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A Review of Smart Technologies Applications on Logistics and Transport

Abstract

The emergence of smart technologies (STs) is inducing significant transformation in logistics and transport nowadays. STs refer to the applications of artificial intelligence and data science technologies, such as machine learning, big data, to create cognitive awareness (autonomous) of an object with the support of information and communication technologies such as IoT and Blockchain. Currently, many applications of STs have demonstrated potential promise in enhancing the efficiency and effectiveness in various logistics operations and transportation systems. Further, these new advanced technologies create huge modelling challenges to traditional optimization approaches and thus create rich new research opportunities for developing new optimization methodologies in the field of logistics and transport studies. As such, our aim is to conduct a comprehensive review on noteworthy contributions made in the applications of STs in improving logistics operations and transportation network efficiency. More importantly, we explore and discuss the technical difficulties encountered by researchers in the development of optimization methodologies caused by the applications of STs. Finally, we conclude the studies with suggestions for future research.

Keywords: Smart Technologies; autonomous; logistics; transport.

1.0 Introduction

Smart technologies (STs) refer to the applications of Artificial Intelligence (AI) and data science technologies, such as Machine Learning (ML), Big Data (BD), to create cognitive awareness of an object (e.g., a system) with the support of information and communication technologies, e.g., the Internet of Things (IoT), and Blockchain (BC), etc. (Winkelhaus and Grosse 2020, Qiao et al. 2020, Liu et al. 2021). The idea is to make the object become autonomous. STs have been applied in diverse areas and have created many new and interesting research topics, e.g., smart manufacturing, smart city, smart home, smart agriculture, smart hospitality, smart shopping and so on (Tang and Veelentruf 2019, Mulcahy et al. 2019, Ismagilova et al. 2019, Roy et al. 2020, Kotsiopoulos et al. 2021, Wu and Chen 2021). They have demonstrated its significance and benefits not only in enhancing operations efficiency but also in costs reduction. As reported by CNBC, in the manufacturing sector, Smart Manufacturing is expected to add up to US$1.5 trillion to the economy, enabling factories to produce faster with lower costs.[1] While in the logistics sector, new topics such as smart logistics and smart warehouses are also emerging and have become hot topics in recent years (Mahroof 2019, Liu et al. 2020, Issaoui et al. 2021).

Nowadays, STs have resulted in rapidly transforming the logistics industries and transportation networks. Back to 2016, DHL identified six technologies that will cause significant changes in logistics by 2030, namely Big Data, Sensor Technology, Augmented Reality, 3D printing, Robots, and Drones.[2] As such, DHL has launched its trail smart warehouses in three European locations (Germany, Netherlands, and Poland), the success of which is reported not only by the improved operational efficiency, but also in supporting operational data visualization. Through the pilot sites, DHL also stated that they had clear insights on how well their warehouses were operating. Recently, UPS also launched its smart warehouse technology, aiming to make distribution centers smarter and more efficient by leveraging autonomous capacities, such as autonomous mobile robots, autonomous guided vehicles, automated sorting system, etc.[3]

1.1 Research Motivation

Autonomy enabled by STs is believed to be the coming trend in the logistics industry and transportation in the near future (Winkelhaus and Grosse 2020, Liu et al. 2021). Traditional processes done by humans are gradually being replaced by autonomous systems (e.g., item sorting in distribution centers, transferring items in factories), or being supported by autonomous systems (e.g., order picking in warehouses, material supply on shop floors) (Roy et al. 2015a, Draganjac et al. 2016, Qiao et al 2020). Applications of Autonomous Vehicles (AVs), Autonomous Robots (ARs), Unmanned Aerial Vehicles (UAVs), are becoming more

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[1] https://www.cnbc.com/advertorial/how-smart-technology-is-transforming-the-industrial-world/
[2] https://ecommercenews.eu/dhl-6-technologies-will-change-logistics-2030/
[3] https://pressroom.ups.com/pressroom/ContentDetailsViewer.page?ConceptType=PressReleases&id=1587644992637-678

prevalent and mature (Lee and Kim 2017, Boyesen 2018). These advancements cause significant changes in many logistics operations and transportation networks, and because of which, many new scheduling problems, optimization methodologies and solution approaches have emerged in this STs era. However, there are no prior studies that have comprehensively explored this topic. Motivated by this, we aim to conduct a comprehensive review on the existing papers regarding the applications of STs in logistics operations and transportation, particularly those related to optimization problems.

1.2 Research Gaps and Contributions

In the last decade, because of the blooming of advanced technologies, many review papers have been published for various kinds of work in logistics and transport studies. We have conducted a search in Google Scholar by using keywords, "review paper", "survey paper", "technologies", "logistics", and have identified 13 related review papers in the period of 2010-2020 with one recent review paper from 2021, as summarized in Table 1. The papers are ranked in chronological order.

Govindan et al. (2015) conducted a very detailed survey on reverse logistics and the closed-loop supply chain. Some works have included the applications of technologies. More specific to technologies, Wang et al. (2016) focused on the applications of big data analytics in logistics and supply chain management. Gunasekaran et al. (2017) focused on information technologies (IT) related papers. They have given a very critical discussion on each stream and drawn some theoretical and managerial implications of using IT to increase companies' competitive advantage. Nguyen et al. (2018) proposed a classification framework based on the level of analytics, type of big data models, and big data techniques used for big data analytics papers in supply chain management. Yang et al. (2019) conducted a critical review of papers using big data in automatic identification system for data applications in maritime studies. Ben-Daya (2019) explored the impacts of the Internet of Things (IoT) on supply chain management. Sharam et al (2020) also carried out a systematic review on machine learning applications with the main focus on sustainable agriculture supply chain performance. Aryal et al. (2020) aimed to study the evolution of big data analytics and IoT in business and literature. Müßigmann et al. (2020) conducted a bibliometric literature review on Blockchain from 2016 to January 2020 in logistics and supply chain management. Pournader et al. (2020) also conducted a systematic review on Blockchain in supply chains, logistics, and transport management, focusing on four main co-citation analysis (i.e. Technology, Trust, Trade, and Traceability/Transparency). Queiroz et al. (2020) analyzed the main disruptions and challenges brought about by Blockchain in supply chain management. Winkelhaus and Grosse (2020) gave an excellent discussion on Logistics 4.0 and explained how Logistics 4.0 is supported by various technologies (i.e., IoT, cyber-physical systems, big data, cloud computing, mobile-based systems, social media-based systems). More recently, Kaffash et al. (2021) focused on big data applications on intelligent transportation systems.

Table 1. Summary of review papers on emerging technologies in logistics.

