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EFFECT OF CONNECTED AND AUTONOMOUS VEHICLES ON SUPPLY CHAIN PERFORMANCE

Final Report

by

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Table of Contents

List of Figures

List of Tables

EXCUTIVE SUMMARY

Connected and autonomous vehicles (CAVs) are an emerging technology that has great potential for increasing road capacity and reducing traffic incidents, congestion, fuel/energy consumption as well as emission, all of which may support safer and more reliable and efficient (and potentially sustainable) transportation systems. Given that transportation network plays a key role in a supply chain system in terms of its performance and cost, CAVs will ultimately change many aspects of a supply chain system. While the effects of CAVs on transportation network have been extensively studied through simulations or empirical data, only a limited number of studies have been conducted to investigate potential opportunities (or challenges) that may arise from the introduction/adoption of CAVs in the context of supply chain design, operation and performance. Moreover, their quantitative effect on a supply chain system has yet to be explored in any depth.

This project proposes a simulation framework that quantitatively assesses the direct and indirect effects of CAVs on a supply chain system by varying the levels of CAV market penetration and driverless truck adoption. To quantify CAV effects on transportation network, this project first collects secondary data and adopts simulation parameters and equations from existing literature. The results from transportation analysis are then incorporated into supply chain analysis to evaluate how CAVs would change supply chain performance measured by total travel time, greenhouse gas emissions, and supply chain cost. As the performance of supply chain systems involving perishable or semi-perishable products is highly sensitive to CAV market penetration rate and driverless truck adoption rate mainly because of reduced travel time, this project uses fresh potato supply chain systems as an illustrative example. The case study results indicate that CAVs can greatly improve supply chain performance directly and indirectly by decreasing total travel time and supply chain costs, whereas emissions are reduced primarily through the adoption of driverless trucks in the supply chain system. The effect of CAVs on supply chain performance becomes even greater when commodities travel longer distances. Moreover, with the adoption of connected and autonomous vehicles, the geographic distribution of the supply chain system can be extended. This project will allow supply chain managers (and grocery delivery companies) to better understand how supply chain design and operation could be transformed and reoptimized in response to the introduction of CAV technologies. The research outcomes would help them better utilize the opportunities and address possible challenges that may arise as a result of CAVs.

Chapter 1. Introduction

1.1 Problem Statement

Transportation is a key function of supply chain systems in that it creates spatial links between two nodes (e.g., production site and short-term storage; distribution center and retailer) and supports the movement of goods from raw-material suppliers to end-users. Freight transportation costs account for a large percentage of the total supply chain cost. Any form of disruptions to or opportunities for transportation systems may interrupt or improve the flow of commodities, thus affecting the performance of a supply chain system [1]. Connected and autonomous vehicles (CAVs) are a transformative technology in the transportation industry and are identified as one of the twelve disruptive technologies that will "transform life, business, and the global economy" in the coming years [2]. By combining autonomous technology (that enables all driving tasks without human intervention) with connected vehicle technology (that enables bidirectional communication with the surrounding traffic conditions) [3], CAVs may present great potential for improving the capacity, safety, efficiency, and stability of transportation systems with lower environmental impact. In addition, CAVs are expected to constitute about 30% of total vehicles, 40% of all vehicle travels, and 50% of vehicle sales by 2040 [4]. Although future CAV market penetration rate is highly uncertain, its market penetration rate will continue to increase in the coming decades given the accelerated pace of CAV technological change. In light of potential changes in transportation systems that CAVs will bring about as well as their increasing feasibility in the near future, CAVs will ultimately transform supply chain systems in many different ways. Thus, it is critical for understanding the direct and indirect effects of CAVs on supply chain performance to better prepare for and respond to the changes resulting from CAVs. Quantitative assessment of the impact of CAVs on supply chain performance is specifically necessary for finding optimal supply chain design and management, as the optimization process requires quantitative information.

1.2 Objectives

The objective of this report is to propose a simulation framework for quantitatively assessing the effect of CAVs on supply chain at different levels of CAV market penetration and driverless truck adoption. The framework is illustrated with fresh potato supply chain systems in which all potatoes are produced in the State of Washington, U.S.A., and delivered to other states. These supply chain systems are selected because systems involving perishable or semi-perishable products would greatly benefit from the introduction of CAVs and their performance may be highly sensitive to CAV market penetration rate and driverless truck adoption rate. The proposed framework will provide quantitative information that allows supply chain managers to better understand how supply chain design and management should be transformed in response to the introduction/adoption of CAVs to optimize the flow of goods and freights.

1.3 Expected Contributions

To accomplish these objectives, the following tasks have been conducted:

(1) Summarize existing studies that have examined CAV effects on transportation networks and supply chain systems and collect the secondary data;

(2) Develop simulation framework that quantitatively assesses the direct and indirect effects of CAVs on supply chain system performance;

(3) Illustrate the proposed framework with fresh potato supply chain systems located in the State of Washington, USA.

1.4 Report Overview

The remainder of this report is organized as follows. Section 2 summarizes existing studies that have examined CAV effects on transportation networks and supply chain systems. Following this, the conceptual and simulation framework that quantitatively assesses the direct and indirect effects of CAVs on supply chain system performance is described. The fourth section illustrates the proposed framework with fresh potato supply chain systems located in the State of Washington, U.S.A., and the case study results are then presented. Finally, we conclude with a general discussion of the findings.

Chapter 2. Literature Review

2.1 Introduction

This chapter provides a review of the literature on the effects of CAVs on transportation and supply chain systems. The literature review indicated that there is a lack of quantitative assessment of the effect of CAVs on supply chain performance, which has motivated this project. In this chapter, Sections 2.2 and 2.3 illustrate the positive effects of CAVs on transportation systems and supply chains, respectively. Then, its negative effects are separately summarized in Section 2.4. Finally, Section 2.5 gives a summary of this chapter.

2.2. Literature Review: Positive Effects of CAVs on Transportation System

A review of the literature shows that CAVs may change the landscape of transportation systems by (a) increasing roadway capacity, (b) improving traffic safety, and (c) reducing fuel consumption and emissions. CAVs can potentially improve roadway capacity by allowing better utilization of roadway space [3,5]. For highways, capacity is defined as the daily maximum number of vehicles capable of being handled by a given highway section and is determined by road geometry, the number and width of lanes, inter-vehicle spacing, driver behavior, incidents, and so forth. [6]. Although the physical characteristics of a highway section remain the same, CAVs may change other factors relevant to drivers, thereby increasing highway capacity. Shorter headways or spacing between vehicles can be achieved through sensors that constantly monitor leading vehicles and control acceleration/deceleration [4]. Connected vehicle technology enables communication between nearby vehicles and reduces uncertainties in their behaviors, which leads to significant reduction in reaction time and smoother braking without compromising safety [7]. Moreover, unlike human-driven vehicles, road geometry (e.g., curved or narrow lanes) does not affect the speed of CAVs, allowing smoother traffic flows. In arterial or local roads, the features of CAVs further enable smaller startup lost times and idle times at signalized intersections and result in much less intersection delay. As such, road capacity can be greatly increased by the introduction of CAVs [8]. The effects of CAVs on road capacity have been extensively studied often through microscopic traffic simulations to incorporate driving behaviors in CAVs, and it has been revealed that even an intermediate penetration rate (e.g., 40%) of CAVs could improve road capacity significantly. Therefore, increased roadway capacity resulting from CAVs may substantially reduce delay and congestion, thus enabling more reliable and reduced travel times [9,10]. Subsequently, the flow of goods in supply chain systems can be more expedited and be more reliably predicted, which may affect routing decisions and travel time and ultimately expand the geographic areas of supply chain systems.

CAVs are also expected to improve traffic safety by reducing traffic conflicts [11]. Papadoulis et al. [12] found that the estimated traffic conflicts could be reduced up to 94% in a complete CAV traffic environment. CAVs may reduce the number of vehicle crashes and secondary incidents by eliminating human errors in driving [5] which account for 94% of vehicle crashes [13]. Vehicle crashes may produce physical impedance by blocking one or more lanes and distract other drivers passing through the sites, both of which contribute to traffic flow and delay. Thus, 25% of traffic congestion is attributed to traffic incidents [14]. By reducing traffic incidents and the associated delays, CAVs may enable safer and more efficient transportation systems. Although it is controversial that CAVs may increase traffic demand and the total vehicle kilometer traveled (the amount of travel for all vehicles in a geographic region over a given period of time), the benefits of CAVs associated with increased roadway capacity and traffic incident reduction may offset the negative impact of increased demand on traffic congestion. Thus, from a supply chain management perspective, CAVs promise to ensure the safety of truck drivers, the reduction in damaged products during transportation, and the efficient and timely delivery of commodities between nodes.

CAVs provide additional opportunities for reducing fuel consumption and emissions through eco-driving (e.g., optimized acceleration and deceleration behaviors, minimized repeated braking cycles) [11]. CAVs may also reduce the fuel wasted during traffic congestion by lowering traffic incident rates and improving road capacity and traffic flow. Moreover, a reduction in aerodynamic drag induced by platooning CAV heavy trucks may also contribute to the reduction in fuel consumption and emissions [15]. In this context, a supply chain system utilizing CAVs may reduce total fuel/energy consumption and negative environmental impact during its operation while decreasing transportation costs as a result of the fuel efficiency of CAVs. As illustrated above, the effects of CAVs on transportation systems are categorized into three aspects – roadway capacity, traffic safety, and fuel consumption and emissions. The studies relevant to each aspect are summarized in Table 2.1. We will build on these existing studies and use the major results from them to formulate Transportation Analysis of the simulation framework that will be introduced in Section 3.3.

