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Shipment sizing for autonomous trucks of road freight

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Abstract

Purpose – Unprecedented endeavors have been made to take autonomous trucks to the open road. This study aims to provide relevant information on autonomous truck technology and to help logistics managers gain insight into assessing optimal shipment sizes for autonomous trucks.

Design/methodology/approach – Empirical data of estimated autonomous truck costs is collected to help revise classic, conceptual models of assessing optimal shipment sizes. Numerical experiments are conducted to illustrate the optimal shipment size when varying the autonomous truck technology cost and transportation lead time reduction.

Findings – Autonomous truck technology can cost as much as 70% of the price of a truck. Logistics managers using classic models that disregard the additional cost could underestimate the optimal shipment size for autonomous trucks. This study also predicts the possibility of inventory centralization in the supply chain network.

Research limitations/implications – The findings are based on information collected from trade articles and academic journals in the domain of logistics management. Other technical or engineering discussions on autonomous trucks are not included in the literature review.

Practical implications – Logistics managers must consider the latest cost information when deciding on shipment sizes of road freight for autonomous trucks. When the economies of scale in autonomous technology prevail, the classic economic order quantity solution might again suffice as a good approximation for optimal shipment size.

Originality/value – This study shows that some models in the literature might no longer be applicable after the introduction of autonomous trucks. We also develop a new cost expression that is a function of the lead time reduction by adopting autonomous trucks.

Keywords Economic order quantity, Lead time, Autonomous truck, Shipment size

Paper type Research paper

1 Introduction

What happens in a sci-fi movie may not always stay in a sci-fi movie. In the 2017 American superhero movie *Logan*, one of the most intense scenes involves Australian actor Hugh Jackman driving a car that almost gets hit by a number of speedy self-driving trailers on the highway. A year later, the Swedish automotive company Volvo released a TV commercial for its autonomous truck (AT) that looks similar to the self-driving trailers in the movie. Back in 2016, Anheuser-Busch InBev, a multinational drink and brewing company based in Belgium, and Uber Technologies Inc.'s autonomous trucking unit Otto worked together and successfully made the first commercial delivery of Budweiser beer using a self-driving truck (Phillips, 2016; King *et al.*, 2017). While automated vehicles in controlled areas such as transportation terminals or mining sites have been around for many years, only in the last five years have we seen major trucking companies make unprecedented endeavors to take ATs to the open road (Tita and Ramsey, 2015). In this era of disruptive technologies, we seek to learn how the ATs could revolutionize the way logistics mangers make decisions on shipment size.

Considering the magnitude of the logistics industry and how driverless technology can fundamentally disrupt the industry, government agencies have been playing an active role in guiding the private sector and steering the development of automated vehicles. In 2013, the US National Highway Traffic Safety Administration (NHTSA) published a description of developments in automated driving and explained the automation levels (NHTSA, 2013). In the spirit of continuously encouraging innovations to self-driving technology, NHTSA published federal guidance for automated vehicles in recent years (NHTSA, 2017; DoT, 2018). In 2016, the UK chancellor pledged to remove impediments to adopting the technology and announced plans in the budget to roll out driverless haulage technology by the end of the decade (Cambell, 2016). In 2017, Germany permitted the automotive industry to develop and test self-driving cars with much more flexible ways to road-test vehicles (Wacket *et al.*, 2017). It is commonly believed that the biggest barriers to technology deployment usually are not technical but rather inadequate or unclear government regulations. Thankfully, governments have proposed legislation and issued licenses that are crucial and necessary for improving the development of automated vehicles (Spector, 2016).

Automated vehicles entail many modern technologies costs as well as viable social and commercial benefits. ATs need hardware and software to be able to better sense and judge the surrounding environment (e.g., traffic, pedestrians, objects, lane markings, weather) (Anderson *et al.*, 2014). Among all kinds of vehicles, freight-carrying commercial motor vehicles (e.g., trucks and tractor trailers) are commonly believed to be more commercially viable than passenger-carrying consumer vehicles for the following reasons (Kilcarr, 2016a; Markoff, 2016; Cheng, 2019). First, the substantial hardware and software investments necessary for enabling automation are relatively less costly for a truck than a car (Waters, 2019). Second, labor costs account for a substantial percentage of road-freight operating costs; ATs can, theoretically, cut labor costs to as little as zero (O'Brien, 2017; Kilcarr, 2017). Third, the ongoing truck driver shortage is a worldwide phenomenon, with trucking companies having a hard time recruiting and retaining drivers (Schouten, 2016; Ramsey, 2016; O'Marah, 2016; Millett, 2017; Meahl, 2017; Woodward, 2017; Cambell, 2018; Meyer, 2018). Last, in view of the federal Hours of Service (HOS) rules, ATs promise great economic benefits as they allow freights to arrive at their destinations sooner because no human driver needs to take a break during the trip (FMCSA, 2013). In many ways, ATs are poised to promote benefits and alleviate imminent issues facing the logistics industry.

Anticipating promising advantages, trucking companies have tried to bring automated vehicles out of controlled settings (e.g., mining sites, construction sites, transportation terminals, distribution centers, production plants, and agricultural fields) and into uncertain environments (e.g., streets and highways) (Meldert, 2016). In 2016, a fleet of self-driving trucks from major companies, including Volvo, Daimler, and Volkswagen, completed a cross-continent journey as an effort to not only take ATs onto real roads but also demonstrate the tangible cost-saving benefits of ATs (Vincent, 2016). More recently, Ford and Volkswagen have collaborated on developing self-driving cars to share the cost of new technologies (Boudette and Ewing, 2019). Other collaboration examples among companies can be found in Wilmot (2019) and Vaish (2019). UPS, a multinational package delivery and supply chain management company, has invested in a self-driving trucking start-up company with a goal of testing the capabilities and limitations offered by a fully autonomous delivery fleet (Vartabedian, 2019). Despite many successful cases of ATs to date, exact costs for enabling ATs remain elusive due to the lack of commercially available systems (Kilcarr, 2015b; Woodward, 2017; Banks, 2017; Chottani *et al.*, 2018). As a result, studies of the implications of AT hardware or software costs on the inventory decision are scarce. It is necessary to gain a better understanding of the AT enabling costs because many major companies have shown determination to move forward with AT in ways that will capitalize the savings of this disruptive technology.

