Artificial Intelligence in Smart Logistics Cyber-Physical Systems: State-of-The-Arts and Potential Applications

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(Review Paper)

***Abstract*—Logistics creates tremendous economic value through supporting the trading of goods between firms and customers, thereby improving the welfare of the society. In order to continuously improve the quality of logistics service, a great variety of cyber-physical techniques have been utilized in the modern logistics systems, which help tackle the grand challenges in multiple aspects including time efficiency, economic cost, safety risk and cyber-security. The fast development of artificial intelligence (AI) has gained significant popularity and success in various domains, and hence, it has been adopted to construct high-quality solutions that can facilitate the monitoring, operation and decision in logistics systems. Furthermore, the deployment of advanced sensoring and computing components forms a cyber-physical system (CPS) infrastructure, which promotes the capability and scalability on data acquisition, transmission, storage and processing, thereby enabling the further penetration of AI technologies. Based on the existing advances, this article is devoted to conducting a comprehensive survey of the AI applications in the modern logistics CPSs. In specific, we focus on the AI-based research and industrial solutions that can improve the time/economic efficiency, safety and cyber-security of logistics systems. The potential applications of AI to tackle the remaining challenges are also discussed to investigate the way to continuously improving the quality of logistics service.**

***Index Terms*—Artificial intelligence, cyber-physical systems, smart logistics, smart supply chain.**

I. Introduction

LOGISTICS has become critical in the modern world with strong connectivity on business. It provides a networked platform to the firms and consumers to facilitate the tradings and movement of goods, thereby creating grand economic value. Therefore, the corporations in logistics industry have devoted large efforts to improve the quality of logistics service and the efficiency of society over the decades. A modern logistics system usually deploys a large-scale logistics network to guarantee the goods to be processed in a methodical fashion [1]. As a large-scale logistic network can contain a large number of facility nodes including warehouses, distribution centers and terminal stations, each component, including the transportation routes between those components, needs to be optimized to guarantee the fast, safe and economic delivery.

In nowadays, a great variety of technical approaches have been utilized to improve the quality of logistics service promoted by the trend of Industry 4.0. In specific, the advanced sensoring and computing technologies such as Internet-of-things (IoT), cloud computing and edge computing are widely deployed to construct cyber-physical system (CPS) infrastructures, thereby supporting the efficient acquisition, transmission, storage and analysis of data [2]. In the logistics CPS, the components for data acquisition and transmission act as the cyber components and the entities to be controlled act as physical components. For instance, the inventory management system works in a CPS fashion such that it achieves the market data through the information system and make decisions on replenishment to keep a reasonable inventory level. Based on this infrastructure, the extensive deployment of artificial intelligence (AI) is enabled to facilitate the monitoring, operation and decision making in the logistics field, thereby improving the efficiency and reliability of logistics instead of the conventional approaches. The conventional logistics systems rely on traditional techniques such as operations research and human labor/experience when no AI technology is involved. The traditional techniques in these domains usually rely on restrictive assumptions or case-specific limitations. In contrast, the AI techniques allow the decision making with more flexibility to handle the dynamics in real-world scenarios, and generalize the experience for solving a problem to other problems in the same family to rapidly reduce the computational cost. The methods based on human labor/experience can usually be employed to monitor the state of resources in logistics scenarios. However, these methods are usually labor intensive and even dangerous. In

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contrast, the AI-based solutions using computer vision provides an alternative of feasible monitoring.

The connectivity offered by the CPS infrastructure and the integrated AI technologies will lead to the realization of smart logistics, which can respond to the rapid dynamics and uncertainties of the external environment. Based on that, the continuous development of AI will enable the further penetration of automatic and data-driven solutions, which lessens the reliance on human labor and experience, thereby generating appropriate decisions to guarantee the quality of warehousing, transportation, distribution and delivery under less cost and risk. Despite these offered advantages, the logistics CPS still faces the following grand challenges.

- *Time Efficiency:* Time efficiency is critically important for logistics such that it can potentially induce severe consequences (e.g., economic losses and degradation of customer experience) if the promised time efficiency cannot be met [1]. As the time efficiency can be impacted by a large number of complex and random issues, it is usually a challenging task to identify the impacting factors and improve the time efficiency correspondingly.
- *Cost:* The operation of logistics is associated with multiple types of costs such as the cost of energy, material and human labor. Cost reduction is an important target of logistics planning and scheduling in sake of economic efficiency, which can simultaneously avoid the excessive resource usage and greenhouse gas emission.
- *Safety:* The safety of logistics contains two perspectives including the safety of goods and human. Due to the high complexity of logistics scenarios, the inappropriate operations can potentially induce severe consequences like the damages of goods and injury of employees.
- *Cyber-Security:* The modern digitilized logistics systems are managed by information systems such as warehouse management system (WMS) and transportation management system (TMS). Furthermore, the deployment of AI techniques are enabled by the information acquisition/transmission components such as the networked sensors. This poses new challenges on cyber-security such that the weakness of these parts can be utilized by attackers for malicious purposes.