Table 2.1: A summary of literature review: CAV effects on transportation systems

Category	Literature	Major results
Roadway capacity	3	CAVs can improve traffic stability and throughput.
	4	AV technologies can increase highway capacity, which may highly promote traffic circulation.
	5	AVs can enhance roadway capacity and reduce traffic congestion.
	6	AVs penetration growth can cause roadway capacity improvement.
	7	Average travel time is found to decrease by up to one-fifth at the 90% AV market penetration level.
	8	The introduction of CAVs can mitigate communication delays, and thus greatly increase road capacity and safety.
	10	CAVs promise numerous improvements to vehicular traffic: an increase in both highway capacity and traffic flow through faster response times and less fuel consumption and pollution thanks to more foresighted driving.
	26	Cooperative Adaptive Cruise Control (CACC) systems may have the potential for producing significant increases in the achievable highway lane capacity.
	27	With the help of advanced artificial intelligence and vehicle-to-vehicle/vehicle-to-infrastructure communication, CAVs can keep higher speed with

		shorter headway and drive with neighboring vehicles to formulate platoons.
	28	CAVs in the traffic stream can significantly enhance the roadway capacity, not only on basic freeways but also on merge and weaving segments, as the CAV market penetration rate increases.
	29	The introduction of CACC in mixed traffic flow can highly increase the highway capacity.
	30	CAVs are expected to address the safety, mobility and sustainability issues of current transportation systems.
	31	A higher CACC market penetration rate results in an increased roadway capacity.
	32	When human-driven vehicles are mixed with AVs, capacity utilization degrades quickly as a function of the share of human-driven vehicles.
	33	CACC is able to increase roadway capacity greatly after its market penetration reaches moderate to high percentages.
	34	The estimation of CAVs platoon length is of much importance as it is the main factor driving capacity improvements on freeways.
	35	A significant increase in roadway capacity is expected by using AVs, and this would also enable more efficient use of the existing transport infrastructure.
Traffic safety	4	AVs can decrease the accident rate and the associated transportation cost.
	9	AVs have the potential for decreasing traffic congestion by reducing the time headway, enhancing the traffic capacity and improving the safety margins in car following.
	11	Driving behavior patterns in CAVs has positive effects on road safety.
	12	CAVs bring about compelling benefits to road safety as traffic conflicts significantly reduce even at relatively low market penetration rates.
	36	Google self-driving cars are safer than conventional human-driven passenger vehicles.
	37	CAV driving mode, collision location, roadside parking, rear-end collision, and one-way road are the main factors contributing to the severity level of CAV-involved crashes.
	38	AVs improve safety significantly with high penetration rates, even when they travel with shorter headways to improve road capacity and reduce delay.
Fuel consumption and emissions	11	Driving behavior patterns in CAVs can have positive effects on pollutant and noise emissions.

	15	Automation may affect road vehicle energy consumption and greenhouse gas emissions by causing changes in travel demand, vehicle design, vehicle operating profiles, and choices of fuels.
	44	Eco-driving can reduce fuel consumption by 10% on average, thereby reducing CO_2 emissions from driving by an equivalent percentage.
	45	CAVs can significantly benefit fuel consumption savings, even with low levels of market penetration.
	46	CAVs improve the dampening of traffic oscillation and reduce fuel consumption and emissions.
	47	Fuel efficiency of a vehicle equipped with automatic transmission can be improved when it travels on rolling terrain.
	48	The driver costs and emissions can be reduced substantially through automation.
	49	Fuel consumption could be reduced by incorporating autonomous mechanisms into individual vehicles.
	50	Compared to human-driven vehicles, CAVs provide a feasible way of minimizing fuel consumption.
	51	Fuel efficiency is expected to increase as the introduction of CAVs.

2.3 Literature Review: Positive Effects of CAVs on Supply Chain System

In light of CAVs bringing about a safer, smoother, and more efficient operation of transportation systems in the coming decades, CAVs will also present substantial benefits for supply chain operation and management. Alicke et al. [16] stated that CAVs could significantly reduce lead times and the related operation costs while decreasing manual intervention during the whole process from production to final delivery in supply chain network. Heard et al. [17] extensively discussed the economic and environmental effects of CAVs on food supply chain system. They stated that CAVs could (a) decrease the quantity of energy and refrigerants used in distribution; (b) reduce fuel consumption and greenhouse gas (GHG) emissions; (c) lower marginal cost of transportation by reducing fuel use and not paying a driver wage; (d) transform the current post-processing food distribution model by delivering commodity directly from production sites to end-users; and (e) enhance profits though the increased efficiency and greater flexibility in vehicle deployment. Bechtsis et al. [18] also showed that automated guided vehicle systems could enhance supply chain normal operation and promote economic, environmental, and social sustainability. However, these statements in Alicke et al. (16), Heard et al. (17), and Bechtsis et al. (18) were not supported by any empirical or quantitative evidence. As most of current supply chain systems do not utilize CAVs, there is a lack of empirical evidence which supports the impact of CAVs on supply chain. This has motivated a simulation-based approach to assessing its impact. Gružauskas et al. [19] utilized a food industry logistic network model developed based on a specialist interview to evaluate the effect of an autonomous vehicle distribution strategy. The simulation results showed that the strategy reduced the transportation costs by 5% and CO_2 emission level by 22% as compared to the traditional distribution system. Bechtsis et al. [20]

developed simulation software tools to integrate intelligent autonomous vehicles systems into digital supply networks and analyzed their effect on the environmental sustainability of the supply networks. However, the simulation software tools lacked generalizability and did not assess other aspects of network performance such as unmet demands or total costs. A very limited number of studies have attempted to investigate the direct and indirect impact of CAVs on supply chain system design, operation, and performance through simulation models.

2.4 Literature Review: Negative Effects of CAVs on Transportation and Supply Chain Systems

Although CAVs have been considered a key innovation that transforms the landscape of transportation systems (and potentially supply chain systems) in a beneficial way, for every good thing there are always unintended negative consequences. As briefly mentioned earlier in this section, the introduction of CAVs could encourage people to drive and live farther away from cities where jobs are concentrated. It may induce higher transportation usage, greenhouse gas emissions, and oil imports [21]. Moreover, many jobs will likely be lost with a rapid transition to AVs. These jobs include not only driving jobs (e.g., delivery and long-haul truck drivers, bus and taxi drivers) but also the maintenance and support staff working at truck stops on highway [22,23]. Another important concern is related to liability in accidents involving AVs. It is unclear whether a person in an AV should bear part of the responsibility for an accident if he/she fails to use a manual override function [24]. If third parties involved in the design of AVs (e.g., manufacturers, designers, software developers) should take full or partial responsibility for an accident, how can liability be apportioned between them [24]? These questions should be answered to develop a legal framework for liability. Although it is important to consider these untended consequences in analyzing CAV effects on transportation and supply chain systems, it may be difficult to quantify such concerns and the resulting costs at present until a significant number of CAVs is introduced in transportation systems. Therefore, this project will focus on well-known positive effects of CAVs on transportation systems and propagate them through a simulation framework.

2.5 Summary

A comprehensive review of the effects of CAVs on both transportation networks and supply chain systems has been discussed in the preceding sections. Based on the literature review, CAVs have been demonstrated to be effective in providing a safer and more reliable and efficient traffic environment, which can ultimately enhance supply chain performance. Moreover, the adoption of driverless trucks in a supply chain network would directly affect system economic and environmental efficiency.

Chapter 3. Methodology

3.1 Introduction

This project contributes to filling the research gaps identified in Section 2 by proposing a quantitative framework for assessing the effect of CAVs on supply chain performance. The following subsections are organized as follows. This chapter begins with constructing a conceptual framework showing causal relationships between independent and dependent variables. Section 3.3 presents a simulation framework to quantitatively assess the direct and indirect effects of CAVs on supply chain long-term performance. Finally, Section 3.4 concludes this chapter with a summary.

3.2 Conceptual Framework

The conceptual framework introduced in this subsection is primarily used to identify causes and effects and to formulate their interrelationship, which is needed to develop a simulation framework. As described, CAVs present numerous opportunities and have far-reaching implications for supply chain systems. Figure 3.1 summarizes the potential effect of CAVs on a food supply chain system through a causal loop diagram. Independent variables are CAV market penetration rate and driverless truck adoption rate that represent the indirect and direct effects of CAVs, respectively: the use of driverless trucks in a supply chain system affects system performance directly, while CAVs in a traffic environment may have an indirect impact on supply chain performance by changing transportation-related variables. As shown in Figure 3.1, changes in the independent variables cause intermediate key parameters (e.g., traffic incidents [12-14], roadway capacity [8], travel time [9-10], driver wage [21], fuel economy [11,15], emissions [11,15]) to increase or decrease interactively, which will consequently affect dependent variables (e.g., fresh food loss, cost components, total emissions). Accordingly, this diagram is divided into three parts, which are defined as (a) causes (i.e., the red region), (b) processes (i.e., the green region), and (c) effects (i.e., the yellow region).

More specifically, reduced traffic incidents/accidents and increased road capacity through the introduction of CAVs would improve transportation system reliability and traffic flow patterns, and therefore enable efficient and intelligent routing decisions and an optimal driving cycle of a supply chain system. Thus, it would greatly reduce travel time between nodes while ensuring the reliable delivery of products. If traditional human-driven trucks would be replaced with fully autonomous (or driverless) trucks (i.e., Level 4 or 5 autonomous vehicles where human drivers are not needed) in a supply chain system, driver wages could be excluded from total supply chain costs. Truck accidents during transport can also be reduced, which improves driver safety and reduces product losses. Moreover, driverless trucks would enable 24/7 truck service at higher speeds and efficiencies, thus reducing transportation time between suppliers and end-users [17]. Specifically, such 24/7 truck service could provide enormous benefits to perishable or semi-perishable food supply chain systems in which the timely transport of products is a key priority. Given that reduced accident rates and enhanced road capacity may induce an additional reduction in traffic congestion and the associated travel time, CAVs would, directly and indirectly, ensure the expedited and efficient delivery of fresh food without its quality degradation. Therefore, waste disposal costs at retailers caused by bad quality products could be reduced, and at the same time, products could be delivered to the end-users located even farther away from the current end-user locations without compromising product quality. As also shown in Figure 3.1, higher fuel economy of CAVs and less travel time could substantially reduce transportation costs considering that trucking accounts for a large portion of the supply chain transportation [25]. Lastly, CAVs may decrease GHG emissions during transport processes which are responsible for a substantial portion of total supply chain emissions.

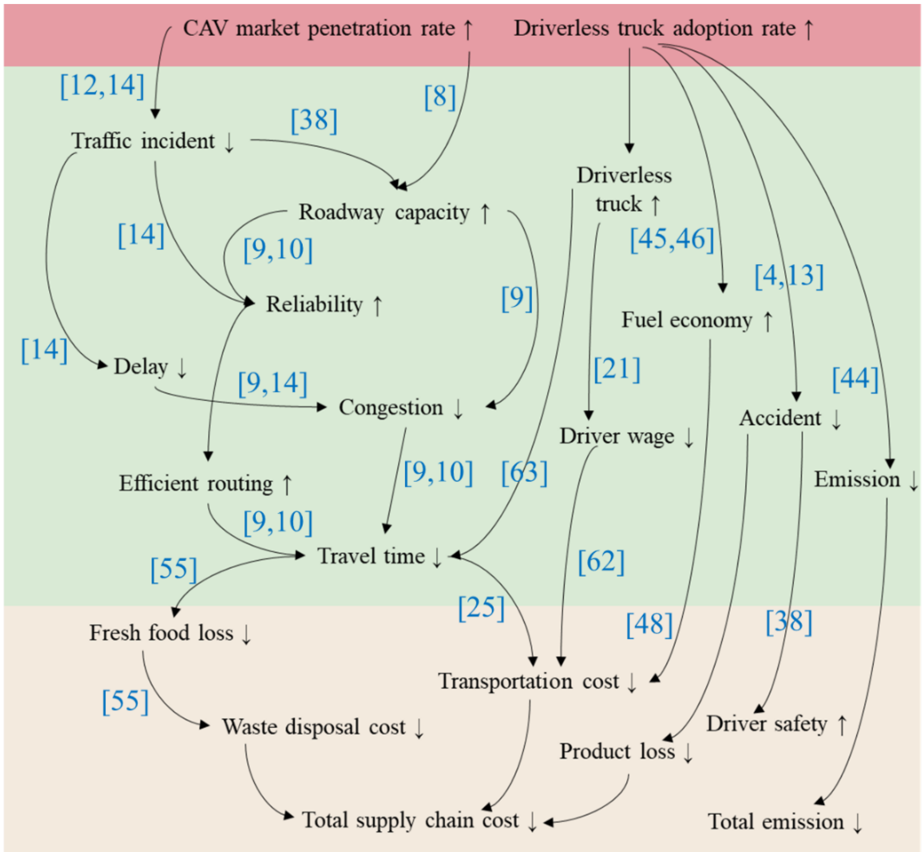

Figure 3.1: Causal loop diagram of a food supply chain system affected by CAVs (literature evidence supporting each causal relationship is shown next to each arrow)