Putting aside AT costs for a moment, we believe the logistical benefits of ATs are undeniable. One of the major competitive advantages introduced by this disruptive technology is *transportation lead time reduction*. This does not mean that ATs can violate speeding laws (that said, speed limits are meant for humans and should be revised when ATs on average require less response time than humans do). In comparison to human drivers, ATs need no break time and can continue running for as long as there is fuel left in the tank. As such, a better percentage of a truck's lifetime can be spent running on roads rather than sitting idle, thereby increasing the truck's utilization and cutting transportation lead time for clients (Crandall and Formby, 2016). Nonetheless, enabling automation requires substantial capital investment on each truck. For example, in the 2018 PwC survey, "*Costs are prohibitive*" was one of the main barriers to adopting AT (PwC, 2018). Given the novelty of the autonomous technologies, the literature about ATs in the domain of logistics management simply lags behind. We suspect previous models offer little insight into how the features of ATs, namely AT enabling costs and reduced transportation lead time, might affect a logistics manager's decision-making in inventory management. Specifically, how should a manager alter the shipment size when ATs incur additional costs but take less time to arrive at their destinations? We are motivated to improve logistics management by answering this question.

Therefore, we believe it is necessary to reexamine the literature and see if previous research results are still applicable in the advent of ATs. To this end, this study collects recent AT cost information available in the domain of logistics management. Through the lens of ATs, this study not only reevaluates classic models but also develops new models that can be used to consider the trade-offs between transportation and inventory costs when determining optimal shipment sizes. Ultimately, we seek empirical evidence and analytical results that can shed light on what implications ATs have on evaluating optimal shipment size. Some of the findings of this study are as follows. First, we find that the AT-related cost estimates vary substantially and can cost up to 70% of the price of a truck. Second, the optimal shipment size for ATs derived in this study is larger than the optimal shipment size derived from some classic models. Last, shipment sizing solutions derived from some classic models might not be applicable until the AT costs can be significantly offset. Overall, this study contributes to the literature with respect to empirically examining AT cost estimates and theoretically revising conceptual models to illustrate the implications of ATs on shipment sizing problems.

The remainder of this study is organized as follows. In Section 2, we sample some research work that is closely related to our study. In Section 3, we describe the scope and scale of the data collection and briefly tabulate the AT cost estimates. In Section 4, we introduce our conceptual models, which allow us to consider the cost information summarized in the previous section. In Section 5, we conduct numerical experiments to illustrate the results of the theoretical findings for logistics managers' decision-making in shipment size. In Section 6, we discuss the implications of the ATs on the logistics industry. In Section 7, we conclude this study and provide ideas for future research.

2 Literature review

The economic order quantity (EOQ) model has been the foundation for many decision-making models (Harris, 1913; Erlenkotter, 1990). Blumenfeld *et al.* (1985) used the EOQ model to establish the interface between transportation and production setup costs. The trade-offs between transportation and inventory costs are assumed to be functions of shipment size. The closed-form optimal shipment size solutions are constrained by the truck capacity. Hall (1985) investigated an optimization problem in the context of "collecting"—a way to consolidate freight that involves trucks picking up material from multiple suppliers for a single customer. The author determined the optimal dispatch frequency and time between dispatches by assessing a trade-off between inventory and transportation costs. Again, any given load size delivered at a destination was assumed to be binding to the truck capacity. Our study relaxes the conventional truckload capacity constraint because when ATs are fully automated, *platooning* becomes much safer to execute as compared to manual maneuvers. Platooning refers to multiple trucks that are dispatched at one time and drive closely one after another to form a convoy (De Jong and Ben-Akiva, 2007). Platooning has been scientifically proven to improve fuel efficiency by reducing aerodynamic drag for all trucks in the convoy (Janssen *et al.*, 2015; Banks, 2017; Mele, 2017). The 2018 McKinsey report indicated that a fully automated platooning convoy of trucks may need a human driver only in the lead truck, and the following ATs can be unmanned, revoking the need of the truckload capacity constraint.

The classic EOQ model was capable of investigating the nature of the trade-offs existing among variables in freight transportation. Burns *et al.* (1985) considered two distribution strategies: shipping separate trucks from the supplier to each customer or dispatching trucks to multiple customers per load. The authors used the EOQ model to derive the optimal shipment size that minimizes the total transportation and inventory costs, and the costs had little AT implications. Abdelwahab and Sargious (1990) considered that freight charges increased with shipment size (or the logarithm of shipment size), and the identified relationship between the total cost and the parameters was largely aligned with those in Blumenfeld *et al.* (1985). Ernst and Pyke (1993) assumed that the shipping costs comprised a fixed cost per shipment that is function of truck capacity and a variable cost that is associated with the distance traveled for a trucking company. The authors relaxed the capacity constraint by allowing the trucking company to use some common carrier to deliver the shipment. While these results did not directly inform the implications of the AT features on the optimal shipment size, the analytic methods of these studies shed light on the models in our study.

Even under the stochastic demand assumption, the solution of optimal quantity under the EOQ model continues to provide a useful reference when investigating the optimal order quantity (Liberatore, 1979; Eppen and Martin, 1988). Comparing to the optimal quantity determined by the stochastic system, Zheng (1992) and Axsäter (1996) showed that the EOQ caused little or no relative cost increase for the continuous-review, reorder-point, order-quantity inventory control system. Chung *et al.* (2009) and Çakanyildirim *et al.* (2017) used an iterative approach to find the optimal reorder point and order quantity by using the EOQ as the starting point. Essentially, the conventional shipment size optimization theory assumed that firms use the EOQ to minimize total logistics costs by balancing ordering costs, transport costs, and inventory holding costs (Baumol and Vinod, 1970). We find the EOQ model has the conceptual framework that can account for the trade-offs between transportation and inventory costs when analyzing optimal shipment sizes.