Due to the rapid development of modern logistics systems, a comprehensive survey of AI applications in the logistics domain is urgently needed as a guideline to explore the potential solutions to tackle the aforementioned challenges. However, the existing survey papers [2], [3], [4], [5], [6], [7], [8] focus on either the engineering frameworks or the operations research in modern logistics systems. Although [7] and [8] have pointed some potential application directions of AI, they did not provide details on the specific AI techniques that can be used to improve the quality and efficiency of logistics, and their application scenarios. In contrast, a survey that comprehensively reviews the specific utilization of AI approaches to facilitate the operations of logistics systems remains lacked in existing literature despite its critical importance to the industry and social welfare. In order to fill this gap, this work presents the first survey to investigate how AI technologies can help improve the quality of logistics service, especially under the CPS context. In this survey, we aim to pursue the high-quality solutions to tackle the grand challenges in the logistics domain through continuously investigating the applications of AI technologies. This survey summarizes the tasks in logistics CPSs into 5 categories including resource allocation, planning & scheduling, measurements & monitoring, autonomous driving and logistics systems simulation. For each category, we discuss in details how the aforementioned challenges are studied and addressed in existing works. Furthermore, the new challenges in modern logistics cyber-physical systems and the prospective applications of AI technologies are explored accordingly.

In summary, the contributions of this article can be highlighted as follows.

- This paper presents the first survey on the applications of AI in logistics systems associated with the CPS context, which provides a guideline to both researchers and practitioners to explore the AI-based solutions to tackle the grand challenges in the logistics domain.
- This survey summarizes the tasks of Logistics CPS into 5 categories, where the AI-based solutions are discussed in details for each category to illustrate how the corresponding challenges are resolved using AI techniques.
- Challenges for utilizing AI techniques in logistics scenarios are discussed in depth and the potential solutions are pointed to inspire future research in this domain.

The remainder of this article is organized as follows. In Section II, a overview is provided on the architecture of the logistics CPS. In Section III, the applications of AI for resource allocation in logistics systems are discussed. In Section IV, the relevant works on smart logistics planning and scheduling are reviewed. In Section V, the AI-based solutions for automatic monitoring and measurements in logistics scenarios are presented. In Section VI, the recent autonomous driving techniques for logistics are investigated. In Section VII, the intelligent approaches to facilitate the simulation of logistics systems are studied. In Section VII the new challenges and potential applications of AI for modern logistics are explored. Finally, we conclude in Section IX.

II. Architecture of Logistics Cyber-Physical System

The architecture of a logistics system is depicted in Fig. 1, where a huge logistics network containing up to thousands of facility nodes and the transportation routes between them is build to support the warehousing, distribution, transportation and delivery operations. For instance, in the retailing scenario, the logistics system serves the manufacturers through keeping their products in stock based on supply chain management methodologies to guarantee the high time efficiency. Subsequently, the purchased items are shipped from the corresponding warehouses, sorted at the regional distribution center(s) and forwarded through the transportation network to the local stations for final delivery to the customers [9]. In order to guarantee the high quality and low operational cost of logistics service, plenty of efforts have been devoted to the optimization of the logistics system in multiple aspects.

