^2)**							**0-500 ft. Average acceleration rate (ft/s^2)**	
Heavy-duty	71	a_{0-20}	a_{20-50}	a_{50-100}	$a_{100-200}$	$a_{200-300}$	$a_{300-400}$	$a_{400-500}$	Mean	S.D.
		2.12	1.97	2.04	1.91	1.91	1.94	1.86	1.93	0.42

However, the statistics found are static and the trucks are working under various conditions so that its dynamic characteristics vary in different working conditions. In a summery, the characteristics of trucks can be divided into two categories: constant and variant. The constant characteristics include length, shape, number of wheels, et al. The variant characteristics are the ones that change with working mode: such as air resistance force and energy consumption rate. To achieve an accurate estimation of the variant characteristics, we proposed a method that combines mapping the driving speed to working mode and mapping the working mode to energy consumption rate. Aa an important part of this procedure, the analytical model of typical diesel engines and electric engines need to be implemented and tested with driving cycles. Drive cycles are files that document the speed of a specific vehicle interval by interval under some driving mode. The analytic model [60] is used to describe the diesel engine and [61] to describe the electric engine of heavy-duty freight vehicles. In this project, we use the following typical drive cycles provided by National Renewable Energy Laboratory (NREL) [62]:

- California Air Resources Board (CARB) Heavy Heavy-Duty Diesel Truck (HHDDT) Composite Cycle
- CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Creep Segment (a drive cycle with average speed 1.76 mph, average driving speed 3.00 mph, max speed 8.20 mph)
- CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Cruise Segment (a drive cycle with average speed 39.86 mph, average driving speed 43.22 mph, max speed 59.30 mph)
- CARB Heavy Heavy-Duty Diesel Truck (HHDDT) Transient Segment (a drive cycle with average speed 15.36 mph, average driving speed 18.20 mph, max speed 47.50 mph)
- City Suburban Heavy Vehicle Cycle (CSHVC)

By testing drive cycles with diesel and electric engines, we gained the results showed in Table V.

Table V: Amount of energy consumed (kWh) by the diesel & electric engine

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

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%

2.2 Traffic simulator for real time traffic predictions

In this section, we selected a road network in Southern California that includes the twin ports and used a commercial software to develop traffic simulation models. The simulation software chosen is VISUM, which is a macroscopic traffic simulator. The advantage of the macroscopic traffic simulator over the microscopic one is that a macroscopic traffic simulator can efficiently generate the predicted traffic states, which is required for on-line large-scale applications where complexity makes microscopic simulations difficult if at all possible. The road network is shown in Fig 1. The network covers an area from the Los Angeles/Long Beach terminal port area from the south to I 105 freeway in the north. The numbers with circle represent the locations of service network nodes. The service network nodes are composed of O/D nodes as well as intersections of freeways and major arterial ways. The traffic simulator serves as a predictor for the traffic status during the whole method procedure. The numbers in the circles are service nodes used in service network, which is introduced in the method.

Figure 1: Road network configured in Visum

2.3 Optimum truck routing

2.3.1 Optimization model

In this subsection, we developed the optimization models for the centrally coordinated mixed freight routing system where different shippers send their demand to a central coordinator. We also developed a co-simulation optimization approach to solve the problem, which can be 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.

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, $i \in O, j \in D$;

- $X^u_{i,j,r,k}$: The number of trucks of type u from i to j, $i \in O, j \in D$, using route r in route set $R^u_{i,j}$ with a departure time k;
- $S^u_{i,j,r,k}(X)$: 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 $R^u_{i,j}$ with a departure time k;

Given the above notation we formulate the problem as follows:

$$min_X \sum_{k\in K}\sum_{i\in O}\sum_{j\in D}\sum_{u\in U}\sum_{r\in R^u_{i,j}} S^u_{i,j,r,k}(X)X^u_{i,j,r,k} \tag{1}$$

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

$$\sum_{k\in K}\sum_{j\in J}\sum_{r\in R^u_{i,j}} X^u_{i,j,r,k} \leq m^u_i, \forall\, i \in I, u \in U \tag{3}$$

$$X^u_{i,j,r,k} \geq 0 \tag{4}$$

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. $S^u_{i,j,r,k}(X)$ 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 $S^u_{i,j,r,k}(X)$ is given by:

$$S^u_{i,j,r,k}(X) = C^u_{i,j,r,k}(X) + \eta\, T^u_{i,j,r,k}(X) \tag{5}$$

where $C^u_{i,j,r,k}(X)$ is the cost of the consumed energy, $T^u_{i,j,r,k}(X)$ 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 parts. 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. 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.