To understand the implications of ATs on the optimal shipment size, we explicitly incorporate the features offered by ATs–the shortened lead time and AT enabling costs–into the EOQ model framework. As ATs are expected to effectively reduce the transportation lead time, the property of the optimal shipment size under stochastic lead time appears to require a separate investigation. Song *et al.* (2010) showed that while a stochastically smaller or less-variable lead time can lead to a smaller reorder point, the order quantity is not necessarily smaller. In the case where the transportation lead time is controllable, not all studies explicitly considered the transportation cost a part of the total inventory cost (Ertogral *et al.*, 2007; Abate and De Jong, 2014). We found a stream of literature that assumed that the shorter the desired lead time is, the more expensive it would be to shorten one unit of lead time. Liao and Shyu (1991) assumed the crashable lead time consists of multiple mutually independent components: administrative, transport, and supplier speed-up costs. Ouyang *et al.* (2007) assumed that the lead time was controllable by a piecewise cost function when optimizing the order quantity for the reorder-point, order-quantity inventory system. (Glock, 2012) pointed out that many studies assumed a piecewise linear function for the relationship between lead time reduction and lead time crashing costs, but the relationship is not necessarily linear in nature. Please see Sarkar and Moon (2014) for more references on the piecewise linear lead time crashing functions. One disadvantage of the piecewise linear crashing cost function is that it requires exhaustively assessing the total inventory system cost at each lead time break point of the intervals for optimality. On the other hand, Ben-Daya and Raouf (1994) proposed an alternative crashing cost function differentiable with respect to the lead time, but specific roles of the function parameters were unclear beyond fitting empirical data. Nakandala *et al.* (2014) proposed a revised crashing cost function to consider both linear and non-linear relationships between lead time and ordering cost, but the joint optimal lead time and order quantity were not investigated. In our study, we aim to bridge the gap in the literature between the optimal shipment size and the controllable lead time in the presence of nonlinear AT enabling costs.

3 Empirical data

We focused on collecting cost figures related to AT technologies of heavy trucks. Considering the history and nature of autonomous technologies span many decades and disciplines, this data collection is not intended to be exhaustive or comprehensive. To reduce the scope and scale of the literature review to some manageable size, we reviewed the literature in the domain of logistics management. Specifically, we used *ProQuest* and *Google Scholar* to search articles with the keywords “driverless,” “truck,” “autonomous,” and “cost” under “Trade Journals” and “Scholarly Journals” source types. According to the ProQuest search results, the number of publications on “autonomous trucks” had stayed small until a sudden increase in 2015. Thus, we searched articles published after January 1, 2015, for more relevant empirical data. In addition, we omitted articles about applying ATs in controlled areas. In the end, we reviewed 187 articles, most of them being trade journal reports. Overall, we found that little cost information is available. Particularly, we found that only around 20 articles have specific cost figures or estimates relevant to our study. In general, AT equipment costs refer to cameras, Lidars (laser sensors for 3-D imaging), radar, and onboard computers (Ohnsman, 2019). Cost estimates for special add-on software such as driver-assist technology and hardware such as automated mechanical transmissions were scarce. Note that costs external to trucks such as infrastructure are not considered in this study. Extended discussions on ethical, legal, regulatory, and insurance issues are also beyond the scope of this study; interested readers may find Insurance (2017), Riehl (2018), or Ross (2018) useful.

In terms of automation levels, DoT (2018) and SAE (2018) define six levels of driving automation in the context of motor vehicles and their operation on roadways as follows: from No Driving Automation (Level 0), where the driver handles the entire dynamic driving task, to Full Driving Automation (Level 5), where some automated driving systems are able to unconditionally perform entire dynamic driving tasks without any human intervention. It has been reported that Waymo, a self-driving technology development company, is about to conditionally attain Level 4 in fair-weather Phoenix, Arizona (Kessler, 2019). Nonetheless, most of the cars in the consumer market are equipped with the technologies associated with Level 1 or lower (e.g., adaptive cruise control), and only high-end cars are currently equipped with Level 2 technologies (e.g., Tesla Autopilot, Volvo Pilot Assist, Mercedes-Benz Drive Pilot, and Cadillac Super Cruise) (Hughes, 2017). Similarly, ATs are expected to phase through six stages of automation (Kilcarr, 2016b). In comparison to consumer vehicles, ATs are considered by many experts to be one of the most disruptive yet viable technologies to the logistics industry. Similar to the development of automated consumer vehicles, ATs have recently attained Level 4 automation in Florida Roberts (2019). The influences of ATs are generally believed to be profound and multifaceted, and many people believe that the prevalence of ATs is no longer a question of if but when.

We found that the cost of adopting AT technologies can be significant and hence should be considered when making decisions on shipment size. On the one hand, the manufacturing cost of a regular truck is fairly mature and stable over the years. On the other hand, estimates of AT equipment costs vary substantially. For a Class 8 truck costing around \$150,000, estimated additional AT equipment costs can be as much as 70% of the truck cost, according to the trade journal publications. Table 1 tabulates the cost information we have found in the literature.

Due to the small sample size, we did not attempt to elaborate any statistics in the figures. Nonetheless, we noticed that the *range* of the AT equipment costs increased over the years, which signals how uncertain experts might be about the potential costs to

Table 1: A sample of publications that estimate AT-related costs

Year	Truck Costs ($)	AT Technology Costs ($)	References
2015	140,000	20,000	Kilcarr (2015b)
2015	140,000	35,000	Kilcarr (2015b)
2016	-	23,400	Kilcarr (2016b)
2016	-	30,000	Kilcarr (2016a)
2016	135,000	65,000	Kilcarr (2016d)
2016	125,000	75,000	Kilcarr (2016d)
2016	150,000	75,000	Markoff (2016)
2016	-	13,100	Short and Murray (2016)
2016	-	19,000	Short and Murray (2016)
2016	-	23,400	Short and Murray (2016)
2016	-	30,000	Crandall and Formby (2016)
2016	-	75,000	Short and Murray (2016)
2017	-	23,000	Turnbull (2017)
2017	-	100,000	Freedman (2017)
2018	160,000	-	Massey (2018)
2018	-	20,000	Zurschmeide (2018)
2018	-	30,000	Chottani *et al.* (2018)
2018	-	80,000	Zurschmeide (2018)
2018	-	100,000	Zurschmeide (2018)
2018	-	100,000	Chottani *et al.* (2018)
2019	150,000	50,000	Ohnsman (2019)

enable ATs. Another plausible explanation is that as more knowledge about required AT equipment is acquired, companies may choose to develop equipment of different calibers, which then implies different costs (Chottani *et al.*, 2018). Before autonomous driving systems are more widely produced and gain economies of scale, the range of the estimated costs may not decrease anytime soon (Healey, 2017).