Authors	Technologies						Review focus	
	IT	ML	BD	AI	IoT	BC	Applications	Optimization
Govindan et al. (2015)		✓					✓	✓
Wang et al. (2016)			✓				✓	
Gunasekaran et al. (2017)	✓						✓	
Nguyen et al. (2018)			✓				✓	✓
Yang et al. (2019)			✓				✓	
Ben-Daya et al. (2019)					✓		✓	
Sharma et al. (2020)		✓					✓	
Aryal et al. (2020)			✓		✓		✓	
Müßigmann et al. (2020)						✓	✓	
Pournader et al. (2020)						✓	✓	
Queiroz et al. (2020)						✓	✓	
Winkelhaus and Grosse (2020)			✓		✓	✓	✓	
Kaffash et al. (2021)		✓	✓				✓	
Our paper		✓	✓	✓	✓	✓	✓	✓

Our paper is similar to Winkelhaus and Grosse (2020) in terms of technologies coverage. Moreover, similar to many other review papers, we also review the applications of STs. However, our paper also focuses on the technical difficulties and challenges encountered by researchers during the development of the optimization methodology caused by the applications of STs. Our contribution is threefold. First, this paper provides a comprehensive review on papers that are related to the applications of STs in logistics operations or transportation systems in the period of 2010-2020. Moreover, we categorize the papers according to the STs involved and then area of application. Second, we explore and discuss on the difficulties and challenges in the optimization methodology. Lastly, based on the findings, we suggest future research in the area of applications and the development of optimization methodology.

The rest of the paper is organized as follows. Section 2 explains the survey methodology regarding the paper searching methodology and selection criteria. Section 3 – Section 6 give an overview on the applications of STs and the technical challenges in optimization methodology development. Lastly, Section 7 provides the conclusions and gives suggestions for future research.

2.0 Survey Methodology

2.1 Source of literature

The objective of this paper is to carry out a comprehensive literature review on the current state of research related to STs in logistic operations and transportation, and to analyze its impacts on the development of optimization methodologies, as well as an in-depth analysis to explore the future trends in order to identify new research directions regarding value-added applications and optimization methodology development. The literature surveyed in this paper was mainly selected from Web of Science and is based on articles in SCI journals.

As we intend to survey studies on recent trends on ST related to logistic operations, we mainly confined our search to papers published in the period of 2010-2020. The search process was conducted in two dimensions: horizontal and vertical. In the horizontal dimension, attention was paid to the evolution of ST on the timeline. In the vertical dimension, different focuses and applications of ST were employed to distinguish each article.

2.2 Classification schemes

A comprehensive and feasible taxonomy of STs in logistics and transport is essential to reveal the problem's nature and to identify the impacts as well as benefits that can lead to meaningful future research. Instead of using algorithms, area of applications, or logistics operations, we propose to classify according to the STs concerned in the papers. One advantage of this scheme is that it enables an in-depth classification of the applications of the technologies, so that the area of applications and its benefits can be further revealed in a more explicit manner.

2.3 Distribution of publications

STs refer to enabling objects or systems to become autonomous provided by technologies like AI, ML, BD, and which can be facilitated by IoT, BC, etc. Thus, we used those keywords as well as the field keywords in the full text query, including "Smart", "Smart Technologies", "Autonomous", "Artificial Intelligence", "Machine Learning", "Big Data", "Internet of Things", "IoT", "Blockchain", "Logistics", and "Transport" in abovementioned database searches mentioned above. Duplications due to overlap, articles other than from academic journals, and papers in languages other than English were discarded. The full text of each paper was read to screen and identified its relevance to the field. The papers that matched with the query but did not focus on smart, smart technologies, logistics or transport were also rejected. For example, some only mentioned STs as an example for improving logistics operations but in fact no research was actually conducted in the domain. This left 84 journal papers and the distribution of these papers by publication year is summarized in Figure 1, which shows that the number of publications in the area of STs in logistics grew significantly in recent years, especially after 2018. This demonstrates that STs have a very promising future.

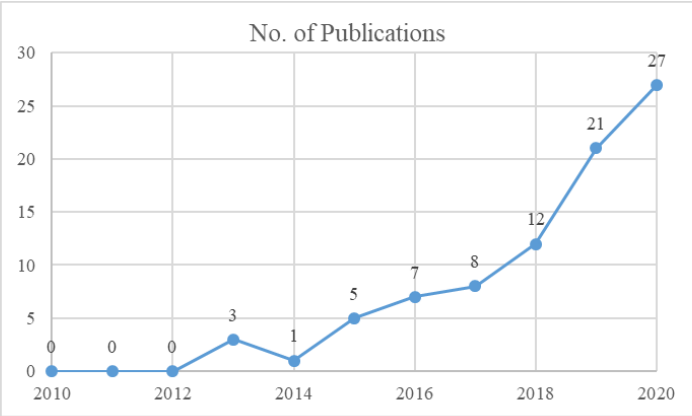

Figure 1. Summary of the number of papers published since 2010.

We excluded out the 15 review papers discussed before. Now based on our classification scheme, we analyzed the distribution of the publications. We found that some papers can clearly be categorized into BD and ML. For some papers that have discussed both BD and ML, we categorized into ML. For the papers that have not been explicitly explained what technology enabling the applied autonomy, we categorized them into AI. Lastly, we also found that there are a few papers using the terms Smart Logistics, and Smart Warehouse. As we believe these terms may be commonly used in future, thus we would like to highlight them out for a separate discussion. As a result, the papers are now categorized into BD, ML, AI, Smart Logistics, and Smart Warehouse. In the following sections, we first show the development and significance of STs in various areas. Then, surveys of the above categories are elaborated.

We further counted the number of publications in each category and obtained Figure 2, from which we can see that the number of publications regarding BD is relatively stable since 2014 and gradually grew after 2017. In the meantime, the number of publications regarding AI issues grows significantly, especially since 2019. It is interesting to see that there are a few publications regarding smart logistics since 2016. Moreover, since 2018, publications regarding smart warehouse appeared as well.

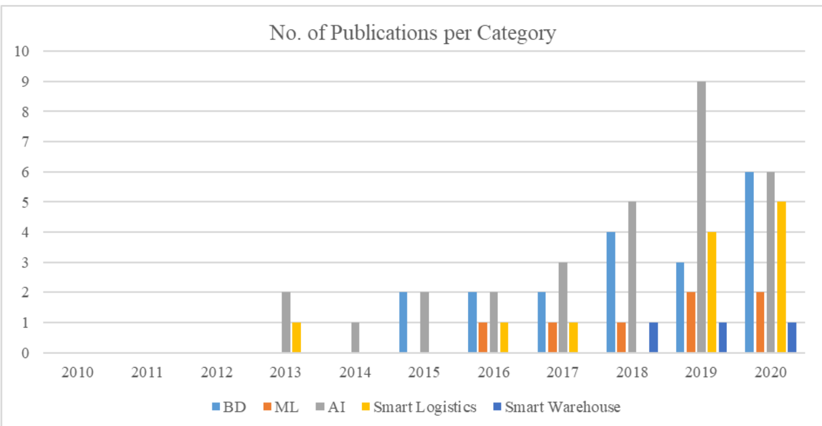

Figure 2. Summary of the number of papers published in different categories since 2010.