3.3 Simulation Framework

Based on the conceptual framework, a simulation framework is proposed to quantitatively assess the direct and indirect effects of CAVs on supply chain performance. Figure 3.2 presents the proposed simulation framework. As described in the conceptual framework, CAV market penetration rate and driverless truck adoption rate are used as independent variables. The market penetration rate of CAVs in the future depends on many different factors, such as the pace of CAV technological maturity, customer preferences for CAVs, government policy and traffic laws, CAV costs, and traffic environment. On the other hand, the adoption rate of driverless trucks in a supply chain system is governed by the willingness of trucking companies to adopt driverless trucks, as transportation in a supply chain system is often handled by third parties. Although CAV market penetration rate may affect driverless truck adoption rate in trucking companies (and supply chain systems), its relationship is hardly defined because of a lack of data and substantial uncertainties. Therefore, it is assumed that these two variables are statistically independent in the simulation framework.

As shown in Figure 3.2, the simulation framework first assesses the effects of CAVs on transportation-related factors (in the Transportation Analysis stage) and incorporates the changes in these factors into supply chain analysis to evaluate their combined effects on supply chain performance (in the Supply Chain Analysis stage). In the Transportation Analysis stage, the indirect and direct effects of CAVs on transportation-related factors are assessed by varying the levels of CAV market penetration and the adoption rates of driverless trucks, respectively. Based on the secondary data that quantify CAV effects on highway capacity, free-flow speed, and traffic incidents, a CAV-involved travel time model is developed to estimate travel time for each transportation edge in a mixed traffic environment (Transportation Analysis I). On the other hand, the adoption of driverless trucks in commodity transportation can directly reduce fuel consumption, GHG emissions, and the likelihood of product losses induced by truck accidents during transport (Transportation Analysis II). In the Supply Chain Analysis stage, the outputs from the first stage are incorporated into supply chain analysis to assess system performance in terms of (a) total supply chain cost, (b) total transportation time, and (c) total GHG emissions. Detailed procedures for each stage will be described in the remainder of this section.

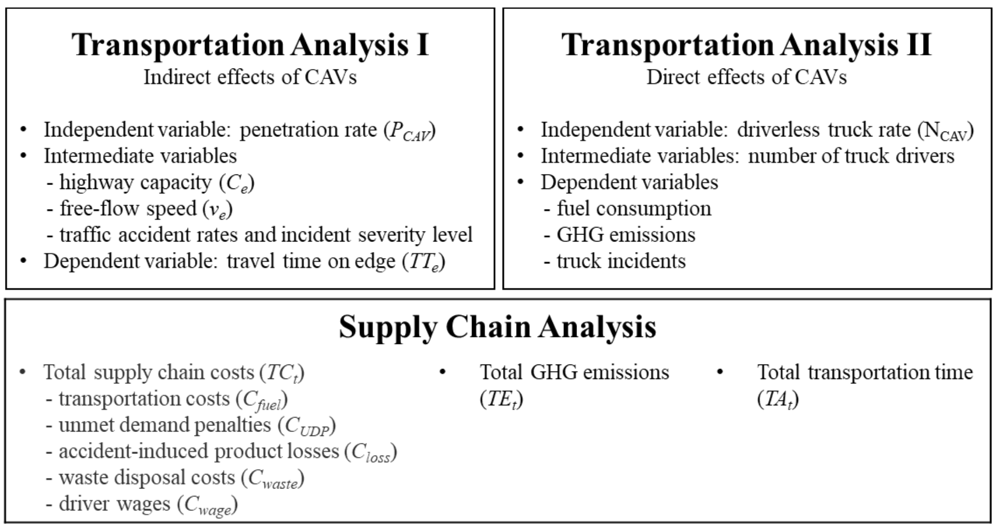

Figure 3.2: Simulation framework for assessing the effects of CAVs on supply chain performance

3.3.1 Transportation Analysis I

Transportation Analysis I is designed to estimate the effect of CAVs on transportation systems, which will be utilized in assessing their indirect effects on supply chain performance.

3.3.1.1 Highway capacity & free-flow speed

Highway capacity enhancement in a complete or partial CAV environment has been well supported by recent studies. Using a mixed model experiment, Nowakowski et al. [26] found that CAVs could operate with 0.6 s inter-vehicle time gap, while the following time is recommended to be 2 -3 s for human-driven vehicles. Such shorter following gaps may enhance highway capacity. Talebpour and Mahmassani [3] utilized a multi-model framework to simulate the behaviors of different types of vehicles (i.e., human-driven vehicles, connected human-driven vehicles, and CAVs). The results showed that the rate of roadway capacity improvement increases with the CAV penetration rate. Similar results were also found in Wang et al. [27] and Adebisi et al. [28]. Although its positive impact on the capacities of arterial or local roads has also been well studied, this report limits its scope only to the effect of CAVs on highway capacity because in many cases, highway system is the first choice for commodity shipments in supply chains.

In recent years, a considerable number of studies have quantified the capacity enhancement of highways induced by CAVs using various modeling approaches. For example, Liu et al. [29] proposed an analytical equation to assess highway capacity improvement in the mixed traffic stream as follows:

$$C_{mix} = \frac{3600}{P_{leader}HW_{leader} + P_{follower}HW_{follower} + P_{human}HW_{human}} \tag{3-1}$$

where C_{mix} = the roadway capacity measured by the number of vehicles capable of being handled by a given highway section per unit time; P_{leader}, $P_{follower}$, and P_{human} = the probabilities of any vehicle being a Cooperative Adaptive Cruise Control (CACC) string leader, follower, and manual driver, respectively; and HW_{leader}, $HW_{follower}$, and HW_{human} = the average headway of a CACC string leader, follower, and manual driver in seconds, respectively. Here, CACC allows CAVs to be driven in a cooperative manner [30]. Moreover, Xiao et al. [31] quantitatively investigated the influence of CACC on highway operations through a CACC model. To make it realistic, this model specifically considered the limitations in acceleration and deceleration capabilities of CACC systems by incorporating deactivation and switch to a human-driven mode when conditions are outside the operational design domain. Carrone et al. [32] used a traffic simulator to model mixed vehicle classes combined with human heterogeneity, aimed at investigating the effect of autonomous vehicles on a highway network at different levels of market penetration. The simulation results indicated that the maximum highway capacity in a completely automated driving environment was 30% higher than the capacity in a complete human-driven-vehicle (HDV) traffic environment. On the other hand, Shladover et al. [33] obtained data from a field experiment where participants drove CAVs and investigated time gap settings with which they were comfortable. Then, the distribution of time gap setting was used in microscopic simulation to estimate CAV effect on highway capacity. To address the issues with highly uncertain parameters in microscopic simulations, Sala and Soriguera [34] used four scenarios representing different platooning strategies (i.e., opportunistic and cooperative) with different implementations (i.e., optimistic and conservative). Thus, instead of providing a single value for each CAV market penetration rate, this model showed the range of increased highway capacity resulting from the four scenarios (see Table 3.1). Table 3.1 summarizes the explicit relationship between CAV market penetration rate and highway capacity enhancement found in the existing literature. As shown in the table, the estimates of highway capacity enhancement widely vary primarily because of different simulation approaches used in these five studies, or the assumptions made in the car-following models and the extent of automation. This report uses the mean value of highway capacity enhancement at each CAV market penetration rate by assigning equal probabilities to the five model outcomes.

Table 3.1: Highway capacity enhancement for different rates of CAV market penetration

Literature	CAV market penetration rate			
	25%	50%	75%	100%
Liu et al. [29]	+6.1%	+17.4%	+42.4%	+81.6%
Xiao et al. [31]	+6.2%	+17.1%	+40.0%	+80.1%
Sala and Soriguera [34]	+3.4 – 15%	+12 – 49%	+62.5 – 184%	+159 – 473%
Shladover et al. [33]	+6.0%	+18%	+57.5%	+97%

Carrone et al. [32]	+4%	+8%	+14%	+30%

To quantitatively relate the capacity of the e^{th} highway edge ($C_{a,e}$) to its free-flow speed, the following equation is used [35]:

$$v_{a,e} = \frac{L*C_{a,e}}{T_a*C_{a,e}-1} \tag{3-2}$$

in which $v_{a,e}$ = the free-flow speed of edge e in a complete CAV traffic environment; T_a = the time gap preferred by CAVs; and L = the pass length of a vehicle which is the sum of vehicle length and inter-vehicle distance. Considering technical feasibility and perspective of road users, T_a can be assumed to be 0.5 s [35]. Moreover, given that the primary mode of transportation in logistics is shipments by trucks, the mean length of a truck (i.e., 18 m) with the inter-vehicle distance of 3 m (i.e., L = 21 m) is used in this report [35]. It should be noted that Equation 3-2 was developed for the complete CAV traffic environment. As data on the free-flow speed of each edge in a complete HDV traffic environment is available, the free-flow speed for edge e in a mixed traffic environment (v_e) can be calculated by using linear interpolation between these two extreme values.

3.3.1.2 Traffic incident

The effect of CAVs on reduced traffic incidents has been well supported by experimental and empirical data. Teoh and Kidd [36] tested the self-driving cars developed by Google and found that these cars produced 2.19 crashes per million vehicle miles traveled which was much lower than 6.06 crashes in Mountain View, California during the period of 2009 -2015. Xu et al. [37] examined the characteristics of CAV-involved traffic incidents based on the reported crashes from various companies and revealed that the severity of CAV-involved incidents was lower than that of human-driven vehicles. Some researchers have taken a simulation approach to model CAV-involved traffic incidents. Morando et al. [38] studied the safety impact of CAVs by using a simulation-based surrogate safety measure approach. The results indicated that the complete CAV traffic environment could reduce nearly 65% of traffic incidents and the associated delay, subsequently enhancing traffic safety and efficiency. Similarly, Papadoulis et al. [12] utilized a CAV control algorithm in the standard traffic simulation software Surrogate Safety Assessment Model (SSAM) to assess its impact in a simulated, real-world highway environment. As shown in Table 3.2, traffic conflicts could be significantly reduced by increasing the market penetration rate of CAVs [12].