For assessing the potential transportation lead time reduction by adopting ATs, we excerpt some information pertaining to property-carrying drivers from the section of HOS regulations as follows (FMCSA, 2013):

- *11-Hour Driving Limit: May drive a maximum of 11 hours after 10 consecutive hours off duty.*

- *14-Hour Limit: May not drive beyond the* 14^{th} *consecutive hour after coming on duty, following 10 consecutive hours off duty. Off-duty time does not extend the 14-hour period.*

- *Rest Breaks: May drive only if 8 hours or less have passed since end of driver's last off-duty or sleeper berth period of at least 30 minutes.*

- *60/70-Hour Limit: May not drive after 60/70 hours on duty in 7/8 consecutive days. A driver may restart a 7/8 consecutive day period after taking 34 or more consecutive hours off duty.*

Basically, by regulating the maximum driving time as well as the minimum rest time between driving shifts, the HOS rules aim to reduce accidents attributable to truck drivers' fatigue. Simply put, if a fully automated truck (i.e., Level 5) is adopted, then technically the freight on the truck can be transported from point A to point B without ever needing to stop for the human driver to take a break, since none of the HOS rules would apply here (GAO, 2019). ATs can continue driving while a human driver has to take a break or be off duty for 10 consecutive hours, which means up to 40% potential driving time can be released from a 24-hour time window. For long-haul operations that used to last for more than one day, the transportation time can be reduced by almost half. That is, given the same period of time, ATs are able to travel farther than human drivers can.

4 Conceptual models

4.1 Base model

We developed an EOQ model that treats the shipment size as an endogenous variable and considers the interaction between transportation and inventory costs. We differentiated our EOQ model from those in the literature by considering the features introduced by ATs to evaluate trade-offs between these costs as a function of shipment size. We based our models on direct shipping in a simple supply chain consisting of one supplier site and one customer site. Moreover, trucks make one single stop in a round trip to deliver products to the customer.

The inventory holding cost per unit depends on the time each unit spends in the supply chain, which consists of average production and consumption time and average in-transit time. At the supplier site, the production rate is q. The average time needed to produce the entire load is V/q, where V denotes the shipment size in units. Thus, the average production time *per unit* is $V/(2q)$. In general, supply chain entities in a good business relationship typically have some kind of mechanism in place (e.g., point-of-sales system or electronic data interchange) that allows the entities to synchronously update demand information to mitigate the bullwhip effect. Therefore, we have assumed that the production rate at the supplier site is synchronized with the deterministic product consumption rate at the customer site to simplify the analysis. Thus, once V arrives at the customer site, the average time to consume the entire load is V/q, and the average consumption time *per unit* is $V/(2q)$.

Let T be the in-transit time and h denote the unit inventory carrying cost per unit time period, then the inventory carrying cost per unit is

$$h\left(\frac{V}{q}+T\right).$$

Let the fixed transportation cost $S=\gamma+\epsilon D$, where γ denotes the fixed cost of dispatching a truck, including loading and unloading at a customer stop, ϵ denotes the variable cost per unit of distance, and D denotes the round-trip distance. Thus, the transportation cost per unit is S/V. Given the transportation and inventory holding costs, the classic models derive the optimal shipment size (Burns *et al.*, 1985):

$$V^*=\sqrt{\frac{Sq}{h}}. \tag{1}$$

Thus, the total cost with the optimal shipment size is given by

$$C^*=2\sqrt{\frac{Sh}{q}}+hT.$$

While Eq. (1) is capable of explaining many relationships between the variables, it was not intended to inform the effects of the features of ATs on V^*. Clearly, the variable T was omitted in the formula as it was not considered a decision variable before the advent of ATs. The higher the level of automation that can be achieved in the truck (from Level 0 to Level 5), the more the expected amount of time originally tied up by the HOS rules can be released. Given V^*, the logistics manager would not be able to treat T as one of the decision variables. In the presence of ATs, logistics managers are able to decrease T, within some reasonable range, by better utilizing the trucks. That is, holding D constant, the trucks with AT technologies will spend more time running than idling, thereby increasing the average speed and decreasing T. For enabling a higher level of automation, the additional costs per truck for automation hardware and software would be as follows (Short and Murray, 2016):

- Level 3: \$13,100 added to truck price.
- Level 4: \$19,000 added to truck price.

- Level 5: \$23,400 added to truck price.

Therefore, the classic EOQ model must reflect the fact that the higher the automation levels, the greater the lead time can be reduced, and the higher the costs would be required. To this end, we add an *amortized cost of acquiring and using AT technology* into S:

$$\tilde{S} = \gamma + \epsilon D + \frac{\kappa}{T},$$

where κ denotes the cost increase for each unit decrease in T. The larger κ is, the higher the cost incurred to reduce one unit of the transportation lead time. We may view κ as *AT deployment efficiency* when logistics managers acquire and implement AT technologies. A large κ refers to low deployment efficiency because it renders a higher cost for the logistics manager when adopting AT technologies. We suppose κ is large until the deployment of ATs becomes an industry-wide phenomenon. We then derive the updated optimal shipment size $\tilde{V}^*$ by equating the first derivative of the total costs with respect to V to zero.

Proposition 1.

$$\begin{aligned} \tilde{V}^* &= \sqrt{\frac{Sq}{h} + \frac{\kappa q}{hT}} \\ \tilde{C}^* &= 2\sqrt{\frac{h\left(S + \kappa/T\right)}{q}} + hT. \end{aligned}$$

Clearly, $\tilde{V}^* > V^*$, showing that the classic model was no longer applicable after the introduction of AT technologies in logistics management. Notice that the smaller the lead time is, the larger the optimal shipment size would be. Also, the greater the AT deployment efficiency is, the smaller the optimal shipment size would be. The trend of κ in the short run is unclear as AT technologies are continuously evolving. To the best of our knowledge, no single dominating or standardized hardware or software has been mass-produced to enjoy the economies of scale as of yet. However, in the long run, most experts believe the production and deployment of AT technologies will become increasingly widespread and mature, thereby contributing to a smaller κ.