3.0 Smart Technologies

Nowadays, applications of STs can be found in many areas, e.g., smart city, smart retailing, smart home, smart manufacturing, and smart port. In the smart city, because of the maturity and availability of STs, it enables the measurement and monitoring of the impact and benefits obtained from the implementation of smart city innovations (Hasija et al. 2020). As a result, the benefits obtained can be maximized and resources can be better utilized and allocated. In smart retailing, the applications of STs do not only enhance the shopping experiences and provide conveniences, but also reduce the labor costs and workload of retailing stores (Roy et al. 2020). As a result, both retailers and customers are benefited. In smart home applications, STs are mainly used to provide assistance to household activities, e.g., controlling energy usage, assisting in taking care of elderly (Mulcahy et al. 2019). As a result, household financial is benefited. In smart manufacturing, applications of STs are mainly focus on identifying disturbances and support providing responds in production shop floor (Qiao et al. 2020). Lastly, in container port, applications of STs are crucial, as STs have demonstrated its capability in enhancing port efficiency. As a result, STs benefit the maritime transportation industry, and consequently the world economy as maritime transportation accounts for about 90% of world's cargo volume (June et al. 2018).

Although we can see that applications of STs provide many advantages, technologies involved are varied. For example, in the smart city, Hasija et al. (2020) discussed the modeling challenges and opportunities regarding smart city operations. They stated that the idea of ST is to enable the capability of self-monitoring, analyzing, and reporting in order to address real problem needs, enabled by various technologies, including smartphones, IoT, cloud computing, etc. In smart retail studies, Roy et al. (2020) stated that smart retail technology refers to a ubiquitous and autonomous system that would be able to help retailers to do planning, developing, and offering retail services to customers, such as smart mirrors, smart carts, etc., enabled by technologies such as Beacons and RFID. In smart home studies, Mulcahy et al. (2019) referred to smart home technologies such as household systems that can be remotely accessed, monitored, and controlled, and which can provide services in response to the residents, and can autonomously make decisions or undertake actions on behalf of the residents, enabled by network technologies. In smart manufacturing studies, Qiao et al. (2020) summarized the essential characteristics of smart manufacturing as self-learning, self-organization, and self-adaptability, enabled by Information and Communication Technology (ICT), IoT, cloud computing, Cyber Physical Systems (CPS), BD, etc. Lastly, in smart port studies, June et al. (2018) defined smart port technologies that improve the productivity and efficiency of container ports by using automated systems, which are enabled by technologies, e.g., IoT, Big Data, and sensors.

In a short summary for the above, we can see that smart technologies are widely used and have created many new topics in various industries. Overall speaking, it focuses on autonomous, which allows the systems or devices to make their own decisions in order to provide convenient and increased efficiency, such as in planning, monitoring, controlling, etc. To achieve such goals, AI, BD, and ML technologies are usually used and may be facilitated by information and communication technologies, e.g., IoT, clouding computing, Blockchain, etc. (Chung et al. 2020).

4.0 Big Data and Machine Learning

ML focuses on the development of computing algorithms that enable computers to improve automatically through experience (Jordan and Mitchell 2015). In general, ML can be classified into gradient learning algorithms (e.g., gradient descent) and gradient free learning algorithms, (e.g., extreme learning machine) (Khan et al. 2020a, Khan et al. 2020b). To support the learning through experience, a set of data is required for training, and this is known as the training data. Moreover, another set of data is required for testing and is used for the verification of the performance of the computing algorithms. To manage the massive data sets, BD is a promising approach. BD deals with the massive data, which is usually huge in size, varied, and complex in structure (Sagiroglu and Sinanc 2013).

We first review papers with applications of BD and/or ML in optimization problems in logistics. The related publications are summarized in Table 2. For papers that studied both BD and ML, they are classified as ML. In the period of 2010-2020, ML and BD have attracted much attention. Many excellent review papers have been conducted by many prominent researchers in various areas such as operations management (Choi et al. 2018), supply chain (Richey et al. 2016), intelligent transportation systems (Zheng et al. 2016), city transport (Mehmood et al. 2017), and public transportation (Ghofrani et al. 2018, Welch and Widita 2019). From Table 2, we can see that many researchers are using BD and ML for pattern discovery, classification, and prediction, with applications appearing in diverse areas, e.g., logistics and supply chain management, vehicle routing, logistics performance measurement, and sustainable logistics.

Table 2. A summary of publications in BD and ML.

		Technologies		Areas										Applications			
Authors	Year	BD	ML	R	SL	LSC	ITS	PT	OM	PA	ML	Pattern Identification	Prediction	Classification	Review
Zhong et al. (2015)	2015	✓		✓								Logistics trajectory discovery			
Cottrill and Derrible (2015)	2015	✓			✓							Indicator			
Richey et al. (2016)	2016	✓				✓									Big Data in supply chain
Zheng et al. (2016)	2016	✓					✓								Intelligent transportation system
Becker et al. (2016)	2016		✓	✓									Path routing		
Shang et al. (2017)	2017	✓		✓									Flight delay		
Mehmood et al. (2017)	2017	✓						✓				Transport demands			
Choi et al. (2018)	2018	✓							✓						Big Data in operations management
Ghofrani et al. (2018)	2018	✓						✓							Big Data in railway transportation
Lázaro et al. (2018)	2018		✓	✓									Cash demand		
Kaur and Singh (2018)	2018	✓			✓								Demand and capacity		
Lee et al. (2018)	2018	✓									✓		Vessel speed		
Welch and Widita (2019)	2019	✓						✓							Big Data in public transport
Tang et al. (2019)	2019		✓	✓									Vehicle mobility		
Sodero et al. (2019)	2019	✓				✓							Demand		
Lakshmanaprabu et al. (2019)	2019	✓		✓									Roadways, vehicles		
Mehmood et al. (2017)	2020	✓								✓					Country logistics performance

Zheng et al. (2020)	2020	✓		✓										Distribution modes	
Yao et al. (2020)	2020		✓							✓				Green performance efficiency	
Liu et al. (2020)	2020		✓			✓							Path routing		
Gholizadeh et al. (2020)	2020	✓			✓								Path routing		
Sun et al. (2020a)	2020	✓									✓	Delay pattern			