Table 3.2: Relationship between CAV market penetration rate and traffic incident reduction index (adapted from [12])

CAV market penetration rate	Estimated traffic incident reduction
25%	12-47%
50%	50-80%
75%	82-92%
100%	90-94%

Incident severity is divided into four levels which represent slight to significant impacts on traffic (i.e., short to long delay time caused by incidents). Using the crash data [39], the incident rates and the statistical distribution of incident severity for each transportation edge can be obtained. As the crash data can be applied only to a traffic environment with 100% human-driven vehicles, the incident rates in a mixed traffic environment should be adjusted based on either experimental/empirical data or simulation results as described above (e.g., Table 3.2), whereas the distribution of incident severity is assumed to remain the same. Similarly, the delay time associated with each severity level, which is the time taken from accident initiation to completion (i.e., traffic condition recovered to a pre-accident level), also remains the same. Decreased traffic incident rates induced by CAVs may reduce the number of severe incidents and the consequent delay time, thereby reducing traffic congestion.

3.3.1.3 A CAV-involved travel time model

To calculate the reduced travel time for each transportation edge induced by the aforementioned changes that CAVs bring about, this subsection presents a CAV-involved travel time model. As illustrated in Figure 3.3, a market penetration rate of CAV (P_{CAV}) is considered an independent variable in assessing the indirect effect of CAVs on supply chain. For a given rate, the intermediate variables (i.e., the highway capacity, free-flow speed, traffic incident rate, and the associated delay for each edge) can be estimated by using the procedures described in Sections 3.3.1.1 and 3.3.1.2. CAV-involved travel time for edge e (TT_e) can be computed by the edge travel time under normal condition (TN_e) and the average delay time caused by traffic incidents (TD_e) [40] as shown in Equation 3-3a. More specifically, the travel time under normal condition (TN_e) can be calculated based on the speed-flow relationship recommended by the Highway Capacity Manual [41]. The original equation in [41] has the unit of travel time per distance ($TN_{HCM,e}$). By multiplying it by the length of the edge (L_e), Equation 3-3b becomes the edge e's travel time under normal condition. Equation 3-3c represents the calculation of the average incident-induced delay time for edge e (TD_e).

$$TT_e(P_{CAV}) = TN_e(P_{CAV}) + TD_e \tag{3-3a}$$

$$TN_e(P_{CAV}) = TN_{HCM,e}(P_{CAV}) * L_e$$
$$= \frac{L_e}{v_e(P_{CAV})} + 0.25TL_e\left[(x_e(P_{CAV}) - 1) + \sqrt{(x_e(P_{CAV}) - 1)^2 + \frac{8J_A}{C_e(P_{CAV})T}x_e(P_{CAV})}\right] \tag{3-3b}$$

$$TD_e(P_{CAV}) = \sum_{s=1}^{4}\alpha_{s,e}(P_{CAV})T_{s,e} \tag{3-3c}$$

where P_{CAV} = the CAV market penetration rate (in percentage); v_e = the free-flow speed for edge e in mile/h; T = the flow period; L_e = the length of edge e in miles; x_e = the degree of saturation for edge e which can be expressed as the ratio of volume to capacity; C_e = the traffic capacity (in vehicles per hour) for edge e; J_A = the delay parameter which is used to predict the desired speed of traffic when demand is equal to capacity (e.g., 0.2 for one- or two-lane highway roads, 0.3 for more than two-lane highway road) [42,43]; $\alpha_{s,e}$ = the average rate of accident having the severity level s for travel edge e; and $T_{s,e}$ = the mean delay time of the accident having the severity level s for the edge e. More detailed information on Equation 3-3b can be found in [41]. As presented in Equation 3-3, both TN_e and TD_e, which are affected by highway capacity and traffic incident respectively, are expressed as functions of CAV market penetration rate. In supply chain analysis, commodity shipment and delivery will be determined by the travel time of edges (TT_e). Therefore, by varying the market penetration rate of CAVs, the updated edge capacity and traffic incident rate will ultimately affect the total transport time of commodity between nodes and the associated supply chain performance.

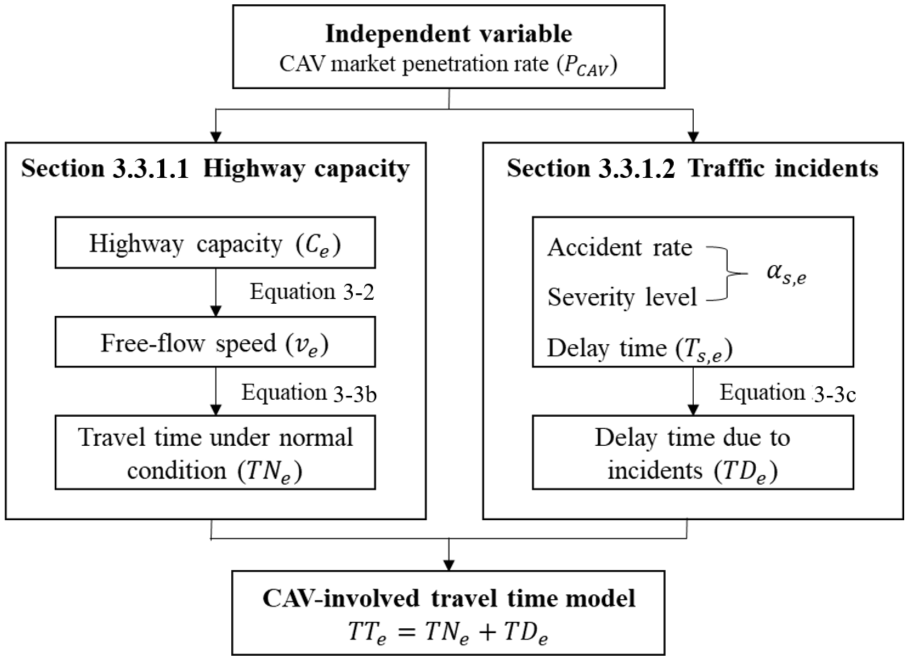

Figure 3.3: A flow diagram of the CAV-involved travel time model

3.3.2 Transportation Analysis II

In Transportation Analysis II, the number of connected and autonomous trucks adopted in a supply chain system will be changed to assess its impact on fuel consumption, GHG emissions, and truck accidents directly associated with the supply chain.

3.3.2.1 Fuel consumption and GHG emissions

CAV technology can enhance fuel economy and reduce GHG emissions by (a) optimizing acceleration and deceleration behaviors, (b) maintaining an even driving pace, and (c) eliminating excessive idling [44]. To assess the effect of CAVs on fuel consumption and GHG emissions, many existing studies have taken a simulation approach. Guo et al. [45] proposed efficient dynamic programming with shooting heuristic (DP-SH) as a subroutine algorithm, which could optimize the trajectories of CAVs and intersection controllers simultaneously. The results indicated that up to 31.5% of fuel consumption could be reduced by CAVs. An optimal controller for vehicles equipped with automatic transmission was proposed by Hu et al. [46] to improve fuel efficiency by optimizing vehicle acceleration and transmission gear position at the same time. This controller reduced fuel consumption of four-speed vehicles by 7.3 – 11.6% and six-speed vehicles by 7.7 – 19.8%. Wadud et al. [47] presented that a maximum 20% of fuel consumption could be reduced by integrating autonomous mechanisms into individual vehicles, while 15 – 30% fuel savings were expected by Meldert and Boeck [48]. Wu et al. [49] showed that real-time advice on optimal acceleration and deceleration behavior could reduce fuel consumption up to 31% and 26% in acceleration and deceleration conditions, respectively. International Transport Forum [50] presented much lower values (4 – 10%) for the expected fuel savings. As revealed by the existing literature, fuel consumption reductions resulting from the use of CAVs vary widely between 4%

and 31%. It is mainly because these rates are highly sensitive to the type and level of an automation system, the participants and assumptions involved in the experiments, and the driving environment. This report takes a mean value of 17.5% as fuel consumption reduction achieved by replacing human-driven trucks with driverless trucks. The relationship between fuel consumption (*fuel*) in unit of L/(100 km) and CO_2 emissions (*emissions*) in unit of g/km is assumed as follows [51]:

$$emissions = 26.87 * fuel - 0.9464 \tag{3-4}$$

Therefore, by adopting driverless trucks in a supply chain system, fuel consumption can be reduced by 17.5% per truck, and the consequent GHG emissions reduction can be calculated from Equation 3-4.

3.3.2.2 Truck accident

The accidents of trucks used in delivering commodities can cause various degrees of negative effects on supply chain operations. For example, truck accidents with slight severity (i.e., level 1) may lead to the delay of commodity delivery, whereas severe truck accidents (e.g., truck turnover) will cause truck damage, driver injury, and product losses. It is assumed that driverless trucks employed in a supply chain system can reduce accident rates by 90% by eliminating human errors [52], whereas the distribution of truck incident severity is assumed to remain the same. As the accident-induced car damage and driver injury are generally covered by car insurance, this report does not consider repair costs and medical payments resulting from severe truck accidents (i.e., level 4). However, the products/commodities in the truck are assumed to be completely lost when a specific loading truck experiences a severe accident, and the consequent product loss cost will be included in total supply chain cost calculation.

3.3.3 Supply Chain Analysis

As discussed in the previous two subsections, CAVs can affect supply chain performance directly and indirectly. In this subsection, the combined effects of employing driverless trucks in a complete/mixed traffic environment will be examined. To quantify CAV effects on supply chain performance more comprehensively, three performance indicators are used, including (a) total transportation time, (b) total GHG emissions, and (c) total supply chain cost over a given period of time.

3.3.3.1 Total transportation time

In a supply chain system, commodities travel along the shortest (or fastest) routes between production sites and end-users. As the route consists of multiple transportation edges, it is essential to incorporate edge characteristics (e.g., length, capacity, free-flow speed, accident rate) into travel time calculation. In addition, the reduced number of truck drivers resulting from the adoption of driverless trucks may induce shorter delay time attributable to hours-of-service regulations, such as 11-hour driving limit and 30-minute driving break [53]. Therefore, the travel time for a route between nodes *i* and *j* involves both the sum of the travel times of all the edges in the route (TT_e) and the additional time required for human-driven vehicles owing to hours-of-service regulations (TH_e) as follows:

$$TA_t(P_{CAV}, N_{CAV}) = \sum_{r \in R} \{N_{r,t} * \sum_{e \in r} [TT_e(P_{CAV}) + TH_e(N_{CAV})]\} \tag{3-5}$$

where TA_t = the total transportation time over a given time period; N_{CAV} = the adoption rate of driverless trucks in a supply chain system; r = the transportation route between two nodes (e.g., between supply and processor nodes; between processor and demand nodes); $N_{r,t}$ = the number of trucks that deliver commodities along the route r over a given time period t; and e = the transportation edge. The term (TT_e) in Equation 3-5 can be obtained from the CAV-involved travel time model in Section 3.3.1.3 and is expressed as a function of P_{CAV}. On the other hand, the term (TH_e) is only affected by the adoption rate of driverless trucks in the supply chain system (N_{CAV}). Thus, the total transportation time between production sites and end-users (TA_{ij}) is expressed as a function of P_{CAV} and N_{CAV}.