To understand our method, we first discuss the configuration of the service network and the changes it brings to the above formulation. 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. 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 $\backslash tau$ 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 $\widehat{w}_{p,n_p,k} \equiv w_{e_{p,n_p},\xi_{k,e_{p,n_p}}}$ 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, the vehicle dispatching problem in the traffic network can be expressed as follows:

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

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 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:

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

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

2.3.2 Optimization algorithm

In this subsection, we discuss the optimization algorithm used to solve this problem. Figure 2 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 inputs to the optimization are demands, truck types and their distribution, emission model and other predetermined parameters. Demands represent the number of containers to be transferred 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.

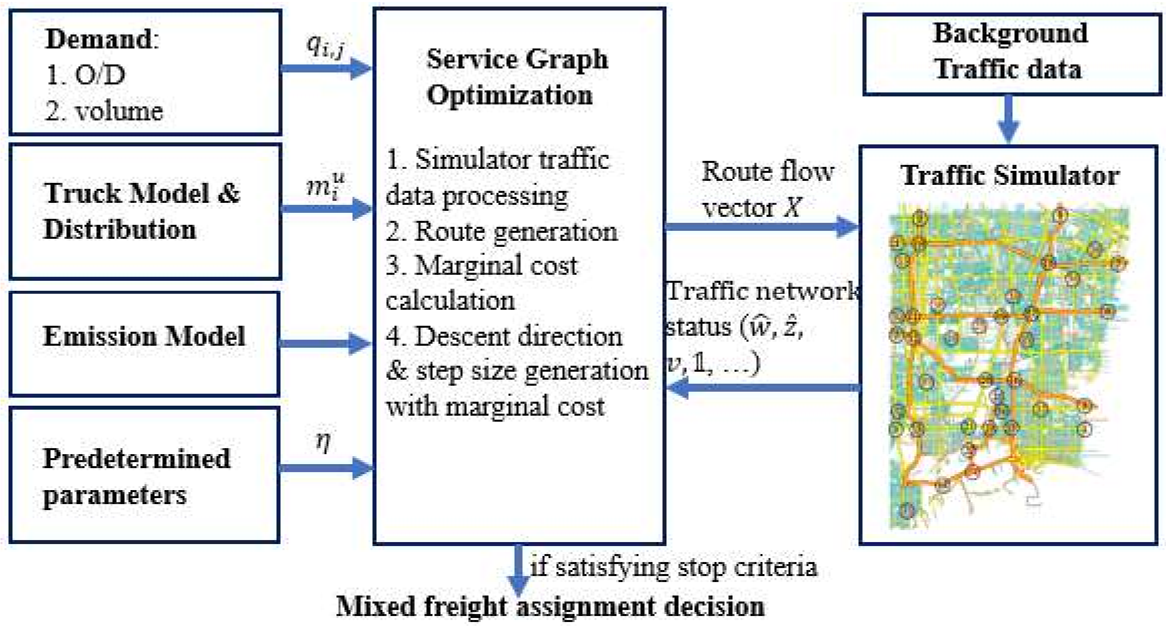

Figure 2: Framework of proposed method

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 [63] and Google Maps [64]. 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:

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

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

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

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

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

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.

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 [37].

In the optimization algorithm, marginal cost of each segment serves as an important role, in pointing out the direction as well as the step size for the next iteration for the optimization algorithm. In the next subsection, we will present the calculation of marginal cost, which in essence tells us the evaluation of the routes. Also, an emission model used for the test of emissions from the procedure is introduced in the next subsection.

2.4 Evaluation of optimum routes

2.4.1 Marginal cost

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

$$MCP^{p',u'}_{l',k'} = \frac{\partial TC}{\partial y^{p',u'}_{l',k'}} = \frac{\partial \sum_{k\in K} \sum_{l\in L} \sum_{p\in P_;} (c^{p,u}_{l,k} + \eta\, t^{p,u}_{l,k}) y^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}}$$

$$= c^{p',u'}_{l',k'} + \eta\, t^{p',u'}_{l',k'} + \eta \sum_{k\in K} \sum_{l\in L} \sum_{p\in P_;} \frac{\partial t^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} y^{p,u}_{l,k} + \sum_{k\in K} \sum_{l\in L} \sum_{p\in P_;} \frac{\partial c^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} y^{p,u}_{l,k} \tag{16}$$