R – Routing

SL – Sustainable logistics

LSC – Logistics and supply chain

ITS – Intelligent transportation system

PT - Public Transportation

OM - Operations Management

PA - Performance analysis

ML - Maritime Logistics

4.1 Classifications with BD and ML

Early in 2015, there are publications already studying pattern discovery by BD techniques. Zhong et al (2015) used BD approach to discover the logistics trajectory on manufacturing shop floors by analyzing the data collected from RFID devices. Cottrill and Derrible (2015) also applied BD approach to improve the identification accuracy of useful indicators for sustainable transportation. They collected data from smartphones and various smart infrastructure. Sodero et al. (2019) conducted studies on using BD for predictive analytics for logistic and supply chain management. Sun et al (2018) and Sun et al. (2020a) applied BD to analyze vessel delay patterns to support production scheduling. Zheng et al. (2020) applied BD approach to support the analysis of different logistics distribution modes in e-commerce companies. In their work, they studied JD.com as a case company and collected massive data for analysis. To enhance the discovery ability, ML is also a promising approach. Yao et al. (2020) applied a machine learning method, named as the functional clustering method funHDDC, to classify the similarities and differences for green efficiency performance to support the development of green logistics industry in China.

4.2 Prediction with BD and ML

From the review, we find that the majority of the BD and ML applications were used for prediction. For example, Chung et al. (2017) used historical flight data on 112 airports to predict flight delay. They proposed a cascading neural network and applied the result to feed into the optimization model. The problem was then solved by using a Column Generation based algorithm. Lee et al. (2018) used weather archive BD to predict the fuel consumption function for speed optimization of voyage routing in maritime logistics. To capture the BD results, they proposed a weather archive data parser and a weather impact miner. By comparing the current information of each route in voyages to historical records, they estimated the net impact of current on the fuel consumption by using regression analysis. In their work, they proposed Particle Swarm Optimization (PSO) as the optimization method. The results demonstrated that with the support of BD in weather forecast, the accuracy of the fuel consumption function was higher, and improvement was even more significant in long voyage legs. Khan et al. (2019) developed a self-organized constructive neural network to estimate trip fuel consumption for airlines. Gholizadeh et al. (2020) used BD to support the modeling of robust fuzzy stochastic programming for a sustainable procurement and logistics problem. Sun et al. (2020b) analyzed the historical flight data regarding the relationship of departure delays to arrival delays. By using the identified relationship, they developed a stochastic model to improve the schedule reliability.

In particular, many of the existing works used using BD and/or ML for demand prediction. Mehmood et al. (2017) proposed a theoretical framework to predict transport demands by using BD to enhance transport efficiency. They proposed to use Markov chains to model a system as an optimization problem. Lázaro et al. (2018) applied ML to predict the cash demands for bank branches in order to support the transport of cash. During the optimization, they demonstrated how to model the output as deterministic as well as in a given interval range. Kaur and Singh (2018) used BD approach to collect real-time demands and carrier capacities, based on which they aimed to reduce the carbon emission caused by procurement and transportation, and proposed a Mixed Integer Non Linear Program and a Mixed Integer Linear Program to tackle the problem.

During the review, it can be seen that many researchers are using BD and ML for prediction to support routing optimization. In 2016, Becker et al. (2016) applied a simplified Neural Network to make routing decisions in a logistics facility. They tested the performance of five intelligent routing heuristics by using the real data set obtained by the Hamburg Harbor Car Terminal. The results demonstrated that with Neural Network support, the performance outperformed 48% of the best heuristics. Shang et al. (2017) used BD to predict the transport risk arising from the deviation of the actual arrival time and planned arrival time in air cargo logistics. Then they fed the result into a Bayesian nonparametric model to estimate the conditional density function of the transport risk for each flight. Lakshmanaprabu et al. (2019) used real time data generated by the Vehicular Adhoc Network (VANET) and applied BD technology, Hadoop, to obtain insights to support the routing optimization. In their work, they applied Ant Colony Optimization (ACO). The results demonstrated that with the application of Hadoop, the processing time required for the algorithm was significantly reduced. Tang et al. (2019) also worked on VANET, applying Artificial Neural Network (ANN) for mobility prediction. They applied ANN to create a vehicle arrival function to predict the transmission probability and the average delay. The results demonstrated that with the mobility prediction, the overall vehicular service delay was reduced. Liu et al. (2020) also applied BD, ML, and IoT to determine the optimal transportation path and the re-routing of the logistics problem for massive scale laundry services. They applied ML to predict the demand preference of customers and to support the routing and resource allocation decision. The results demonstrated that with the new advanced application, it can significantly enhance the operations efficiency.

4.3 Technical difficulties of implementing BD and ML in optimization

Through the review in this section, we can see that many papers focus on capturing uncertainties by analyzing massive historical data or real-time data to discover hidden patterns or for prediction. In general, there are two hurdles: i) converting data into meaningful modeling parameters, and ii) handling the increased problem complexity.

Extracting meaningful data from massive data is a well-known challenge, which has been extensively discussed in various BD studies. Therefore, we will not discuss this issue to avoid duplication of work in the existing literature. We first put our focus on discussing the difficulties of converting data into meaningful modeling parameters. Although BD and ML are promising in forecasting, one of the difficulties encountered by using ML is that the outputs are usually deterministic, which can be regarded as an expected value (*EV*). ML algorithms usually do not provide information about the confidence interval, which means that the reliability of the prediction can be uncertain. In fact, it is known that for the same EV, its variance can be very different as shown in Fig 1, which assumes the solution obtained from a ML algorithm may follow a normal distribution, but which may not necessary be the case. Thus, directly using the EV in the optimization model can be quite risky, because the reliability of the forecasting results obtained are uncertain. To tackle the problem, Lázaro et al. (2018) proposed a new concept called confidence bound ($\mathcal{B}$), with the idea of building a confidence region ($\mathcal{U}$) around the most likely values $\hat{x}$, therefore, hoping that the real actual output can be $P(\mathcal{U} \in \hat{x}) = \mathcal{B}$. Meanwhile, the endpoints of the bound are calculated by the training errors observed, where $\underline{x^t} \leq \widehat{x^t} \leq \overline{x^t}$. In this modeling approach, although P is unknown, it is stated that with a better ML algorithm, $\hat{P}$ can better approximate P. This approach gives users some idea about how reliable the solution is.