Remark 1. *Given deterministic demand, the optimal autonomous truck shipment size tends to be larger than the shipment size prescribed by the classic EOQ expression.*

Corollary 1.

$$\tilde{D}(t) = \frac{q\left(\tilde{C}^{*} - ht\right)^2}{4h\epsilon} - \frac{\gamma}{\epsilon} - \frac{\kappa}{\epsilon t}, \tag{2}$$

where $t \leq T$ denotes some reduced lead time.

Derived from Proposition 1, Corollary 1 shows the impact of the reduced transportation lead time on the AT's travel distance. As such, $\tilde{D}(t)$ is not monotonic in t and can be sensitive to the parameter values.

4.2 Extended model

We would like to consider the reality where the demand during lead time can be stochastic and the AT enabling cost consists of variable and fixed costs. To this end, we create a separate scenario (with a new set of notations) in which the buying firm faces a stochastic demand with mean μ and standard deviation σ. We now assume that $q \gg 0$ so the time for production or consumption is negligible. The inventory control system that the firm operates is a continuous-review, reorder-point, order-quantity system, except we use V in place of the order quantity for this analysis. Let the reorder point be the demand during lead time μT plus the safety stock $k\sigma\sqrt{T}$, where k is the safety factor (Silver *et al.*, 2016). For simplicity, we assume that k is large so that the reorder point achieves a high cycle service level target. That is, out-of-stock events are rare and need not be explicitly specified in the model.

As such, the lowest and highest net inventory levels are $k\sigma\sqrt{T}$ and $V + k\sigma\sqrt{T}$, respectively, and the annual average inventory holding cost can be approximated by

$$h\left(\frac{V}{2} + k\sigma\sqrt{T}\right), \tag{3}$$

where h is the annual inventory holding cost per unit.

As suggested by the literature, different levels of ATs represent stackable opportunities to cumulatively "crash" the transportation lead time. We hereby propose a new model for the annualized lead time crashing cost function for the controllable T:

$$\frac{u}{1+e^{mT}}, \tag{4}$$

where $u > 0$ is the scale of the lead time crashing cost function, and $m \geq 0$ is the shape of the function. m may change under different economies of scale of the AT deployment cost. The smaller m is, the higher the variable cost is to crash the lead time, and even low levels of automation requires significant enabling costs. Conversely, the larger m is, the smaller the variable cost for crashing the lead time until the highest level of automation, where the marginal variable cost increases exponentially ("L"-shaped cost function). Practically, ATs have not only additional costs but also additional savings for reasons such as lower maintenance, less fuel, less labor, lower insurance premium, and so on. Until those costs are more transparent than they are now, we conceptually treat the AT variable cost as the net of all the addition costs and additional savings. Judging by the empirical data, the savings of deployment of the lower levels of ATs (e.g., 2 or lower) might already justify their costs, but it is certainly not the case for the higher levels (e.g., 4 or higher). Intuitively, we suppose that m would be increasing and u would be decreasing over time.

Let A denote the fixed order cost per replenishment. We construct the expected total inventory cost function as follows:

$$K(V,T) = \left(A + \frac{u}{1+e^{mT}}\right)\frac{\mu}{V} + h\left(\frac{V}{2} + k\sigma\sqrt{T}\right) \tag{5}$$

$$\frac{\partial K(V,T)}{\partial T} = \frac{hk\sigma}{2\sqrt{T}} - \frac{\mu u m}{V}\cdot f(mT) \tag{6}$$

$$\frac{\partial^2 K(V,T)}{\partial T^2} = \frac{\mu u m^2}{V} f(mT)\cdot\frac{e^{mT}-1}{e^{mT}+1} - \frac{hk\sigma}{4\sqrt{T^3}}, \tag{7}$$

where $f(mT) = e^{mT}/(1+e^{mT})^2$ is a logistic distribution with mean 0 and variance $\pi^2/3$ (Decani and Stine, 1986). We obtain the optimal lead time T_V^* that can minimize Eq. (5)

by equating Eq. (6) to 0.

Proposition 2. *Let* $[t_{min}, t_{max}]$ *denote a range of crashable* T *of interest.*

- *If* $K(V,T)$ *is concave in* T*, then* T_V^* *is* t_{min} *or* t_{max}*, whichever bears a smaller* $K(V,T)$*.*
- *If* $K(V,T)$ *is convex in* T*, then* T_V^* *is such that*

$$f(mT_V^*)\sqrt{T_V^*} = \frac{hk\sigma V}{2\mu u m}. \tag{8}$$

Remark 2. *The expression of the optimal lead time is subject to the shape of the total cost function with respect to the crashable lead time.*

Proposition 2 and Eq. (7) suggest the circumstances in which logistics managers might decide to minimize the lead time (i.e., implement a higher level of ATs) include, but are not limited to, the following: the products have a high holding cost (i.e., a large h), the inventory system sets a high cycle service level target (i.e., a large k), or the demand is highly volatile (i.e., a large σ). Obviously, a large u would disapprove the decision.

Proposition 3.

- *If* $K(V,T)$ *is concave in* T*, then*

$$\tilde{V}^* = \sqrt{\frac{2\mu}{h}\left(A + \frac{u}{e^{mT_V^*}+1}\right)}. \tag{9}$$

- *If* $K(V,T)$ *is convex in* T*, then* V^* *is such that*

$$\frac{hk\sigma\sqrt{T_V^*}}{\tilde{V}^*\Phi(mT_V^*)} + \frac{\mu}{(\tilde{V}^*)^2}\left(A + \frac{u}{1+e^{mT_V^*}}\right) = \frac{h}{2} + \frac{h^2k^2\sigma^2}{2\mu u m f(mT_V^*)\Phi(mT_V^*)}, \tag{10}$$

where $\Phi(mT_V^*) = 2mT_V^*(1-2F(mT_V^*))+1$*, and* $F(mT) = e^{mT}/(1+e^{mT})$ *is the cumulative distribution function of* $f(mT)$*.*

Please see the derivation of Proposition 3 in the Appendix. We anticipate the difference between the two optimal shipment size expressions will vanish as u decreases and m increases due to the better economies of scale in AT technologies, and both expressions revert to the iconic EOQ expression, that is, $\sqrt{2\mu A/h}$.