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):

$$\frac{\partial t^{p,u}_{l,k}}{\partial y^{p',u'}_{l',k'}} = \sum_{n_p=1}^{N_p} \frac{\partial \widehat{w}_{p,n_p,k}}{\partial y^{p',u'}_{l',k'}} = \sum_{n_p=1}^{N_p} \frac{\partial \widehat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}} \frac{\partial \hat{z}_{p,n_p,k}}{\partial y^{p',u'}_{l',k'}} \tag{17}$$

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 $\frac{\partial \widehat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}}$ 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 [65].

$$w_e = t_f(1 + \alpha_e \left(\frac{z_e}{CAP_e}\right)^{\beta_e} \tag{18}$$

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 $\frac{\partial \widehat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}}$ based on equation (18) can be written as follows:

$$\frac{\partial \widehat{w}_{p,n_p,k}}{\partial \hat{z}_{p,n_p,k}} = \frac{\alpha_{e_{p,n_p}} \beta_{e_{p,n_p}} t_f \hat{z}_{p,n_p,k}^{\beta_{e_{p,n_p}}-1}}{CAP_{e_{p,n_p}}} \equiv B_{p,n_p,k} \hat{z}_{p,n_p,k}^{\beta_{e_{p,n_p}}-1} \tag{19}$$

After the derivation, the final form of marginal cost is:

$$\begin{aligned}
MCP_{l',k'}^{p',u'} &= c_{l',k'}^{p',u'} + \eta\, t_{l',k'}^{p',u'} \\
&\quad + \eta \sum_{k\in K} \sum_{l\in L} \sum_{p\in P;} \sum_{n_p=1}^{N_p} \frac{\partial \widehat{w}_{p,n_p,k}}{\partial y_{l',k'}^{p',u'}} y_{l,k}^{p,u} + \sum_{k\in K} \sum_{l\in L} \sum_{p\in P;} \sum_{n_p=1}^{N_p} \frac{\partial h^u(v_{p,n_p,k})}{\partial \widehat{w}_{p,n_p,k}} \frac{\partial \widehat{w}_{p,n_p,k}}{\partial y_{l',k'}^{p',u'}} d_{p,n_p} y_{l,k}^{p,u} \\
&= c_{l',k'}^{p',u'} + \eta\, t_{l',k'}^{p',u'} + \sum_{k\in K} \sum_{l\in L} \sum_{p\in P;} \sum_{n_p=1}^{N_p} (\eta + \frac{\partial h^u(v_{p,n_p,k})}{\partial \widehat{w}_{p,n_p,k}} d_{p,n_p}) \frac{\partial \widehat{w}_{p,n_p,k}}{\partial y_{l',k'}^{p',u'}} y_{l,k}^{p,u} \\
&\approx c_{l',k'}^{p',u'} + \eta\, t_{l',k'}^{p',u'} + \sum_{k\in K} \sum_{l\in L} \sum_{p\in P;} \sum_{n_p=1}^{N_p} 1_{e'_{p,n_p}, \xi_{k',e'_{p,n_p}}} (e_{p,n_p}, \xi_{k,e_{p,n_p}}) \\
&\quad \cdot y_{l,k}^{p,u} \frac{1}{v_{p,n_p,k} \Delta t} \left(\eta + \frac{\partial h^u\left(v_{p,n_p,k}\right)}{\partial \widehat{w}_{p,n_p,k}} d_{p,n_p} \right) B_{p,n_p,k} \hat{z}_{p,n_p,k}^{\beta_{e_{p,n_p}}-1}
\end{aligned} \tag{20}$$

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 $MCP_{l',k'}^{p',u'}$. The calculation of the marginal cost of a segment requires the knowledge of the propagation of other segments $1_{e'_{p,n_p}, \xi_{k',e'_{p,n_p}}} (e_{p,n_p}, \xi_{k,e_{p,n_p}})$, the basic traffic network status ($\widehat{w}_{p,n_p,k}$, $\hat{z}_{p,n_p,k}$, $v_{p,n_p,k}$, $h^u\left(v_{p,n_p,k}\right)$), 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.

2.4.2 Emission models

The emissions from the whole assignment and routing procedure are estimated using the EPA model MOVES and include $HC, CO, NOX, CO_2, PM25$ [66].