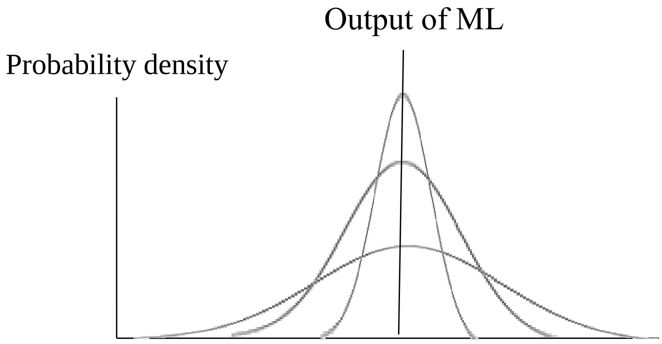

Figure 1. Unknown confidence level of the output from ML algorithms

Another difficulty induced by using BD and ML in optimization problems is the increased problem complexity. By analyzing historical data in finer details, the problem characteristics can be modelled with more details, e.g., into different interrelated phases or stages. For example, Chung et al. (2017) divided a classical crew pairing problem into two phases. First, they analyzed the historical flight data to determine the buffering time for absorbing the impact of flight delay by using ML, and then in Phase 2, the results from ML was feed into the classical crew paring problem. Mehmood et al. (2017) stated that one of the major hurdles is to handle complex and large problems. Thus, they proposed to use other strategies, e.g., concurrent, parallel and distributed computing techniques. Similarly, Kaur and Singh (2018) stated that when the problem has BD characteristics, it cannot be solved in a reasonable time for large-scale problem sizes. Thus, heuristics have to be applied instead.

5.0 AI

Next, we reviewed papers with the application of autonomous in optimization problems in logistics. The related papers are summarized as in Table 3.

Table 3. A summary of publications in AI.

		Areas						Applications						
Authors	Year	RS	MS	WD	SCM	RM	CA	Autonomous AGV	Autonomous vehicle	Autonomous electric vehicle	Autonomous aerial	Autonomous system	Review	Optimization methodology (if any)
Gelareh et al. (2013)	2013	✓						Container Terminal						Mixed Integer Programming
Cai et al. (2013)	2013	✓						Container Terminal						Branch-and-Bound with Column Generation
Roy et al. (2014)	2014	✓							Warehouse					Control policy; simulation
Roy et al. (2015a)	2015	✓							Warehouse					Control policy; simulation
Roy et al. (2015b)	2015	✓							Warehouse					Control policy; simulation
Draganjac et al. (2016)	2016	✓							Warehouse					Control policy; simulation
Lam et al. (2016)	2016	✓							Public transport					Mixed Integer Linear Programming; Genetic Algorithm
Lee and Kim (2017)	2017			✓							Transport service			-
Haas and Friedrich (2017)	2017	✓							Public transport					Control policy; simulation
Chen et al. (2019)	2017	✓							Public transport					Mixed Integer B-level Programming; Simulated Annealing Algorithm
Durazo-Cardenas (2018)	2018		✓									Maintenance services		Genetic Algorithms
Yi et al. (2018)	2018	✓									First-mile delivery			Control policy; simulation

Yu and Lam (2018)	2018	✓							Logistics systems					Quadratic-constrained Mixed Integer Linear Program
Shen et al. (2018)	2018	✓							First-mile delivery					Simulation
Boysen et al. (2018)	2018	✓							Last-mile delivery					Mixed integer programming; tailor-made local search procedure
Bottani et al. (2019)	2019			✓								Wholesales distribution		Artificial Neural Network
Baryannis (2019)	2019				✓								Artificial intelligence in supply chain risk management	-
Cheng et al. (2019)	2019	✓							Searching item					-
Iacobucci et al. (2019)	2019	✓								Transport service				Mixed Integer Linear Programming
Hawkins and Habib (2020)	2019	✓							Public transport					-
Yu (2019)	2019	✓							Logistics Systems					Mixed integer non-linear program
Cao et al. (2019)	2019	✓							Public transport					Control policy; simulation
Cao and Ceder (2019)	2019	✓							Public transport					Genetic Algorithms
Yu and Lam (2019)	2019	✓							Public transport					Mixed integer non-linear program
Dai et al. (2020)	2020	✓							Public transport					Integer non-linear programming; dynamic programming
Simoni et al. (2020)	2020	✓							Last-mile delivery					Dynamic programming
Salama and Srinivas (2020)	2020	✓									Last-mile delivery			Integer program; mixed integer nonlinear program; approximated mixed integer program

Kitjacharoenchai et al. (2020)	2020					✓			Last-mile delivery					Drone-truck routing construction heuristic; large neighborhood search heuristic
Chee et al. (2020)	2020						✓		First and last-mile delivery					-
Kapser and Abdelrahman (2020)	2020	✓							Last-mile delivery					-

RS - Routing and scheduling
MS - Maintenance scheduling
WD - Wholesale Distribution Operations
SCM - Supply Chain Management
RM - Risk Management
CA - Customer Acceptance

Early in 2013, there were publications already exploring on the applications of Intelligent and Autonomous Vehicles (IAV) in container terminals. In the work of Gelareh et al. (2013), it was stated that IAV is different from Automated Guided Vehicle (AGV), which has to follow designated segments on the road and particular route. IAV is enabled by sensors and Geographical Positioning Systems (GPS), and can detect the vehicle spacing. Such technologies provide more flexibility in real applications, such as container terminal operations. Cai et al. (2013) also studied container terminal operations in which the focus was on the autonomous straddle carrier, which was used to lift and set down containers. In the work, the autonomous straddle carrier was found to provide higher efficiency over the traditional AGV, especially in automated container terminal.

Nowadays, applications of autonomous and AI can be found in many areas, e.g., autonomous aerial vehicle for delivering small items (Lee and Kim 2017), autonomous scheduling of maintenance tasks in railways (Durazo-Cardenas 2018), autonomous decision making in wholesale distribution (Bottani et al. 2019), autonomous evaluating supply chain risks (Baryannis 2019), autonomous robot for searching targets (Cheng et al. 2019), etc. Among the papers reviewed in this category, it is interesting that we found that the majority of the work was related to routing optimization or scheduling problems. We also found that we can further subcategorize them into warehousing related, public transport related, autonomous vehicle related, and last-mile delivery related papers.

5.1 Autonomy in warehousing

We first looked into warehousing related papers. In 2014, Roy et al. (2014) conducted research work on autonomous vehicle-based storage and retrieval systems (AVS/RS), in which they focused on the blocking problems existing in autonomous vehicles. In the studied distribution center, a group of autonomous vehicles operates on the same floor, guided by rails. Because of the movement of the autonomous vehicles between different aisles, it causes blocking or even deadlock. The authors have given a comprehensive discussion on various kinds of blocking and deadlock situations. In the work, they demonstrated that the blocking problem can cause delays of up to 20% of the transaction cycle time. Later on, in work done by the same group of authors, they further studied the effect of the vehicle dwell-point and the location of cross aisles on the performance of the AVS/RS (Roy et al. 2015a), and further studied the effect of blocking (Roy et al. 2015b). Draganjac et al. (2016) conducted a very interesting study, which used an algorithm to provide AGV with the capability for autonomous path planning and motion coordination. They stated that the algorithm was deadlock-free and livelock-free.