Remark 3. *Assume the economies of scale of the AT technologies improve over time:*

- *In the short run, the optimal autonomous truck shipment size tends to be larger than the shipment size prescribed by the classic EOQ expression.*
- *In the long run, the optimal autonomous truck shipment size approximates the shipment size prescribed by the classic EOQ expression.*

Given Proposition 3, the solution procedure for convex $K(V,T)$ in T is as follows:

Step 0. Use $V = \sqrt{2\mu A/h}$ to solve Eq. (8) for T. Let $\varepsilon > 0$ be some tolerance.

Step 1. Given T, solve Eq. (10) for V_0, and use V_0 to update T via Eq. (8).

Step 2. Given T, solve Eq. (10) for V_1, and use V_1 to update T via Eq. (8).

Step 3. If $|V_1 - V_0|/V_1 > \varepsilon$, return to Step 1; otherwise, $\tilde{V}^* := V_1$, $T_V^* := T$.

5 Numerical examples

In this scenario where the demand is deterministic, we demonstrate the convex shape of the total transportation and inventory cost using parameter values similar to those in the literature. Also, we illustrate the effects of the reduced lead time on the shipment size. Last, we show the impact of the AT deployment efficiency on the logistics managers' decision to centralize the supply chain network.

Without loss of generality, we set $T = 1$, and so t (i.e., lead time after reduction) will assume the format of percentage. Moreover, let $q = 800$, $h = 5$, $D = 800$, $\gamma = 10$, $\epsilon = 1.4$, and $\kappa = 800$. Figure 1 illustrates the transportation cost, inventory costs, and total cost over the range of shipment size $V = [100, 800]$. The convexity of the total cost suggests the existence of the optimal shipment size that can minimize the total costs. Increasing the transportation cost (by acquiring the AT technology cost) or decreasing the inventory cost (by reducing the transportation lead time) can increase the optimal shipment size. Thus, companies that are developing ATs should consider increasing the truckload size or implementing platooning to increase truckload capacity when dispatching.

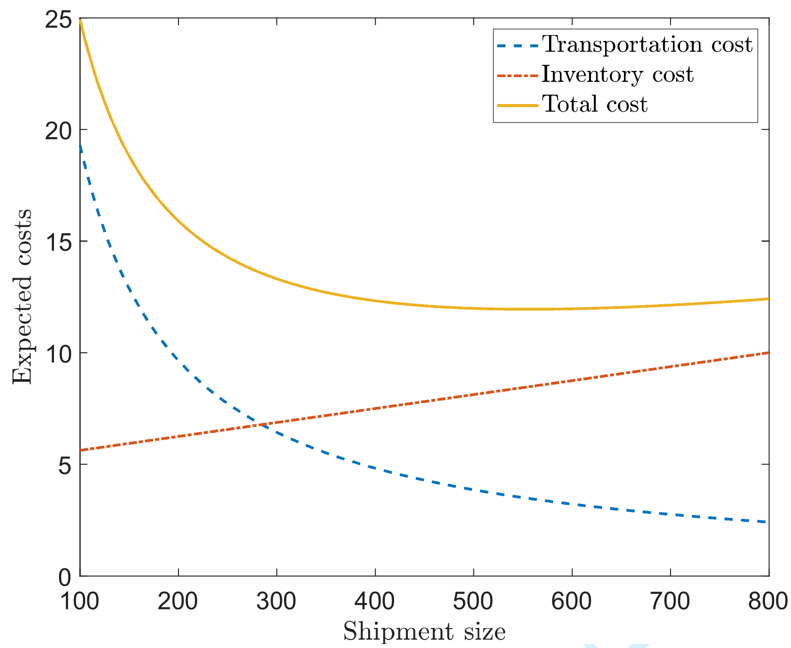

Figure 1: Total transportation and inventory cost is minimized by optimal shipment size.

Figure 2 compares the optimal shipment sizes considering the AT features (i.e., $\tilde{V}^*$) and those disregarding the AT features (V^*). The more the transportation lead time is reduced by ATs, the larger the optimal shipment size will have to be. Note that reducing the lead time essentially decreases the in-transit inventory carrying cost, thereby increasing the optimal shipment size, as implied in Figure 1. This observation helps explain why the platooning technology draws a lot of attention as AT technologies are developed.

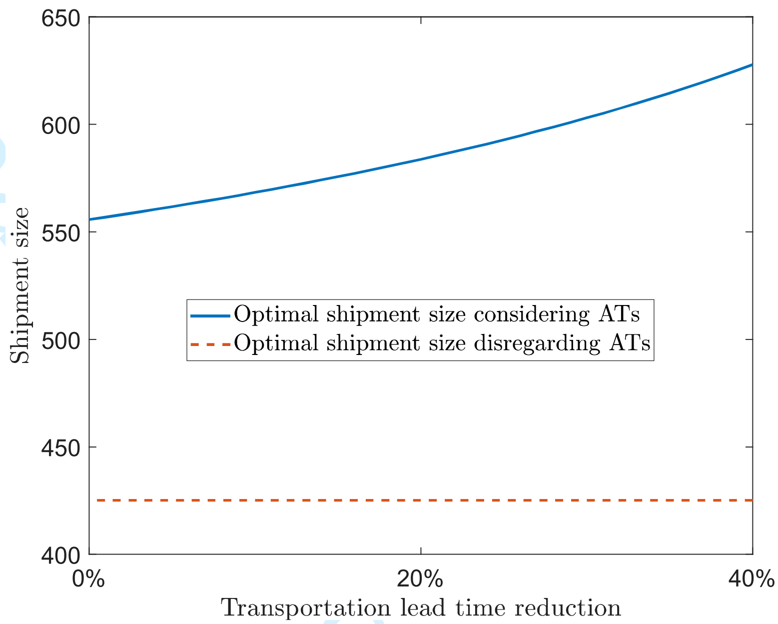

Figure 2: As ATs cut transportation lead time, optimal shipment sizes increases.