2.5 Scalability

The computational complexity of the method comes from two aspects: the number of iterations and the computation in each step. In each step, each route in the route collection is examined. The iteration number is also related to the combinations of dividing demands onto the routes in each route collection. So with the increasing of road network, the routes found for each pair of O/D are increased exponentially and the computation power allocated increases exponentially as well. To deal with the computational complexity induced by the expansion of road network, we introduced a distributed version of our co-simulation load balancing optimization approach. In the distributed version, the road network is divided into several subnetworks. For each subnetwork, a service subnetwork is constituted as in the original method. Then we join all the service subnetwork (joining service subnetwork) according to the boundary service nodes into one network and constitute a service network for it. The interactions between service network and joining service subnetwork are similar as in the service network and road network. Then the demands are first assigned based on the optimization in the service network onto each service subnetwork. From each service subnetwork, the demand is assigned onto the road level. Opposite of the direction of demand, the updates of traffic status are performed from the road subnetwork to service subnetwork, then to the service network. The structure of it is shown in Fig 3.

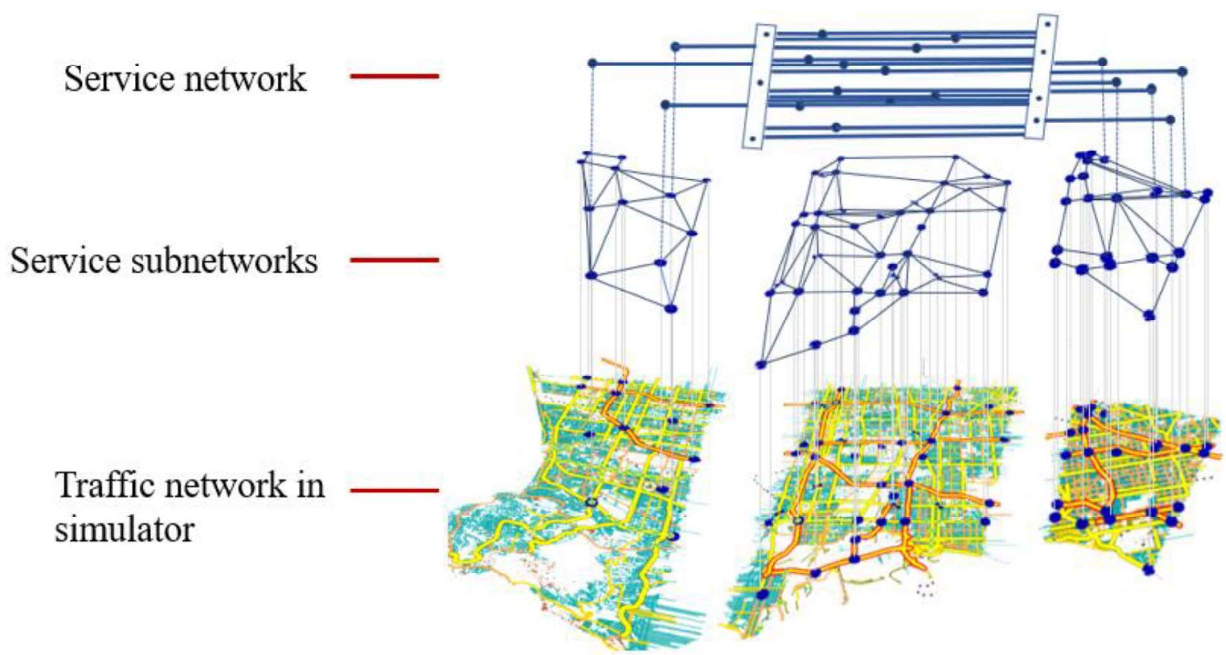

Figure 3: Structure of distributed load balancing co-simulation optimization method

The performance of different partitioning settings of the distributed load balancing co-simulation method will be presented in the numerical subsection including the number of demands, the number of boundary nodes and the number of subnetworks.

2.6 Numerical results

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 and a large road network covers approximately the area of Los Angeles Metropolitan Area. 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 background 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 [63] and Google Maps [64]. 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). We assume that each truck can only load one container and the demand is considered to be fulfilled by a single-direction route. 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.