5.2 Autonomy in public transport

In recent years, we can also see papers applying autonomy approaches in public transport, and among which, the Autonomous Vehicle (AV) is a very hot topic. AV is regarded as one of the most important elements in constructing smart public transportation systems (Lam et al. 2016), providing high mobility and flexibility. In the paper, the authors studied a smart public transportation system, which consisted of a group of AVs providing point to point service, meanwhile allowing ride sharing. They proposed a Mixed Integer Linear Programming to solve the scheduling problem, and a Genetic Algorithm to solve the order admission problem. With the concept of ride sharing offered by AVs, Shen et al. (2018) studied an integrated AVs and public transportation system. They found that during the peak hours, it is wise to keep the high demand bus routes and adjust low demand ones by using shared AVs. Cao et al. (2019) studied a full-scale application of AVs in public transportation systems, which can handle real-time scheduling of AVs. The results indicated that the performance reliability of AVs is much better than traditional transportation in terms of departure time deviation. Cao and Ceder (2019) had another work on the full-scale application of AVs in public transportation, in which, their focus was on the development of a new optimization methodology to solve the service timetabling problem. They tackled the problem by using a genetic algorithm facilitated by a new strategy called the skip-stop tactic. The results indicated that it reduced the passenger travel time by 1.83% and number of vehicles by 8.11%. With the view that AVs will play a significant role in future transportation systems, Yu and Lam (2019) took a further step forward to study how different companies may compete and behave in the new smart public transportation system era. They formulated the problem as core-selecting reverse combinatorial auctions. The results indicated that it may lower the total service charges and avoid unreliable bidders.

5.3 Applications of AVs in logistics

In fact, applications of AVs have become popular in recent years, not only in warehousing. Haas and Friedrich (2017) applied AVs to support an urban freight delivery system. They studied a conceptual framework with a human driver operating a platoon, while the members of the platoon were a group of AVs responsible for deliveries. The idea of the platoon is to minimize the total travelling distance for delivery, and studies of vehicle platoons have become popular. Chen et al. (2017) aimed to develop a mathematical framework to design the AV zones. In their work, they first established a mixed routing equilibrium model, and then modelled it as a mixed-integer bi-level programming model to obtain the optimal design plan. After that, they used a Simulated Annealing Algorithm to solve the model. The results indicated that the total traveling cost was reduced.

Yu and Lam (2018) further enhanced the AVs scheduling problems by considering the charging strategy as well. They proposed an integrated joint routing and charging optimization problem and proposed a Quadratic-constrained Mixed Integer Linear Program. The results indicated that the algorithm can effectively utilize the excessive renewable energy. Iacobucci et al. (2019) also conducted a study on charge optimization in which the electricity price may vary. They modelled the transport services and charging schedule at two different time scales by two model-predictive control optimization algorithms. The problem was solved by using mixed integer linear programming. The results indicated that cost reduction was achieved by the benefits of electric price variability. There is no doubt that charging is an important issue in the practical implementation of AVs, and the energy cost is also important. Yi et al. (2018) conducted a research work on how the ambient temperature would affect the consumption of energy by AVs. They performed a data driven case simulation in New York City. When the network was subjected to the same demands and charging stations, they found that under low and high ambient temperatures, the difference of overall energy consumption can be as high as 20%.

Recently, Yu (2019) further enhance AV studies by considering different types of AVs in last mile delivery problems. In this work, the author proposed a mixed integer non-linear program. In fact, many problems existing in real operations are yet to be uncovered. Dai et al. (2020) studied a model with the co-existence of AVs and human-driven vehicles, using integer nonlinear programming. The objective was to minimize the operating cost and the passenger waiting time by using dynamic programming. Hawkins and Habib (2020) studied how the development and applications of AVs in the near future should be integrated with the planning of land use, e.g., its impacts on parking demand, property development, etc. There was also a paper studying passengers' perception on using AVs to ensure AVs can satisfy customer expectations (Chee et al. 2020).

5.4 Applications of AVs in last mile delivery

The last mile delivery problem is a hot logistics topic in recent times, and is even more important in the pandemic outbreak (Choi 2020a). Studies related to the applications of AVs and Autonomous Robots (ARs) are thus emerging. Boysen et al. (2018) studied a last mile delivery problem with truck-based ARs. In the problem, the ARs are carried by a truck and transported to a certain point for deliveries. Each AR carries the item of a single customer. After delivery, the ARs return to some robotic depot in the city. Trucks can also replenish the ARs there for further deliveries. To tackle such a complicated problem, the authors applied mixed integer programming to determine the assignment of customers to drop-off points, and the truck routing. Based on which, a tailor-made local search procedure was proposed for ARs routing. Similarly, Simoni et al. (2020) also studied developing optimization methodology for last mile delivery, and in which they applied a dynamic programming solution approach.

Other than ARs, we can also see papers studying the use of drones. Having a similar concept as vehicle platoon, a group of drones are operated in conjunction with a truck. Salama and Srinivas (2020) proposed to link the customer clustering with drone routing. They further proposed two policies, i) restricting the truck to stop at customer-only locations, and ii) allowing the truck to stop anywhere. They modelled the first policy as an integer program, and the second policy as a mixed integer nonlinear program. In order to solve the nonlinear program, they approximated it into a mixed integer program and accelerated the solution processing by using knowledge-based constraint and machine-learning based heuristic. Kitjacharoenchai et al. (2020) also studied the development of optimization methodology for a truck-drone operated in last mile delivery. In their work, they proposed a two echelon solution approach with: i) a drone-truck routing construction heuristic for truck routing and drone routing, and ii) large neighborhood search heuristic to refine the solution.

In fact, other than papers on developing optimization methodology, we can also see papers studying the user point of view. Kapser and Abdelrahman (2020) conducted a study to investigate users' acceptance in using AVs, ARs, drones, etc. in supporting the last mile delivery. They found that price was the strongest predictor, followed by expectancy, hedonic motivation and so on. This study brings the idea of using AVs in the last mile delivery closer to reality.

Technical difficulties of implementing Autonomous Approaches in optimization

Through the review in this section, we can see that many papers are focusing on routing problems with AVs and/or ARs. In general, there are two kind of hurdles: i) blocking problems, and ii) depot location problems.