Figure 3 shows the effect of the AT deployment efficiency on the truck's travel distance. To make the graph, we first calculated the cost savings due to a shorter lead time and then calculated how much *more* distance ATs with optimized shipment sizes can travel given the cost savings. Given $D = 800$, $T = 1$, and $\kappa = 800$, the first derivative of Eq. (2) with respect to t is

$$\frac{\partial \tilde{D}(t)}{\partial t} = 1429t + 571.4t^{-2} - 3413.2.$$

As such, we do not completely rule out the cases where a smaller t makes $\tilde{D}$ smaller. However, in the practically feasible region of t, that is, [0.6, 1.0], we see that a smaller t does make $\tilde{D}$ larger, especially for any t close to $T = 1$. Therefore, we conclude that reducing transportation lead time *tends to* increase the travel distance of ATs. Moreover, we use different values for κ to highlight how AT deployment efficiency can affect the supply chain configuration. Overall, the cost savings from a shorter lead time allow ATs to travel farther. Conceptually, increased travel range should be positively correlated to the number of consolidated inventory locations. Therefore, we believe that ATs are likely to contribute to *centralizing the supply chain inventory locations*. Another observation in Figure 3 is that territory expansion or warehouse consolidation would not be obvious when the lead time reduction is minor. In the cases where the transportation lead time can be substantially reduced (e.g., long-haul operations or better truck utilization), the AT deployment efficiency would have a greater impact on the travel ranges of ATs. The

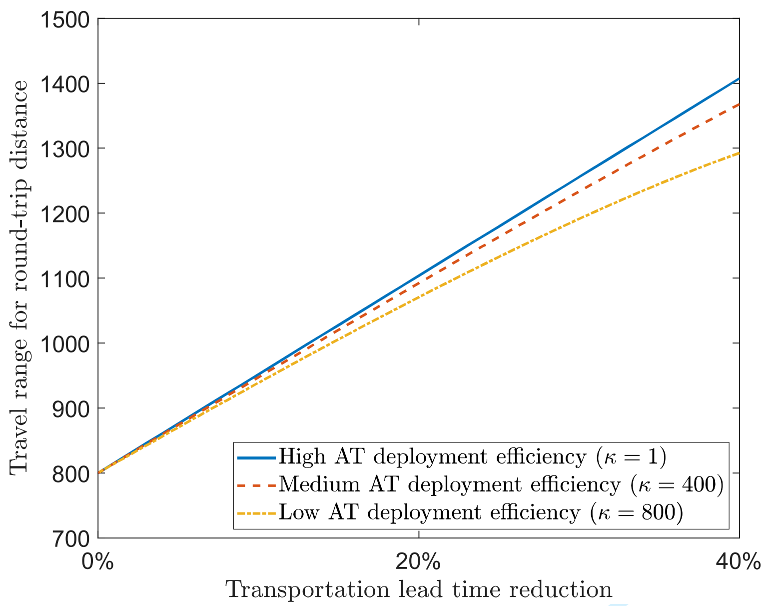

Figure 3: Better AT deployment efficiency leads to better travel ranges.

supposition of centralized inventory locations under ATs depends on the development of the AT deployment costs over time. Optimistically, the AT deployment costs decrease over time. As informed by the extended model, it is possible that the lead time crashing cost stays the same as the lead time is further reduced, thereby supporting Figure 3. With many moving parts in the total expected function, it is also possible that the expected total cost does not remain constant as assumed by Figure 3.

We extend the base model by creating the stochastic-demand scenario where the buying firm operates the continuous-review, reorder-point, order-quantity inventory system. Table 2 illustrates the analytic results from the Conceptual Model section. The optimal shipment sizes offer savings on the total expected inventory system cost as compared to the shipment sizes prescribed by the classic EOQ. As m becomes larger or u becomes smaller, the optimal shipment size becomes similar to the EOQ.

Table 2: Optimal shipment size helps reduce the expected inventory cost.*

W.r.t $T \in [1, 3]$	$hk\sigma$	m	u	EOQ	$\tilde{V}^*$	$\frac{\tilde{V}^* - EOQ}{\tilde{V}^*}$	T_V^*	$\frac{K(EOQ, T_V^*) - K(\tilde{V}^*, T_V^*)}{K(EOQ, T_V^*)}$
Concave $K(V, T)$	45	1	10	1.63	2.03	24.01%	1.00	0.93%
Concave $K(V, T)$	45	1	5	1.63	1.84	12.65%	1.00	0.27%
Concave $K(V, T)$	45	2	10	1.63	1.82	11.28%	1.00	0.22%
Concave $K(V, T)$	45	2	5	1.63	1.73	5.79%	1.00	0.06%
Convex $K(V, T)$	1	1	10	6.32	6.64	5.00%	2.92	0.09%
Convex $K(V, T)$	1	1	5	6.32	6.79	7.40%	1.71	0.21%
Convex $K(V, T)$	1	2	10	6.32	6.53	3.18%	1.70	0.04%
Convex $K(V, T)$	1	2	5	6.32	6.58	3.98%	1.21	0.07%

* $A = 5$, $\mu = 4$, $\varepsilon = 10^{-8}$.

5.1 *Limitations*

The size of the empirical data of cost estimates is limited. Hence, the values of the parameters in the numerical experiments largely follow those in previous conceptual studies or are arbitrarily assigned for illustration purposes. Another limitation is that the allocation between fixed and variable costs of adopting AT technologies is not yet clear in the literature. Besides the aforementioned fixed costs, there can be some other variable costs to maintain the functions of ATs (Bosch *et al.*, 2018; Andersson and Ivehammar, 2019). Furthermore, the variable costs such as data processing or storage costs are rarely mentioned in the publications, making it difficult to assess reasonable values, if any, for the experiments. It was estimated that 15% of the additional cost due to ATs is expected to be from hardware needs, and 85% is expected to be from the need for highly advanced software designed to replace a human driver's sensory capability (Kilcarr, 2016b). When human drivers are still required to be present in the cockpit, attending to driving or not, the additional cost for resources such as data storage and processing may not be entirely offset by the reduced labor costs at least in the near future. Last, the research findings are based on the information collected from trade articles and academic journals in the domain of logistics management. Technical or engineering discussions on the ATs are not included in the literature review.