3.3.3.2 Total GHG emissions

This report considers GHG emissions produced by trucks during commodity transport. The total GHG emissions over a given time period (TE_t) can be expressed as:

$$TE_t(N_{CAV}) = \sum_{e\in E} TE_{e,t}(N_{CAV}) \quad (3\text{-}6)$$

in which $TE_{e,t}$ = the GHG emissions produced by trucks traveling edge e over a given period of time t. The adoption rate of driverless trucks (N_{CAV}) in a supply chain system can significantly reduce GHG emissions.

3.3.3.3 Total supply chain cost

The objective of a supply chain system is to meet customer demands while minimizing total cost. In this report, the total supply chain cost includes five components: fuel cost (C_{fuel}), driver wage (C_{wage}), unmet demand penalty (C_{UDP}), product loss cost (C_{loss}) resulting from truck accidents during transport, and waste disposal cost (C_{waste}). The total supply chain cost and the cost components are summarized in the following equations:

$$TC_t(N_{CAV}, P_{CAV}) = C_{fuel}(N_{CAV}, P_{CAV}) + C_{wage}(N_{CAV}, P_{CAV}) + C_{UDP}(N_{CAV}, P_{CAV}) + C_{loss}(N_{CAV}, P_{CAV}) + C_{waste}(N_{CAV}, P_{CAV}) \quad (3\text{-}7a)$$

$$C_{fuel}(N_{CAV}, P_{CAV}) = \sum_r C_t(N_{CAV}) \cdot x_{t,r}(N_{CAV}, P_{CAV}) \cdot D_r(N_{CAV}, P_{CAV}) \quad (3\text{-}7b)$$

$$C_{wage}(N_{CAV}, P_{CAV}) = \sum_r C_d(N_{CAV}) \cdot TA_r(N_{CAV}, P_{CAV}) \quad (3\text{-}7c)$$

$$C_{UDP}(N_{CAV}, P_{CAV}) = \sum_d C_u \cdot x_{u,d}(N_{CAV}, P_{CAV}) \quad (3\text{-}7d)$$

$$C_{loss}(N_{CAV}, P_{CAV}) = \sum_r C_l \cdot x_{l,r}(N_{CAV}, P_{CAV}) \quad (3\text{-}7e)$$

$$C_{waste}(N_{CAV}, P_{CAV}) = \sum_r C_w \cdot x_{w,r}(N_{CAV}, P_{CAV}) \quad (3\text{-}7f)$$

where TC_t = the total cost of a supply chain system over a given period of time t; C_t = the unit fuel cost in \$/mile/unit (unit can be ton for solids and gallon for liquids); $x_{t,r}$ = the commodity flow along the route r; D_r = the total travel distance of the route r; C_d = the unit driver wage in \$/time; TA_r = the total transportation time of the route r; C_u = the unit unmet demand penalty in \$/unit for not meeting demand at destination node; $x_{u,d}$ = the unmet demand of commodity in unit at the demand node d; C_l = the unit product loss cost in \$/unit; $x_{l,r}$ = the amount of product loss in unit due to truck accidents in the route r; C_w = the unit waste disposal cost attributable to quality degradation in \$/unit; and $x_{w,r}$ = the amount of waste in unit in the route r.

As shown in Equation 3-7, CAVs affect the cost components directly and indirectly. The commodity flow ($x_{t,r}$) and the travel distance (D_r) are expressed as a function of CAV market penetration rate (P_{CAV}) because the optimized network flow and the shortest (or fastest) routes between nodes are found based on the edge capacity and incident rates, both of which are affected by P_{CAV}, in network optimization. In the network optimization process, capacity-constrained analyses are utilized to find the shortest path between two nodes until road capacity is reached, and then route commodity flows to the next shortest path. In this context, the updated edge capacities and incident rates affect routing decisions and subsequently change the associated length of routes and travel time. Moreover, the total commodity flow, driver wage, and unmet demand are updated based on reduced travel time between production sites and end-users. The number of driverless trucks employed in the supply chain affects several parameters: the unit fuel cost resulting from the increased fuel economy of CAVs, the commodity flow attributable to 24/7 trucking service of driverless trucks, and the driver wage that could be excluded by using driverless trucks. As observed in Equation 3-7e, the reduction in severe truck accidents decreases product losses ($x_{l,r}$) during commodity transport. Furthermore, the reduced travel time may decrease the amount of waste disposal of bad quality products at retailers if perishable or semi-perishable product is the main commodity of the supply chain system. It may also release current restrictions on distance a commodity can travel, thus enabling the transport of commodities over longer distances and expanding the geographic distribution of the supply chain system. To track quality changes throughout the entire supply chain system, a product quality degradation model is integrated with the total cost calculation. The quality degradation model is expressed as a function of time and temperature and formulated by [54]:

$$q_{u,t} = q_0 - \sum_{i=1}^{m-1} k_0 t_{i,i+1} exp\left[-E_a/RT_{i,i+1}\right] \tag{3-8}$$

where $q_{u,t}$ = the quality level of a unit product u at time t at demand nodes; q_0 = the initial quality level of the unit product; m = the number of nodes between production sites and retailers; k_0 = a constant; $t_{i,i+1}$ = the time spent between the i^{th} node and the $(i+1)^{th}$ node; E_a = the activation energy; R = the gas constant; and $T_{i,i+1}$ = the absolute temperature during the transport between the i^{th} node and the $(i+1)^{th}$ node.

As shown in Figure 3.4, a quality threshold (q_t) is used for making decision on product waste disposal. If the quality of a unit product becomes lower than the threshold at time t (i.e., $q_{u,t} < q_t$) during shipment or delivery process, it is assumed to be discarded, which causes the related waste disposal cost (C_{waste}) based on Equation 3-7f. Thus, $x_{w,r}$ can be expressed as:

$$x_{w,r} = \sum_{u\in\{1,U\}} \int_{t_{u,i}}^{t_{u,j}} i_{u,t}\, dt \tag{3-9}$$

$$i_{u,t} = \begin{cases} 0 & if\ q_{u,t} \geq q_t \\ 1 & if\ q_{u,t} < q_t \end{cases} \tag{3-10}$$

in which U = the set of products being transported along the route r; $t_{u,i}$ = the time when the product u departs from the node i; $t_{u,j}$ = the time when the product u arrives at the node j; and $i_{u,t}$ = the indicator of the quality of the product r at time t (i.e., $i_{u,t} = 0$ indicating that the quality is acceptable while $i_{u,t} = 1$ indicating that the quality is not acceptable). $x_{w,r}$ is dependent on both CAV market penetration rate and driverless truck adoption rate. For example, in Figure 3.4, a yellow dashed line represents the total travel time of a human-driven truck in a low CAV traffic environment and the corresponding quality degradation. As the quality at the destination node is lower than the threshold (i.e., the green solid line), the product is assumed to be discarded. Compared to the yellow line, the total travel time of a driverless truck in a high CAV traffic environment (see the blue line in Figure 3.4) is shorter, and the product quality is acceptable at the destination node. A higher value of $x_{w,r}$ may increase the final unmet demand, lower the satisfaction of customers, and increase the total cost of the supply chain because of a large amount of waste disposal. Therefore, through Equation 3-8, the effect of CAVs on routing decisions and travel time can be explicitly addressed in $t_{i,i+1}$ and subsequently affect the quality level of a product at a retailer, which is closely associated with waste disposal costs and restrictions on distance a commodity can travel.

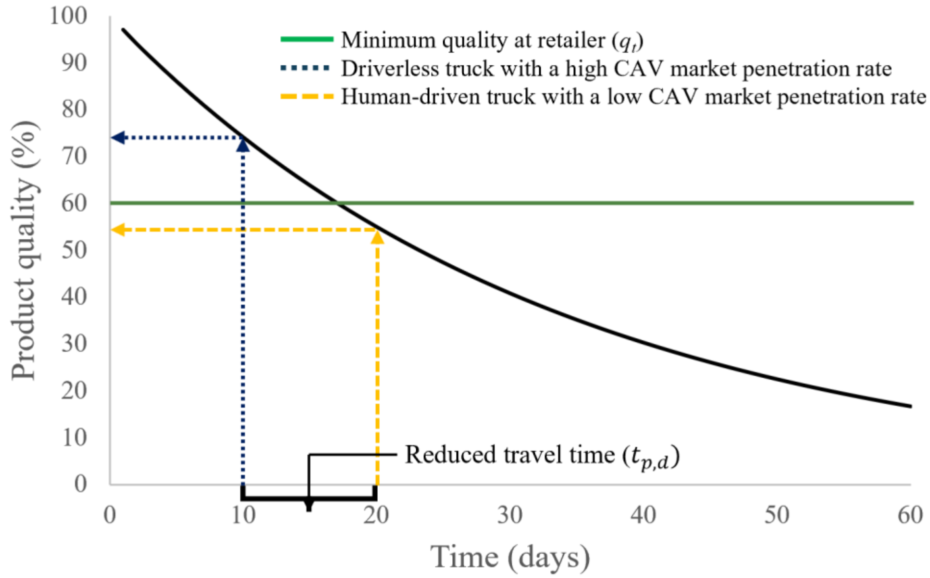

Figure 3.4: Schematic illustration of the quality degradation of a unit product between production site and final destination node

3.4 Summary

The objective of this chapter is to introduce the quantitative framework for assessing the effect of CAVs on supply chain long-term performance. By performing both the transportation analysis (see Sections 3.3.1 and 3.3.2) and supply chain analysis (see Section 3.3.3), this project can be utilized to model (a) total supply chain cost, (b) total transportation time, and (c) total GHG emissions under different levels of CAV market penetration rate and driverless truck adoption rate over system planning horizon. Then, in the following chapter, we illustrate this proposed framework and test its feasibility by using the case study of fresh potato supply chain systems.

Chapter 4. Case Study

4.1 Introduction

In this chapter, the proposed simulation framework is illustrated with hypothetical fresh potato supply chain systems to (a) show the potential effect of CAVs on the systems and (b) demonstrate the feasibility of the proposed framework. A fresh food (specifically fresh potato) supply chain system is selected as an illustrative example because it is expected as a "likely early-adopter" of CAVs because of the potential benefits and profits that CAVs would bring about [21]. Fresh potatoes are semi-perishable and sensitive to time and temperature in nature [55]. They should be delivered based on a constrained timeline to maintain the quality and quantity of products and lower waste disposal costs throughout the entire supply chain. Thus, waste disposal costs resulting from the degraded quality products could be reduced through advanced transportation logistics and CAVs. In this context, a fresh potato supply chain performance may be highly sensitive to the adoption rate of driverless trucks (i.e., the direct impact of CAVs) and the market penetration rate of CAVs (i.e., the indirect impact of CAVs). The rest of this chapter is organized as follows. Section 4.2 describes the proposed framework with the hypothetical fresh potato supply chain systems. Section 4.3 presents the major results and findings from this illustrative example. Finally, the conclusion of this chapter is summarized in Section 4.4.