Blocking problems are commonly found in indoors applications of AVs, i.e., warehouses, manufacturing shop floors, etc. (Roy et al. 2014, Roy et al. 2015a, Roy et al. 2015b, Draganjac et al. 2016). In this kind of problem, given a set of demands ($\mathcal{L}$), which can be order/item pick-up locations, a set of AVs ($\mathcal{A}$) is assigned and scheduled to travel to their destination with a choice of a pre-designed set of routes ($\mathcal{R}$). The objective may be minimizing the travel distance, travel time, carbon emissions, fuel cost, etc., meanwhile, considering the charging and energy level of the AVs. Because of the physical constraints (i.e., the layout of the warehouses), AVs may block each other as shown in Figure 2. One of the difficulties encountered in handling blocking is to identify different blocking scenarios and resolve unexpected blockings.

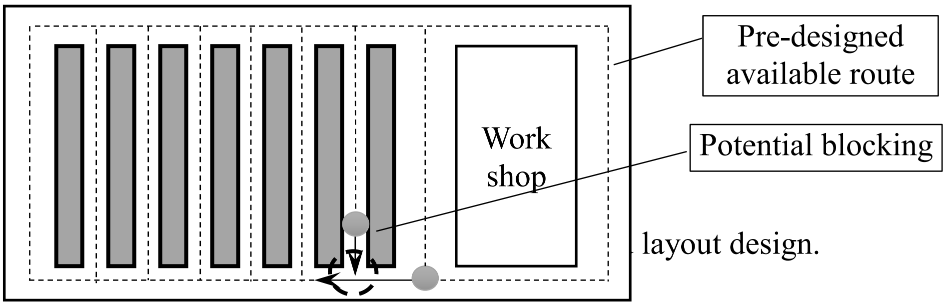

Figure 2. Potential blocking existing in fixed layout design.

The identification difficulty is even more challenging if the layout is not fixed. In other words, if it is dynamically changing over time as shown in Figure 3. As such, modeling with exact algorithms is not commonly found in the existing literature, rather, querying theory or heuristics are widely used.

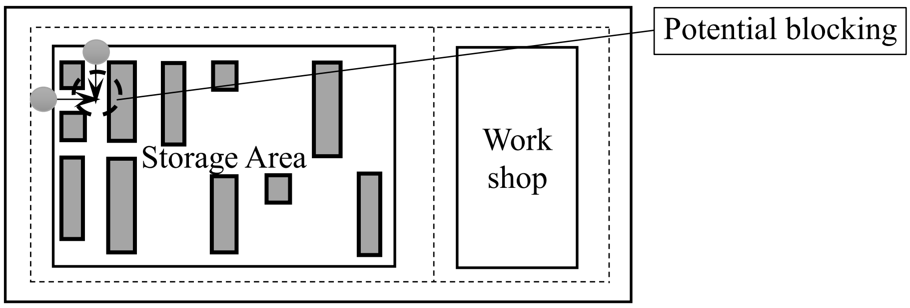

Figure 3. Potential blocking existing in dynamic layout design.

From the review, we also see that the last-mile problems with the support of AVs/ARs/drones are much more complicated than the traditional ones (Kapser and Abdelrahman 2020, Kitjacharoenchai et al. 2020, Salama and Srinivas 2020, Simoni et al. 2020). In this kind of problem, researchers usually have to deal with a set of demands points ($\mathcal{D}$), which can be a mix of upload and unload delivery orders with different geographical locations. A set of transportation modes ($\mathcal{T}$) is available for the transport and delivery, e.g., trucks, bus, AVs, or ARs, etc. In some problems, it can even involve mixed transportation modes, e.g., a mix of trucks with AVs (platoon). The objective is to satisfy all demands and minimize issues such as the total traveling time t_i, and total carbon emission e_i, where $i \in \mathcal{T}$. This kind of problem also considers the capacity limitation ρ_i, and traveling distance limitation δ_i of the transportation mode, in particular the AVs/drones. Similar to the Vehicle Routing Problems (VRPs) solution approach, demands are usually clustered into a number of non-overlapping groups ($\mathcal{D}' \in \mathcal{D}$) for problem simplification, as shown in Figure 4. However, the difficulty encountered here is to optimize the truck locations as depot for the release and return of the AVs. In the reviewed papers, the fixed depot approach was used, either at any location in the region or where in the demand location.

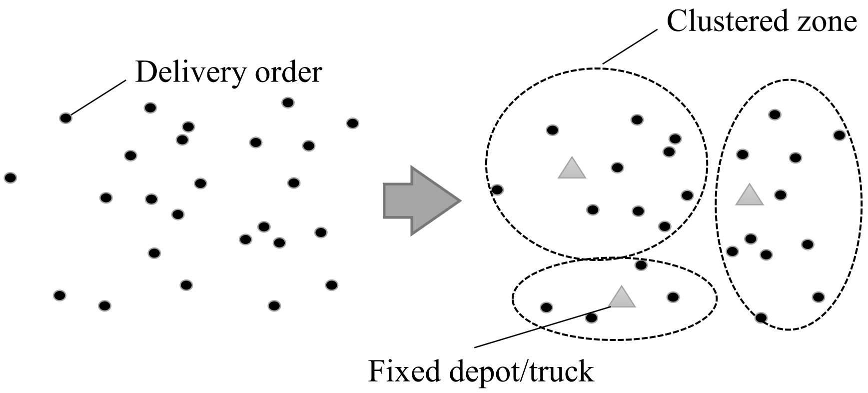

Figure 4. Sample of clustering for problem simplification.

6.0 Smart Logistics and Smart Warehouse

Lastly, we review the newly emerged topics: smart logistics and the smart warehouse. The related papers are summarized as in Table 4.

Table 4. A summary of publications in Smart Logistics and Smart Warehouse.

		Classification		Areas		Applications				
Authors	Year	SL	SW	Logistics	Warehouse	Distribution	Ecologistical chain	Planning and scheduling	Control	Optimization methodology (if any)
Pan et al. (2002)	2020	✓		✓				Carbon emission		-
Liu et al. (2020a)	2020	✓		✓			Logistics and supply chain			-
Liu et al. (2020b)	2020	✓		✓			Logistics and supply chain			-
Liu et al. (2019)	2019	✓		✓		Smart vehicles				Dynamic optimization method
Lee et al. (2016)	2016	✓		✓		Parcel delivery				Dynamic algorithm
Opalic et al. (2020)	2020		✓		✓				Cooling systems	Artificial Neural Network
Mahroof (2019)	2019		✓		✓				Movement of goods	-
He et al. (2018)	2018		✓		✓				Storage	Alternating Minimization method