2.6.1 On mixed freight load balancing co-simulation optimization method performance

To show the benefits of applying load balancing co-simulation optimization assignment, we compared the proposed approach against a mixed freight assignment system without optimized load balancing or co-simulation. The non-optimized-load-balancing system assumes that for each pair of O/Ds, given the cost of each route between the O/D, a diesel/electric truck always chooses the minimal cost route. The non-co-simulation cases assume that the dynamics of traffic status are updated with historical average traffic data, not with the traffic simulator. In the comparison, we will show that in these two cases, the missing of optimized load balancing or co-simulation data will have inaccurate information of the traffic status for the decision of the assignment so that at the end the assignment quality is worse than the one with optimized load balancing and co-simulation. Because in the case of optimized load balancing co-simulation system, the changes of traffic flow characteristics on a certain route as well as the reactions of background traffic will be reflected in the marginal cost so that the freight vehicles assigned on this route may be shifted to another route with lower marginal cost. In this way, the total cost of the assignment of mixed freight can be reduced. The comparison is shown in Figure 4. The system with load balancing achieves the lowest total cost. The average savings by applying optimized load balancing with co -simulation versus non-optimized-load-balancing but co-simulation is 24.8% and around 15% for the case of optimized load balancing based on historical data rather than the dynamic co-simulator.

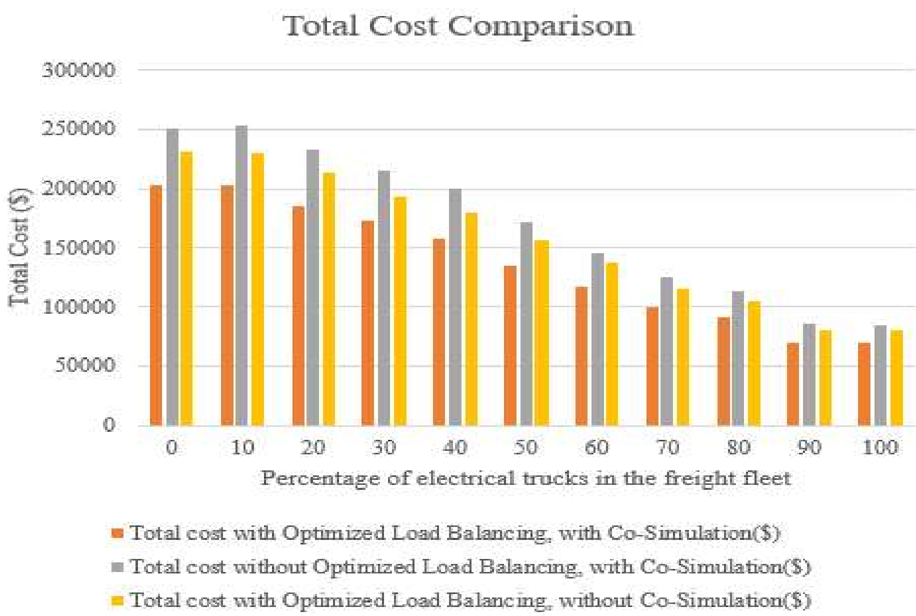

Figure 4: Comparison with cases without optimized load balancing or co-simulation

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 condition (light, medium, heavy), the percentage of electric vehicles in the fleet is varied from 0 % to 100 % in increments of 10 %. The results include total costs in US dollars of the assignment (with and without 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 [66] with speed as input and emissions in units of g/mile as output. The results under light, medium and heavy traffic conditions are shown in Figure 5, 6, 7.