4.2 Illustrative Example: Fresh Potato Supply Chain Systems

The main commodity of the hypothetical supply chain systems is fresh potatoes grown in the State of Washington, USA. Because of climate conditions and soil types, Washington produces the world's highest potato yield per acre, and 20% of all U.S. potatoes are grown in Washington [56]. The data on county-level potato production in Washington were obtained from the United States Department of Agriculture website [57]. Based on the personal communication with the Washington State Potato Commission (WSPC) (WSPC, personal communication, May 5, 2021), only 10% of the total potatoes are grown for fresh potatoes, and the remaining 90% potatoes are processed. Moreover, 25.1% and 31.9% of the total fresh potatoes grown in Washington are consumed in California and Mississippi, respectively [58]. Therefore, as illustrative examples, this project considers two supply chain systems for fresh potatoes grown in Washington which are transported to California and Mississippi respectively. The locations of these three states are presented in Figure 4.1.

Figure 4.2 presents the hypothetical supply chain system consisting of three types of nodes (i.e., potato production sites, potato distribution centers, and ultimate destinations) as well as the transportation edges between them. This supply chain system considers only 25.1% of the total fresh potatoes grown in Washington which are transported to California. The location of each production site is assumed to be the centroid of each county. Total 21 nodes in Washington are generated as potato production sites. As distribution centers are demand-driven facilities which are stocked with commodities to be redistributed to destinations, this project assumes that potato distribution centers are located around demand nodes and collects 26 candidate distribution centers from Google Map. The capacity of each distribution center is assumed to be 4,536 tons of fresh potatoes [59]. Demand nodes are assumed to be located at the centroids of the major cities in California, and thus, 453 demand nodes are considered as ultimate destinations. The total demand of fresh potatoes in California can be obtained from USDA, and the demand for each final destination node is assumed to be proportional to its population [57]. By minimizing Equation 3-7a in a complete HDV traffic environment (i.e., 0% of CAV market penetration rate and 0% of driverless truck adoption rate), the optimal supply chain system layout is obtained from the Freight and Fuel Transportation Optimization Tool (FTOT) developed by the U.S. Department of Transportation Volpe Center [60]. As the results of the FTOT optimization, there are seventeen potato production sites, eight potato distribution centers, and 100 final destinations in the supply chain layout in Figure 4.2.

Figure 4.1: Location of the States of Washington (WA), California (CA) and Mississippi (MS) in U.S.

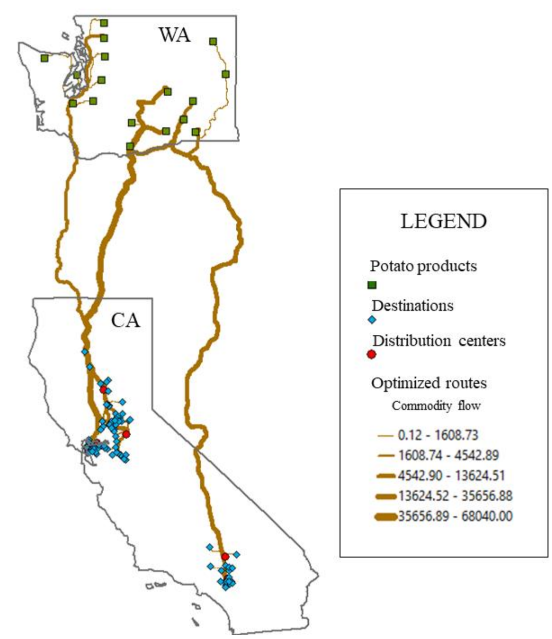

Figure 4.2: The layout of a hypothetical supply chain system for fresh potatoes grown in Washington and transported to California

To estimate the direct and indirect effects of CAVs on supply chain performance, this project considers five different levels (i.e., 0%, 25%, 50%, 75% and 100%) of CAV market penetration rates and driverless truck adoption rates, respectively. These two rates are independent variables in the proposed framework (see Figures 3.1 and 3.2). Thus, various combinations of both rates (i.e., total 25 representative scenarios) are generated to perform sensitivity analyses that assess their impacts on supply chain performance. Here, a complete HDV traffic environment is called the baseline scenario, whereas a complete CAV scenario indicates 100% of CAV market penetration rates and 100% of driverless truck adoption rates.

To quantify CAV effects on edge capacity, traffic incident rate, fuel consumption, GHG emissions, and truck accidents, secondary data are collected and used. Edge capacities for different rates of CAV market penetration are calculated by combining edge capacities in the baseline scenario [60] with the mean values of the highway capacity enhancement shown in Table 3.1. Similarly, the traffic incident rates of each edge in a mixed-traffic environment are estimated by combining the crash data in the baseline scenario [39] with the mean values of traffic conflict reduction indices summarized in Table 3.2. Changes in fuel consumption, GHG emissions, and truck accidents are also captured by using the values specified in Section 3.3.2. For a human-driven truck, the unit driver wage (C_d) is estimated at \$19.99 per hour [61], and an additional travel time (TH_e) needed for human drivers as a result of hours-of-service regulations is estimated at 20% of the CAV-involved travel time (TT_e) [62]. A \$5,000 penalty per unit of undelivered commodity is assumed to avoid no-flow solution in the supply chain optimization process [60].

In the quality degradation model, the quality threshold (q_t) in Equation 3-10 is the appearance of potato spoilage. As shown in Figure 4.3, potato spoils faster in a higher temperature environment. Figure 4.3 indicates that a Gaussian function is well fitted to the experimental data showing the relationship between temperature and the time taken to reach potato spoilage [63]. The Gaussian function is expressed by [63]:

$$T_s = 2616 * exp[-\left(\frac{temp+33.76}{24.2}\right)^2] \tag{4-1}$$

where T_s = the time taken to reach potato spoilage; and $temp$ = the temperature in Celsius. To model potato quality degradation during the transport, temperature changes from the production node to the destination node are recorded for each unit of potato. If the time taken from potato harvest to delivery to the final destination node is greater than T_s, the unit of potato is discarded. This time is uncertain mainly because of variability in harvest time and is modeled as a normally distributed random variable with the mean value of T_s and the coefficient of variation of 0.3. Then, the amount of discarded potatoes is calculated by Equation 3-9.

As the total travel time can be reduced by increasing either CAV market penetration rate or driverless truck adoption rate, CAVs may reduce the total amount of discarded potatoes and the associated waste disposal cost. In this case study, the replenishment cycle in July is used to assess supply chain performance because it is within a potato harvest season in Washington (from July to October) and can reduce uncertainty in the time taken from potato harvest to delivery. Moreover, July is one of the hottest months and can highlight the effect of CAVs on waste disposal cost. Temperatures in July measured at every location along the transportation routes are obtained from weather data available at the National Oceanic and Atmospheric Administration [64]. The spatial distribution of temperature is shown in Figure 4.4. Finally, all the three supply chain performance indicators (i.e., total transportation time, total GHG emissions, and total supply chain cost) are measured over a replenishment cycle. In this project, the replenishment cycle of fresh potatoes is assumed to be one week.

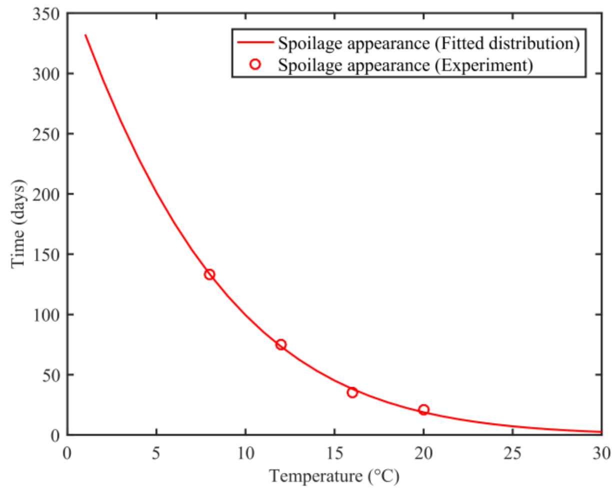

Figure 4.3: Quality degradation model for fresh potatoes

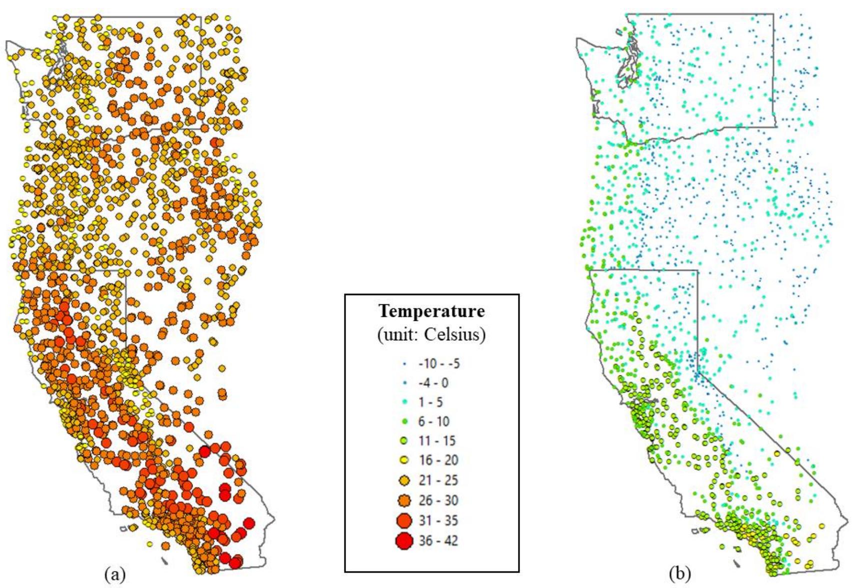

Figure 4.4: Temperature distribution over the study area: (a) maximum temperature in July and (b) minimum temperature in October

4.3 Simulation Results and Discussion

4.3.1 Supply Chain Performance Assessment

4.3.1.1 Total transportation time

In this subsection, the total transportation time is measured by the aggregated transportation time needed to transport potatoes from production nodes to destination nodes over the replenishment cycle. Table 4.1 lists the total transportation time over the replenishment cycle by varying both CAV market penetration rates and driverless truck adoption rates. CAVs can result in up to 53.04% decrease in the total transportation time over the replenishment cycle. As presented in Table 4.1, the indirect effect of CAV on the reduced transportation time is greater than its direct effect. In a complete HDV traffic environment ($P_{CAV} = 0\%$), the adoption of driverless trucks can reduce the total transportation time by up to 16.67%, whereas the total transportation time can be reduced by up to 43.65% in a complete CAV traffic environment ($P_{CAV} = 100\%$) without adopting any driverless trucks ($N_{CAV} = 0\%$). The results indicate that CAV traffic environment can be more effective in reducing total travel time than the adoption of driverless trucks in the supply chain network. It is mainly because the additional travel time (TH_e) needed for a human-driven vehicle is estimated at 20% of the CAV-involved travel time (TT_e) in this case study. Compared to TH_e, TN_e plays a larger role in reducing the total transportation time.