6 Implications

Given the empirical data and analytical results, we summarize the practical and theoretical implications of the study results as follows.

First, we see that, holding everything else constant, the higher the additional cost incurred and the higher the automation level the ATs achieve, the more the transportation lead time can be reduced, but the larger the shipment size has to be. The empirical data suggests that the additional costs for enabling ATs are likely to be high, at least in the beginning. Over time, the lower maintenance costs, increased fuel efficiency, lower labor cost, and improved safety performance tend to bring down the overall AT costs (Kilcarr, 2016c). Thus, the implication of the AT features is that the optimal shipment size for ATs is likely to be larger than the shipment size currently used for trucks without autonomous technologies, at least in the short run.

Second, given the optimal shipment sizes, we see that the higher the AT deployment efficiency is, the more likely that ATs are to contribute to the centralization of inventory locations in the supply chain network. The deployment efficiency refers to the economies of scale of producing and deploying AT technologies on each regular truck. If the deployment efficiency is high, then the trucking companies can enjoy greater cost savings, which can then be used for offsetting the cost of using ATs to travel farther and reach a broader territory. Thus, the implication of using the optimal shipment sizes is that ATs are likely to consolidate or centralize inventory locations.

Third, the analytical results published before the advent of ATs might no longer be applicable in determining optimal shipment size. We have proposed a new framework for determining the AT optimal shipment size. Specifically, the relationship between the crashable lead time and AT technology costs can deviate the optimal shipment size from the classic solution. Concave or convex, the shape of the expected total inventory cost function with respect to the crashable lead time considerably alters the expression of the optimal shipment size. More work needs to be done to examine empirical data as well as formulate models that help logistics managers make informed decisions for ATs in the domain of logistics management.

7 Conclusions and future research

In recent years, trucking companies have made unprecedented endeavors to take ATs to the open road. Automation across transportation system helps increase productivity and facilitate freight movement (DoT, 2018). ATs have the potential to drastically change an organization's entire logistics network (Richards, 2016). Our goal is to help logistics managers make optimal decisions in regard to the shipment size for ATs. In lieu of updated AT research results in the field of logistics management, we reviewed trade journal articles that included cost estimates of AT-related technologies. With limited transparency, the cost estimates suggest that the fixed and variable costs for deploying ATs can be substantial in the short run. Using the cost information, we then updated the classic EOQ model used in the previous research to consider the features offered by ATs—increased technology cost and reduced transportation lead time. The analytical results suggest that AT features prescribe a larger optimal shipment size than is prescribed by the classic EOQ model in the short run. Also, a better traveling range afforded by ATs can promote centralization of inventory locations. In the extended model, we anticipate that the classic EOQ expression would still be a good reference for optimal AT shipment size. ATs hold many promising benefits for the logistics industry and beyond. We hope this exploratory study can shed some light on a path that is worth for future research.

We propose several directions for future research. First, setting AT capacity constraint can be a necessary topic. We omitted the truckload capacity constraint because ATs may form a convoy consisting of multiple trucks. Realistically, a convoy of the length of few football pitches will create problems for other vehicles that need to change lanes to enter or exit the road (Jarvis, 2016). Another interesting direction can be treating the AT shipment sizing as a multiple-period problem as opposed to a single-period problem. Such multiple-period model would require time-correlated parameters with known distributions. Other future research may consider the prospect of inventory location centralization under ATs, which depends on many moving parts in the system. Therefore, the tipping point of inventory centralization requires a separate investigation.

APPENDIX

Derivation of Proposition 3

We aim to solve for the optimal shipment size $\tilde{V}^*$ that can minimize Eq. (5). First, $K(V,T)$ is convex in V:

$$\frac{\partial K(V,T)}{\partial V} = \frac{h}{2} - \frac{\mu}{V^2} \cdot \left(A + \frac{u}{e^{mT}+1}\right) \tag{11}$$

$$\frac{\partial^2 K(V,T)}{\partial V^2} = \frac{2\mu}{V^3} \cdot \left(A + \frac{u}{e^{mT}+1}\right) > 0. \tag{12}$$

In the case where $K(V,T)$ is concave in T, T_V^* is some constant, and we obtain $\tilde{V}^*$ by substituting T_V^* into Eq. (11) and equating Eq. (11) to 0.

In the case where $K(V,T)$ is convex in T, we have some more work to do as follows. First, we know that

$$\frac{\partial f(mT)}{\partial V} = \frac{\partial T}{\partial V}\frac{me^{mT}}{(1+e^{mT})^2}\left[1-\frac{2e^{mT}}{(1+e^{mT})}\right]. \tag{13}$$

Since T_V^* is a function of V, we need an expression of $\partial T/\partial V$ from the first order condition of Eq. (8):

$$\frac{\partial f(mT)}{\partial V}\sqrt{T}+f(mT)\frac{1}{2\sqrt{T}}\frac{\partial T}{\partial V} = \frac{hk\sigma}{2\mu um}.$$

Substituting Eq. (13) into the last equation, we obtain

$$\frac{\partial T}{\partial V}=\frac{hk\sigma\sqrt{T}}{\mu umf(mT)\left[2mT\left[1-2F(mT)\right]+1\right]}. \tag{14}$$

Now, we differentiate Eq. (5) with respect to V:

$$\frac{\partial K(V,T_V^*)}{\partial V} = -f(mT)\frac{\mu um}{V}\frac{\partial T}{\partial V}-\frac{\mu}{V^2}\left(A+\frac{u}{1+e^{mT}}\right)+h\left(\frac{1}{2}+k\sigma\frac{1}{2\sqrt{T}}\frac{\partial T}{\partial V}\right).$$

Substituting Eq. (14) into the last equation, we obtain

$$\begin{aligned}\frac{\partial K(V,T_V^*)}{\partial V} &= -\frac{hk\sigma\sqrt{T}}{V\left[2mT(1-2F(mT))+1\right]}-\frac{\mu}{V^2}\left(A+\frac{u}{1+e^{mT}}\right)\\ &\quad +\frac{h}{2}+\frac{h^2k^2\sigma^2}{2\mu umf(mT)\left[2mT(1-2F(mT))+1\right]}.\end{aligned}$$

We set the last equation to 0 to obtain $\tilde{V}^*$.

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