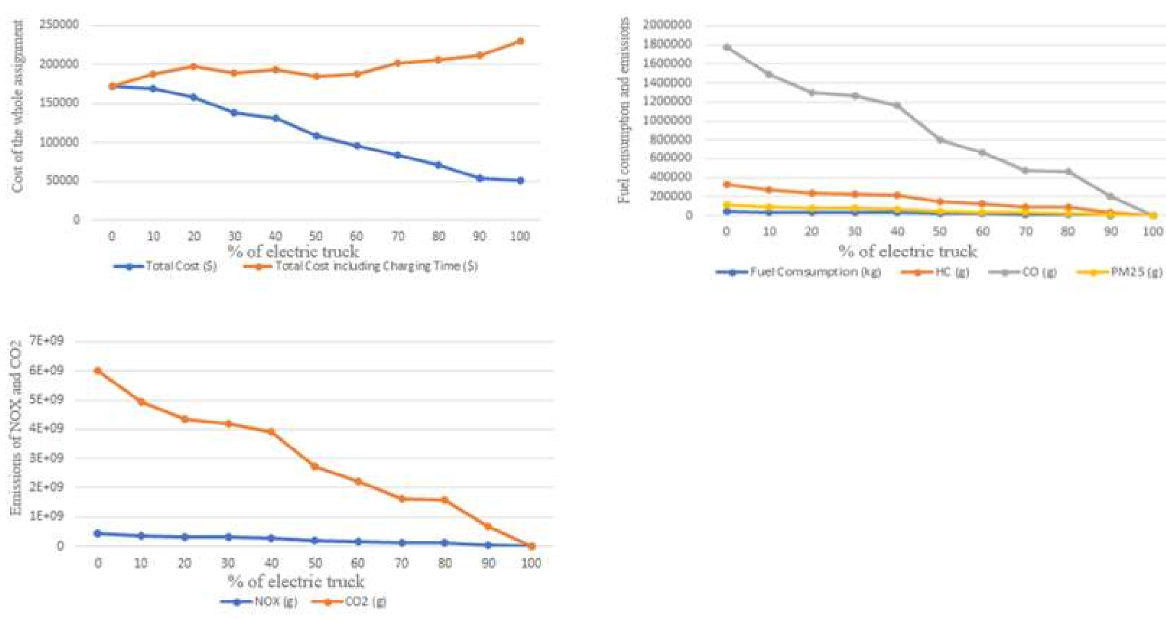

Figure 5: Results under light traffic condition

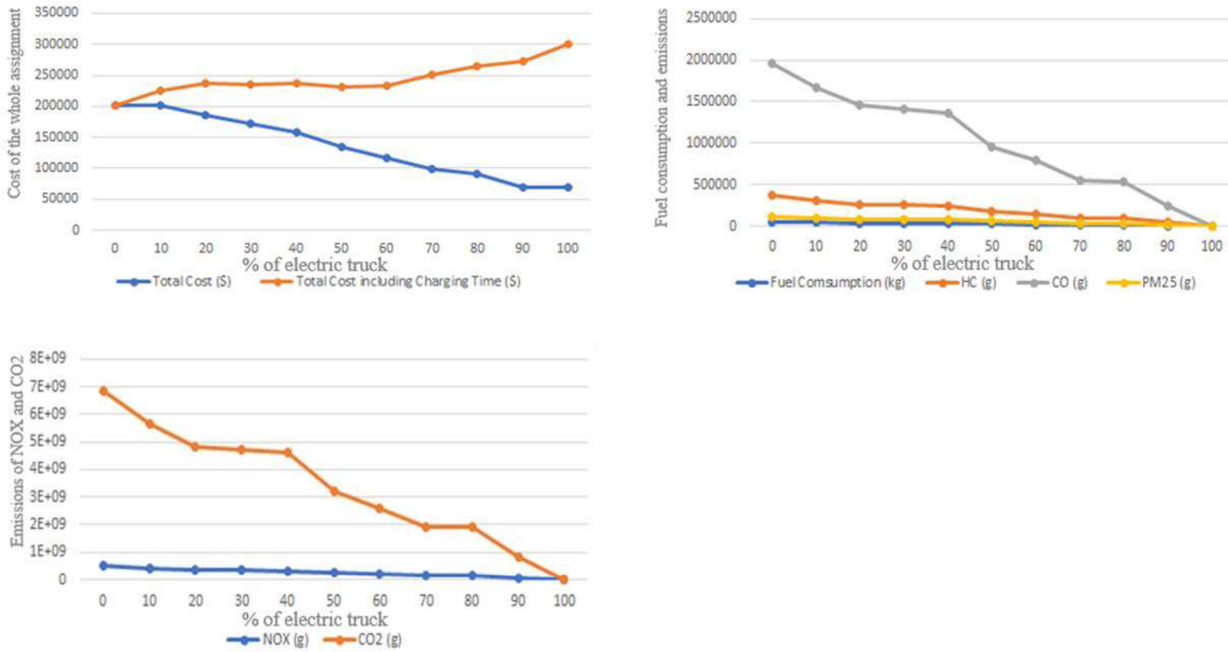

Figure 6: Results under medium condition

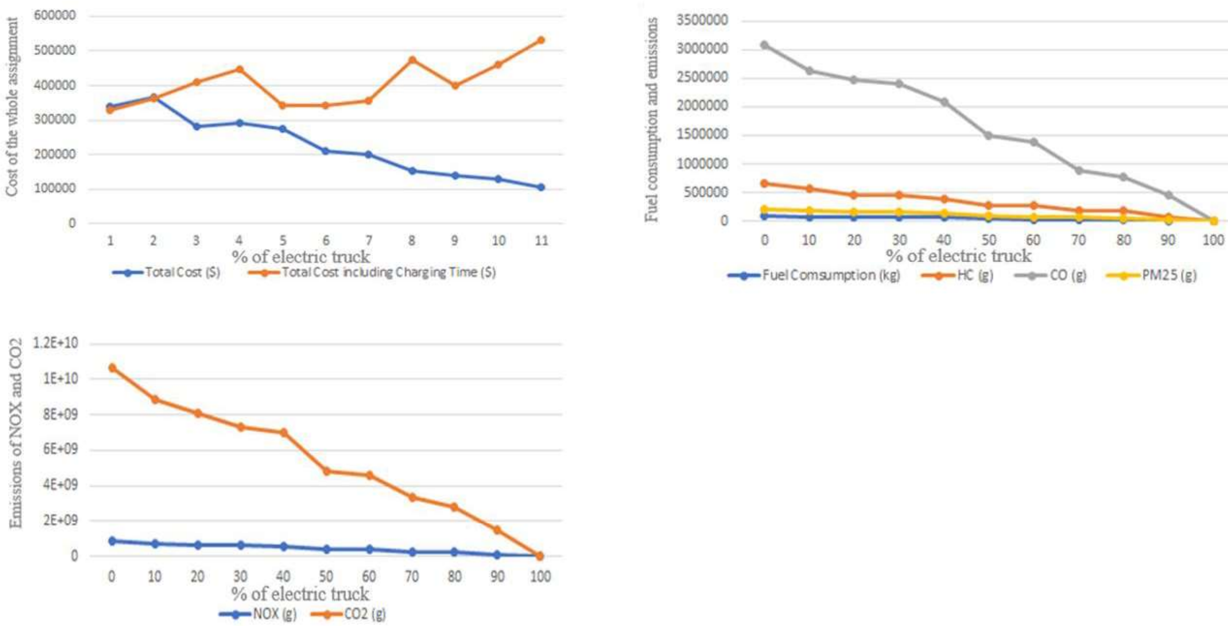

Figure 7: Results under heavy traffic condition

The above results lead to the following conclusions:

- 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.

2.6.2 On distributed optimized load balancing co-simulation method

In this subsection, we examine different aspects that affect the performance of distributed optimized load balancing co-simulation methods. We use two different road networks: the Long Beach network and the Los Angeles Metropolitan area network which is much larger.

For the Long Beach network, we first examine the performance under different number of subnetworks. The results are shown in Table V.

Table V: Results on number of subnetworks for distributed Long Beach network

# of Subnetworks	0	2	3	4
Total Cost (C_1 = $342189)	C_1	$1.053C_1$	$1.091C_1$	$1.147C_1$
Computation Time (second)	T_1	$0.742T_1$	$0.647T_1$	$0.815T_1$

where $T_1 = 4792$ s. The first raw in the table shows the number of subnetworks. The case 0 corresponds to the centralized load balancing approach that produces a total cost C1. When we divide the network into 2 and use the distributed approach the total cost increases by a factor of 1.053 which is about 5% whereas the computational time is reduced significantly by about 26%. When the number of subnetworks is 3 