Table 4.1 Total transportation time over the replenishment cycle (unit: days)

CAV market penetration rate	Adoption rate of driverless trucks				
	0%	25%	50%	75%	100%
0%	299.49	287.01	274.53	262.05	249.58
25%	254.92	244.30	233.68	223.05	212.43
50%	196.43	188.25	180.06	171.88	163.70
75%	174.45	167.18	159.91	152.65	145.38
100%	168.75	161.72	154.69	147.66	140.63

4.3.1.2 Total GHG emissions

The adoption of driverless trucks in the supply chain system can enhance fuel economy and reduce GHG emissions during commodity transport, which is considered as the direct impact of CAVs in this report. Figure 4.5 summarizes total GHG emissions over the replenishment cycle by varying only driverless truck adoption rates. The result indicates that up to 18.77% of GHG emissions can be reduced by completely replacing human-driven trucks with driverless trucks for commodity shipment and delivery. This result implies that the use of driverless trucks in the supply chain system could be an environmentally friendly option.

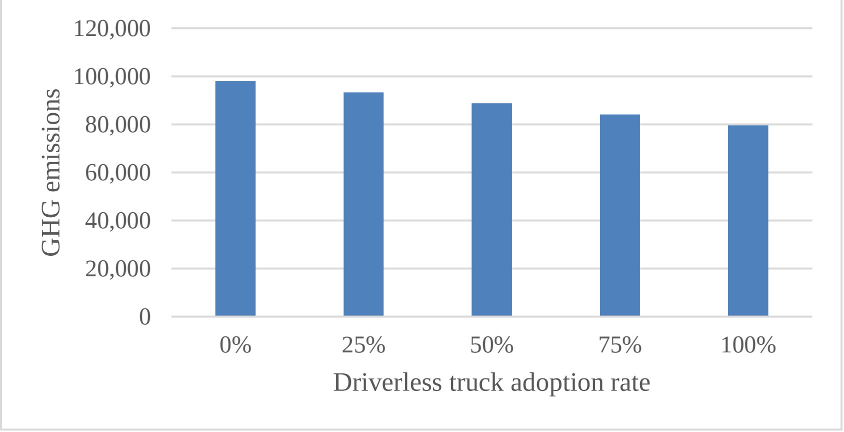

Figure 4.5 Total GHG emissions over the replenishment cycle corresponding to various driverless truck adoption rates (unit: kilograms)

4.3.1.3 Total supply chain cost

Table 4.2 lists the total supply chain costs over the replenishment cycle for all the 25 representative scenarios. As presented in this table, both independent variables reduce the total supply chain cost. However, the total cost decreases at a faster rate by increasing the adoption rate of driverless trucks, which indicates that direct CAV effect on the total supply chain cost is greater than the indirect one. More detailed information about cost breakdown can be found in Tables 4.3 and 4.4. Table 4.3 illustrates the effects of various levels of CAV market penetration on the five cost components (Equation 3-7) holding the driverless truck adoption rate constant at 0%. On the other hand, the sole effect of driverless trucks on the cost components is presented in Table 4.4. Reduced travel time resulting from the direct and indirect effects of CAVs leads to decreases in driver wage, waste disposal cost, and unmet demand penalty. However, fuel cost is mainly affected by the adoption rates of driverless trucks, as it is not dependent on total travel time but dependent on total travel distance (see Equation 3-7b), the latter of which is hardly reduced by other CAVs in a traffic environment. Still, fuel efficient driverless trucks can reduce fuel cost. In summary, the results imply that the use of driverless trucks in the supply chain system is more effective in reducing total cost.

Table 4.2: Total supply chain cost over the replenishment cycle for the 25 representative scenarios (unit: US million dollars)

CAV market penetration rate	Driverless truck adoption rate				
	0%	25%	50%	75%	100%
0%	19.20	17.84	15.99	15.17	13.37
25%	18.55	17.25	15.84	14.62	13.31
50%	17.71	16.40	15.34	14.27	13.21
75%	17.21	16.07	15.11	14.14	13.18
100%	16.96	15.87	14.97	14.07	13.17

Table 4.3: Supply chain cost breakdowns for various CAV market penetration rates over the replenishment cycle (unit: US million dollars)

CAV market penetration rate	0%	25%	50%	75%	100%
Fuel cost	12.80	12.80	12.80	12.80	12.80
Waste disposal cost	0.10	0.06	0.04	0.03	0.03
Driver wage	1.14	1.12	1.10	1.09	1.06
Product loss cost	2.04	1.82	1.57	1.41	1.37
Unmet demand penalty	3.12	2.75	2.20	1.88	1.70

Table 4.4: Supply chain cost breakdowns for various driverless truck adoption rates over the replenishment cycle (unit: US million dollars)

Driverless truck adoption rate	0%	25%	50%	75%	100%
Fuel cost	12.80	12.10	11.41	11.72	11.03
Waste disposal cost	0.10	0.09	0.08	0.06	0.06
Driver wage	1.14	1.01	0.71	0.34	0.00
Product loss cost	2.04	1.79	1.55	1.31	1.06
Unmet demand penalty	3.12	2.85	2.25	1.75	1.26

To examine the effect of CAVs on potato quality degradation in different weather scenarios, the waste disposal cost in July is compared to the one measured in October. The two weather scenarios are chosen because these two months are within the potato harvest season in Washington and can reduce uncertainty in the time taken from harvest to arrival at ultimate destinations. Furthermore, as shown in Figure 4.5, temperature differences between these scenarios are large enough to show the sensitivity of the CAV effect on potato quality degradation to temperature. The waste disposal cost is a small component of the total supply chain cost in this supply chain system because potato is a semi-perishable product. For perishable products that are much more sensitive to temperature and time, however, it is worth performing such sensitivity analysis to demonstrate how CAVs can reduce waste disposal cost, thereby enhancing supply chain performance. Figure 4.6 presents the potato waste disposal costs in both July and October in a mixed-traffic environment. The adoption rate of driverless trucks is set to be 0%, as its effect on the total travel time and the associated waste disposal cost is less significant than CAV market penetration rate. As expected, higher temperature in July causes greater amount of potato spoilage, and waste disposal cost is greatly reduced by expediting commodity transport. However, in October, the reduced travel time does not bring much benefit to the waste disposal cost because potato spoilage rarely appears even in the baseline scenario, because of low temperature. Therefore, this potato supply chain case study indicates that the effect of CAVs on the reduced waste disposal cost becomes greater during summer.

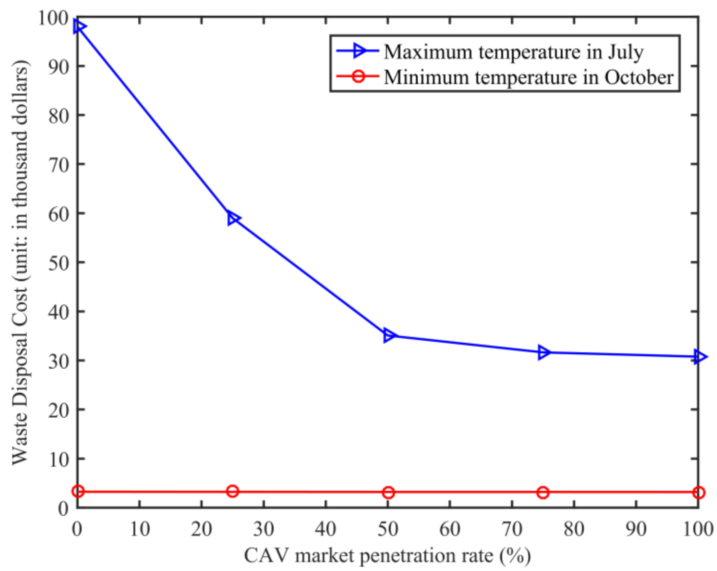

Figure 4.6 Comparison of potato waste disposal costs between two weather scenarios

4.3.2 CAV Effects on the Number of Required Trucks

This subsection quantifies the effect of CAVs on the number of trucks required to transport potatoes from production nodes to destination nodes over the replenishment cycle to illustrate how the reduced travel time can decrease the number of required trucks and driver wage. This subsection can provide an insight on how truck driver shortage can be partly resolved by CAVs so that supply chain managers can effectively determine the adoption of driverless trucks and the associated truck assignments over a given time period. Figure 4.7 presents three transportation routes from production nodes to destination nodes. It is assumed that the amount of potatoes requested by the demand nodes at the beginning of the replenishment cycle should be transported by the end of the cycle according to the On-Time Delivery (OTD). Moreover, trucks are allowed to make multiple trips between the nodes during the replenishment cycle. The total number of trucks required to meet the OTD during the replenishment cycle for the route r (DT_r) can be calculated as:

$$DT_r = \frac{CA_r}{TL} * \frac{1}{THS/(2*TA_r)} \tag{4-2}$$

in which CA_r = the total amount of potatoes in unit transported through the route r; TL = the truck load in unit/veh, which is assumed to be 24 tons per truck here [60]; THS = the total time in hours over the replenishment cycle (i.e., 168 hs in this report); and TA_r = the travel time for the route r (see Equation 3-5). The travel time and total number of trucks required to transport potatoes along each route over the replenishment cycle are presented in Table 4.5. As shown in this table, the full CAV traffic environment ($P_{CAV} = 100\%$ and $N_{CAV} = 0\%$) reduces the total travel time and subsequently allows less trucks to be employed to meet the OTD during the cycle. Such reduction can be observed more clearly in the longer routes, such as Routes 1 and 2. The results indicate that CAVs may directly and indirectly address the issues with truck and driver shortages by reducing total travel time and employing driverless trucks.