SL – Smart logistics
SW – Smart warehouse

6.1 Smart Logistics

Early in 2016, Lee et al. (2016) already gave a description of smart logistics. At that time, they mentioned that the main focus of smart logistics was to deal with problems such as increased vehicle fleets, complicated transportation networks, and an increased variety of delivery demands. The objective was to satisfy delivery demand in a green manner with the support of various information and communication approaches. In their studied problem, they proposed a decision-making framework to handle on-demand parcel delivery with the consideration of just-in-time, fuel consumption, and carbon emissions. To tackle the problem, they proposed an integrated dynamic algorithm. The results indicated that the framework was able to reduce the fuel consumption by 6.4% and carbon emissions by 2.5%. Later on, Liu et al. (2019) conducted research work on distribution problems in which they applied IoT to obtain real-time information, which was then shared among logistics companies in order to enable a real-time information-driven dynamic optimization strategy for smart vehicles and logistics tasks. The objective was again to minimize the logistics costs and fuel consumption. The optimization methodology used was the dynamic optimization method, and reducing carbon emissions was crucial. In order to promote the development of smart logistics, Pan et al. (2002) conducted research to investigate the main factors that influence the establishment of smart logistics in China. They analyzed the effect of smart logistic policy by using a difference-in-differences model and found that freight volume, logistics employment, and total social retail were the important factors.

In our review, we can also see a new concept derived from smart logistics, called the Smart Logistics Ecological Chain (SLEC), which consists of three main elements: i) a supply ecological group, ii) a core ecological logistics platform, and iii) a demand ecological group (Liu et al. 2020a). In such a chain, smart logistics play a significant role to connect the upstream with the downstream group. Liu et al. (2020b) also studied the influencing factors of implementing SLEC and found that empowerment capacity and information sharing were the most important ones.

6.2 Smart Warehouse

Similar to smart logistics, we also see several papers using a term called "smart warehouse" to describe those warehouses which are enabled by automation and various technologies (e.g., AI, ML robotics, etc.) to increase their operation efficiency and reduce latency. He et al. (2018) proposed to apply differentiated service levels to different customer orders. A strategy named Differentiated Probabilistic Queuing policy was proposed. By solving the problem with Alternating Minimization method, they found that the performance was improved by about 19.64%. With the rapid development of advanced technologies, Mahroof (2019) conducted studies to explore the barriers and opportunities of using AI in warehouses. The results indicated that implementation and technology teams may be too optimistic about AI in the near future, while management with little knowledge on AI will then not perceive its significance. Similar to Smart Logistics, the environmental issue is also a focus. Opalic et al. (2020) conducted studies on controlling industrial cooling systems in smart warehouses by using artificial neural network to learn the optimal operational parameters. They found that the performance had a 3.2% improvement compared to the traditional approach.

7.0 Conclusions and Future Directions

In conclusion, we can see that STs have been a very hot topic and getting more popular in recent years. The applications have covered a wide spectrum, including public transport, production shop floors, warehouses, last mile deliveries and so on. Enabled by AI/BD/ML with the support of IoT/blockchain, autonomy provides us with a lot of significant benefits and contributions, e.g., higher operation efficiency, higher service levels, and lower operating cost. Although we have seen and discussed many of its advantages, there are many challenges to optimizations, e.g., dramatically increased problem complexity, converting data to meaningful optimization parameters, etc. It is believed that the applications of STs will be critical and crucial in the near future. More interesting research and challenges are yet to be explored. Here we share a few directions that we believe are significant.

7.1 Blockchain Technology in logistics digitalization

Many shipping and logistics companies are still relying heavily on using paper for various verifications and records, which result in poor operational efficiency and high operating costs. Nowadays, the concept of logistics digitalization is being promoted and developed rapidly to replace and improve operations efficiency and information sharing, e.g. verification of bill of lading. However, business logistics involve much sensitive and confidential information, e.g., freight rates between shippers and forwarders, shipper demands, storage capacity of distribution centers, etc. As such, information integrity and accuracy become critical and challenging. Many excellent papers have shown that with the support of blockchain technology, this can ensure honesty and eliminate cheating (Choi et al. 2019). As a result, it avoids moral hazards and secures fair trade (Choi 2019, Choi 2020b).

7.2 Sharing economy in public transport

From the reviewed papers, we can see that many studies show that the application of AVs to replace existing public transport, i.e., the public bus/shuttle approach is promising. Some researchers further demonstrate that the support of AVs in supplementing public transportation systems during the peak hours can help in reducing passengers' waiting time, in other words improving the service level. However, the actual operations mechanism is still in the conceptual phase, and studies are small scale, considering only a single route. Overcoming the optimization complexity is also challenging. In order to satisfy the complex transportation network in reality with multiple routes, more work is yet to be explored in this area.

7.3 Integrated Smart In-house logistics

Currently, the majority of the work in smart manufacturing and smart warehousing is separated. Smart manufacturing focuses on automation in production shop floors with the support of ARs, while the smart warehouse focuses on automation in the storage and retrieval of items with the support of AVs. In practice, raw materials, parts, and components are stored in warehouses and will be moved to the production shop floors. The finished or semi-finished product will then be moved back to warehouse for storage. In-house logistics between the two places are indeed frequent. However, the mechanism of connecting the two existing separated problems is yet to be explored, including the challenges in the robotics technologies and optimization methodologies. For the enhanced overall efficiency of factory and production, integrating the operations through integrated smart in-house logistics is promising.

7.4 Robust logistics optimization with machine learning

From the existing works, we can see that the applications of BD for pattern identification, and ML for prediction contribute to significant new insights in many problems, i.e., vessel scheduling, bus scheduling, etc. However, the technical difficulties encountered in determining the confidence level of the predicted output is yet to be explored, the success of which can definitely create a new research direction on robust optimization in logistics and transport problems.

7.5 Smart Technologies in last-mile delivery

There is no doubt that the application of AVs, ARs, and drones in last-mile delivery is one of the hottest topics. With the rapid development and creation of many new conceptual delivery models (e.g., platoon by Mercedes, flying warehouse by Amazon), it is expected that new modelling approaches are waiting to be developed. Meanwhile, as we have explored in our discussion on the technical difficulties regarding the optimization complexity, the efficiency of solution approaches is critical and is believed to be the main focus in this area of studies.

7.6 Space Logistics

Lastly, we would like to share our views on space transport. Nowadays, the development of space transport has already been started. Many feasibility studies have been conducted, e.g., the idea and prototype of the Starship spacecraft and the Super Heavy rocket, developed by SpaceX[4], have already emerged. These new space transport tools are designed to be a fully reusable transportation system aiming to carry crew and cargo in to Earth orbit. Combining with the concept of Amazon's flying warehouse, it is believed that the deliveries through the integrated space and air logistics will be even more efficient in the future.

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[4] https://www.spacex.com/vehicles/starship/index.html

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