the cost is increased by about 9.1% whereas the computational time is reduced by about 35%. In the case of 4 subnetworks the cost is increased by 14.7% and the computational time is reduced by 18%. The results indicate that the benefits in computational time reduction is much higher than the additional cost increase as long as the number of subnetworks is not too high. Large number of subnetworks will increase the computational time associated with the interactions between assignment flows between subnetworks which may outweigh the computational time saved by the decomposition.

We now proceed to check if the same conclusion can be made if we change the number of demands. Table VI presents the results.

Table VI: Results on number of demands for distributed Long Beach network

Demands	# of Subnetworks	0	2	3	4
# of demands = 3514	**Total Cost**	C_1	$1.053C_1$	$1.091C_1$	$1.147C_1$
	Computation Time (second)	T_1	$0.742T_1$	$0.647T_1$	$0.815T_1$
# of demands = 7028	**Total Cost**	C_2	$1.059C_2$	$1.096C_2$	$1.151C_2$
	Computation Time (second)	T_2	$0.784T_2$	$0.664T_2$	$0.827T_2$

# of demands = 14056	**Total Cost**	C_3	$1.073C_3$	$1.117C_3$	$1.194C_3$
	Computation Time (second)	T_3	$0.806T_3$	$0.675T_3$	$0.862T_3$

where $c_1 = \$342189.00, c_2 = \$728162.00, c_3 = \$1708326.00,\ T_1 = 4792\ s,\ T_2\ =\ 5238\ s\ , T_3 = 7965\ s$. With doubling and quadrupling the demand, we can see similar pattern with respect to optimality and computation time for the Long Beach network.