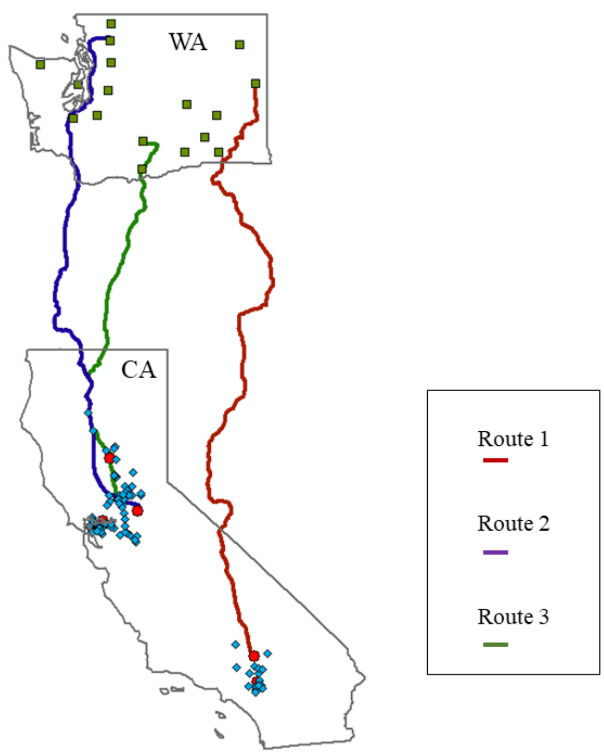

Figure 4.7: Selected transportation routes in the potato supply chain system

Table 4.5: Total travel time and the number of trucks required to transport commodities for each route over the replenishment cycle

Route	Commodity flow (metric ton)	Baseline scenario	Full CAV scenario	Baseline scenario	Full CAV scenario
		Travel time (hours)		Number of trucks	
1	1817.14	86.0113	38.4084	10	5

2	4440.19	61.014	28.0196	4	2
3	550.85	46.8382	21.9467	1	1

4.3.3 A Fresh Potato Supply Chain System Involving Longer Transportation Routes

This subsection is designed to examine the effect of CAVs on a fresh potato supply chain system involving longer transportation routes. Using the same procedure described in Section 4.2, a hypothetical supply chain system for fresh potatoes grown in Washington and transported to Mississippi is developed as shown in Figure 4.8. Mississippi is chosen because (a) 31.9% of the fresh potatoes grown in Washington are consumed in Mississippi [58], and (b) longer-distance commodity shipment is required in this supply chain system, which may highlight the benefits of CAVs. For the purpose of comparison, only the effect of CAVs on total supply chain cost is assessed and presented in Table 4.6. Similar to the supply chain system having the demand nodes in California, the direct effect of CAVs on the total cost outweighs their indirect effect because of the significance of the fuel cost in the total supply chain cost calculation. In this supply chain system, a 39.08% reduction in the total supply chain cost is expected in a complete CAV traffic environment. This reduction is higher than the one observed in the supply chain system between Washington and California (31.80%), indicating that CAV effect becomes greater for a supply chain system involving longer transportation routes by reducing travel time and the consequent fuel cost, driver wage, waste disposal cost, and unmet demand penalty.

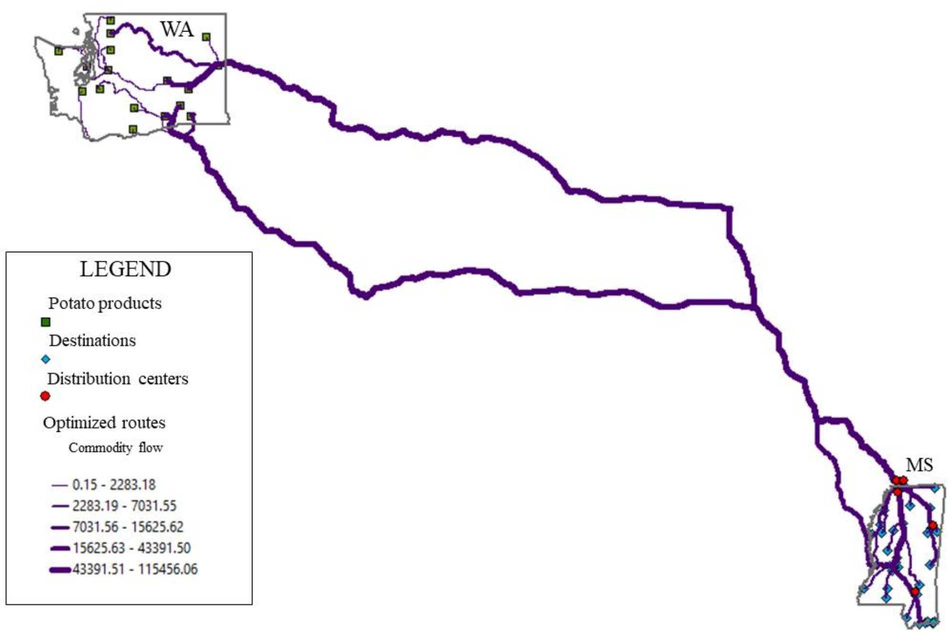

Figure 4.8: The layout of a hypothetical supply chain system for fresh potatoes grown in Washington and transported to Mississippi

Table 4.6: Total supply chain cost over the replenishment cycle (unit: US million dollars)

CAV market penetration rate	Adoption rate of driverless trucks				
	0%	25%	50%	75%	100%

0%	83.20	79.13	70.34	62.95	56.74
25%	79.28	75.13	68.29	60.26	54.12
50%	75.96	70.30	65.38	57.90	53.30
75%	72.10	69.85	63.34	56.42	52.15
100%	69.35	66.69	60.23	53.23	50.68

Based on personal communication with the WSPC (WSPC, personal communication, May 5, 2021), one of the main barriers in expanding their markets (especially to the East Coast) is the difficulty finding long-haul truck drivers. In this context, driverless trucks may provide an opportunity to expand their markets. In addition, reduced travel time enables the supply chain layout to be extended because the amount of potatoes requested by the original demand nodes can be delivered before the end of the replenishment cycle. Thus, additional commodities can be delivered to the areas around the original destination nodes. Figure 4.9 presents the extended layout of the supply chain system. Using the same cost as the total supply chain cost of the baseline scenario (i.e., \$83.20 M in Table 4.6), fresh potatoes can be delivered to thirteen additional destinations under the complete CAV scenario ($P_{CAV} = 100\%$ and $N_{CAV} = 100\%$) over the replenishment cycle. Specifically, the red lines in Figure 4.9 shows the newly added transportation routes, and additional 15% of fresh potatoes grown in Washington state can be delivered to the expanded markets. Therefore, CAVs also enable the extension of the geographic distribution of a supply chain system and bring about more profits and efficient delivery patterns, while holding the total cost is unchanged.

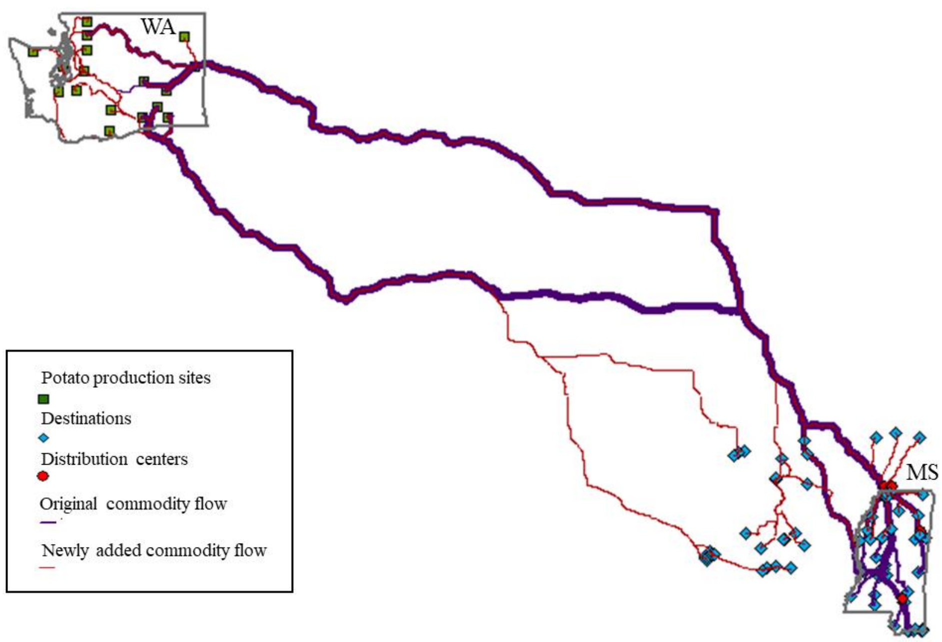

Figure 4.9: Expanded markets enabled by CAVs

4.4 Summary

To illustrate the proposed framework, two hypothetical fresh potato supply chain systems are used in this chapter. The simulation results revealed that CAVs affected supply chain performance directly and indirectly by reducing total supply chain cost, expediting commodity shipment and delivery, and decreasing GHG emissions. Furthermore, CAVs present even greater benefits to perishable or semi-perishable supply chain systems. Finally, CAVs enables the extension of the geographic distribution of a supply chain system and bring about more profits and efficient delivery patterns to existing systems.

Chapter 5. Summary and Conclusions

5.1 Introduction

This project fills the research gaps in current literature by quantitatively assessing the direct and indirect effects of CAVs on supply chain performance. The results from this project can be used by supply chain managers to better understand how supply chain design and operation could be transformed and reoptimized in response to the introduction of CAV technologies. In this chapter, Section 5.2 provides a summary of the major findings of this project by presenting the effects of CAVs on supply chain system. Section 5.3 details the limitation of this project, as well as the directions that should be taken in future research in order to improve model accuracy.

5.2 Summary and Conclusions

This project proposed a quantitative simulation framework to assess the direct and indirect effects of CAVs on supply chain performance by varying the levels of driverless truck adoption and CAV market penetration. Supply chain performance was measured by three indicators, which were total transportation time, GHG emissions, and total supply chain cost. Finally, the proposed framework was applied to hypothetical fresh potato supply chain systems in which the expedited and efficient delivery of product is of vital importance because of product quality degradation over time. Major findings from the case study include the following: (a) CAVs can greatly improve supply chain performance; (b) the indirect effect of CAVs plays a more significant role in reducing total transportation time, whereas the decreases in total supply chain cost and GHG emissions are mainly induced by employing driverless trucks in the supply chain network; (c) CAVs present greater advantages when commodities travel longer distances; (d) CAVs allow fewer trucks to be employed to meet the OTD during the replenishment cycle; and (e) with the same total cost, CAVs provide an opportunity to expand the existing markets. In addition to these findings, driverless trucks may potentially resolve the issue with finding drivers who transport potatoes from production sites which can be often reached through unpaved roadways (WSPC, personal communication, May 5, 2021). In summary, CAVs have the potential for improving supply chain performance in many aspects, which may ultimately address the limitations of current perishable or semi-perishable supply chain systems and human-driven trucks.

Given that online grocery shopping and delivery have received great attention especially during the COVID-19 situation (and assuming that this will be a new normal), this report on CAV effects on supply chain performance related to grocery products would provide even greater benefits to grocery delivery companies who deal with perishable or semi-perishable products because CAVs could address their major concerns about restrictions on distance and time a commodity can travel because of product quality degradation.

5.3 Directions for Future Research

This project collected and utilized the secondary data from existing studies to estimate the effects of CAVs on various transportation-related factors (highway capacity, speed, traffic accident) and incorporated them into a CAV-involving travel time model (see Section 3.3.1). Thus, the accuracy of this proposed framework highly depends on the reliability of the results from existing studies. To address the current limitation, it is recommended to perform both macroscopic and microscopic traffic simulations to validate the study results.

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