We then check the performance of distributed optimized load balancing co-simulation method under different number of boundary nodes. Table VII shows the results.

Table VII: Results on number of boundary nodes for distributed Long Beach network

# of demands = 3514	**# of Boundary Nodes**	5	6	7
# of subnetworks = 2	**Total Cost**	$1.024C$	$1.012C$	C
	Computation Time (second)	T	$1.037T$	$1.083T$

where $C\ = \$355880.00, T =\ \ 3558\ s$. We observe that with the increase of the number of boundary nodes, we gain benefits on total cost (better assignment), while lose some computation time.

For the Los Angeles Metropolitan network, we check if the performance under different number of subnetworks is similar to that in Long Beach network and if the pattern remains under different number of demands. The results are shown in Table VIII.

Table VIII: Results on number of subnetworks for distributed LA Metropolitan network

Demands	**# of Subnetworks**	3	4	5
# of demands = 13600	**Total Cost**	C_4	$1.096C_4$	$1.155C_4$
	Computation Time (second)	$1.648T_4$	$1.217T_4$	T_4
# of demands = 27200	**Total Cost**	C_5	$1.114C_5$	$1.189C_5$
	Computation Time (second)	$1.918T_5$	$1.39T_5$	T_5

The results share the similarities with those from Long Beach network, which is by dividing networks more, we gain much more benefits on the computation time than loss on the assignment optimality.

In a summary, the conclusions for this subsection are:

- The scalability issue can be solved by using distributed load balancing method.
- The distributed optimized load balancing co-simulation method is tested and validated under two networks: Long Beach network and large Los Angeles metropolitan network.

- For Long Beach network, the distributed load balancing is tested based on different number of subnetworks, demands and boundary nodes. By increasing the number of boundary nodes, we can achieve better assignment with more computational time. By increasing the number of subnetworks, we can achieve a large reduction in computational time with a relatively small loss on the optimality. However, a proper decomposition is needed since if the network is decomposed too much, the interactions between subnetworks will compromise the computational time gained from decomposition.
- For the large metropolitan network, similar relation between performance and number of subnetworks is revealed.

2.6.3 On incorporated platooning optimized load balancing co-simulation

By assuming that platoons of trucks are allowed in the assignment decision, we introduce different functions of energy savings as well as merging and splitting time into the origin optimized load balancing co-simulation method. The first case is stated in [67], where the following truck will save 21% energy consumption relative to the truck it follows and we assume the emerging and splitting time for each truck are both 2 minutes. The test is performed in Long Beach network with 3 subnetworks and 3514 demands. The results show that by allowing platooning, the total cost can further be reduced by 6.4%. The second case is from [51], where the energy consumption savings are 4.3%, 10%, 14% for the first, second and third truck in the platoon. The merging time is 25 seconds and the splitting time is 35 seconds. Under the same network setting, it achieves 5.3% total cost saving. From the observation, we can see that part of the savings on energy consumption from the introduction of truck platoons is compromised by the merging and splitting time. However, if platoons are used for long distance routes, the time spent on emerging and splitting may be very small relative to the overall travel time along the route and the advantage of energy savings can be maximized under such condition.

3. Conclusions

In this project, 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 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. We also proposed a distributed variation of the method to address the computational complexity induced by the expansion of road network. Different techniques of truck platooning are incorporated with the method and tested. Realistic traffic networks including the Los Angeles/Long Beach network that includes the two ports and the larger Los Angeles Metropolitan network have been used to evaluate the approach and the impact of electric trucks in a mixed fleet. The system shows 24% savings over one without optimized load balancing and 15% savings over one without co-simulation. 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 way 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. The results on the performance of distributed optimized load balancing co-simulation reveal the trade-offs between computation time and assignment optimality with respect to the number of subnetworks, boundary nodes and demands. The use of truck platoons may have benefits whose level depends on the distance travelled by the platoons as merging and exiting the platoon may take away some of the benefits.

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