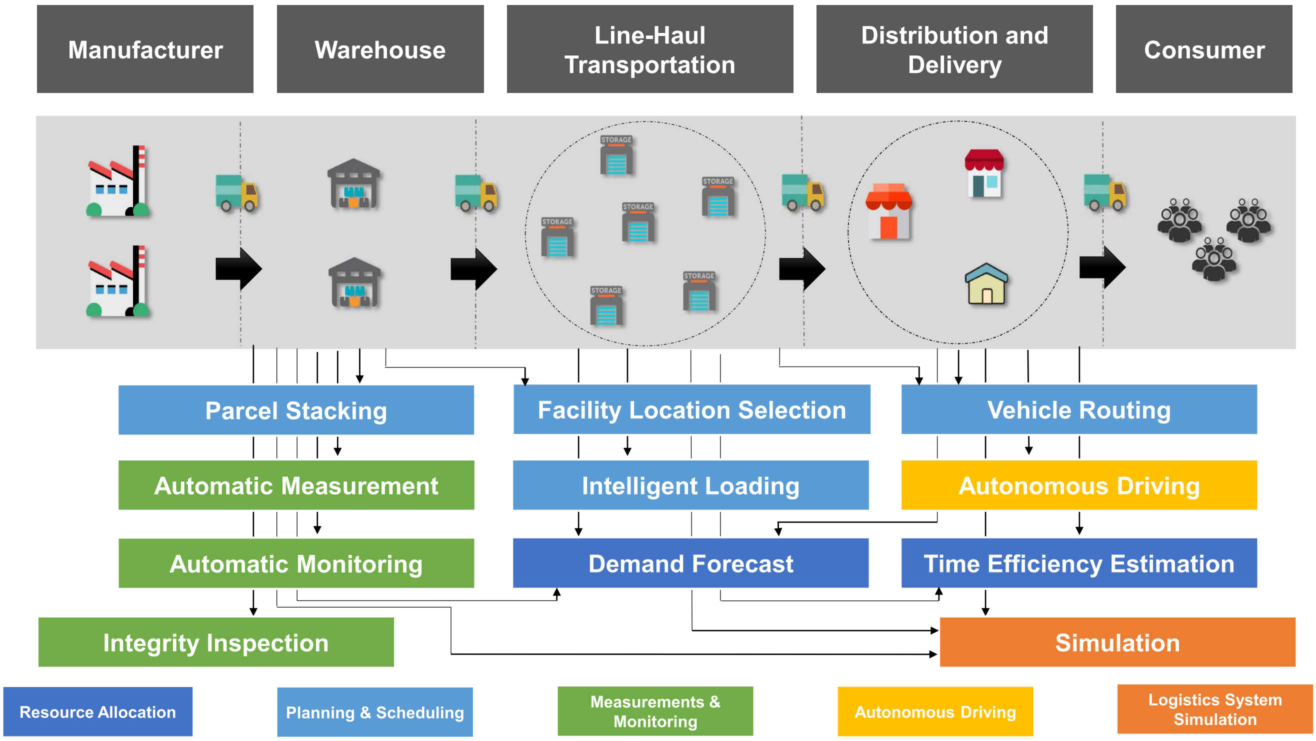

Fig. 1. The logistics service is supported by a huge network consisting of the facility nodes including warehouses, distribution centers and terminal stations, with the transportation routes between them as edges. This infrastructure benefits the trading between firms and customers through fetching the products from the manufacturers and delivering them to the customers. In this architecture, the plan, operation and optimization of each component rely on the specific technical approaches to guarantee the high quality of service.

In the aforementioned logistics system, the plan and operation of each component faces the grand challenges in terms of time efficiency, cost, safety and cyber-security, and hence, it critically relies on the advanced technical approaches to guarantee the high quality of service. In order to tackle these challenges, the modern logistics systems are usually constructed in a digitalized fashion, where the advanced sensoring and computing technologies are employed for the acquisition, transmission, storage and analysis of data, and finally facilitate the decision making of logistics operations. This naturally forms a CPS, such that the information infrastructures act as the cyber components and the entities in the logistics system act as the physical components. The cyber and physical components collaboratively accomplish the functionalities that are critical to the quality of logistics service.

In the modern logistics system CPS, the information acquisition is enabled by a large variety of connectivity technologies, which forms an IoT architecture. The IoT architecture in logistics systems can usually be divided into 4 layers including sensing layer, network layer, processing layer and application layer [2]. Taking advantages of this architecture, the information of physical entities is collected by the sensing layer using sensoring techniques such as video camera and LiDAR. Subsequently, the collected information is forwarded to the processing layer for storage and computing through the network layer, where the communications techniques like wireless sensor network (WSN), wireless local area network (WLAN), Wi-Fi and 5G communications can be adopted based on the specific needs of the application scenarios. Finally, the forwarded information is analyzed through computing techniques in the processing layer and the outputs are utilized for decision making in the application layer. Since such an architecture can usually result in heavy communication overhead, edge computing provides a reliable alternative to move the computing tasks to the local scenarios in contrast of the centralized cloud [10]. Another usage of edge computing is to extract the most informative patterns from the collected data for further transmission and storage to save the related costs.

In the aforementioned logistics system CPS architecture, the functionalities considered in this survey can be organized in three ways. As we divide logistic system into four modules including warehousing, transportation, distribution and delivery, a natural organization is to summarize the functionalities based on the specific modules they are applied in. Furthermore, we also divide these functionalities into five technical categories including resource allocation, planning & scheduling, measurement & monitoring, autonomous driving and logistics system simulation according to their specific targets. Finally, the functionalities can be grouped based on the challenges they are expected to address. For clear illustration, we summarize the considered functionalities associated with the corresponding module and technical categories in Fig. 1. Table I further summarizes them associated with the specific challenges to be addressed in the corresponding modules.

Compared with other types of CPSs, the logistics CPS features the very large scale and high complexity. In the logistics network,

TABLE I
THE SUMMARY OF SPECIFIC TECHNIQUES EMPLOYED IN EACH COMPONENT OF THE LOGISTICS SYSTEM

	Time Efficiency	Cost	Safety	Cyber-Security
Warehousing	Demand Forecast inventory optimization Simulation Automatic Measurement Automatic Monitoring	Facility Location Selection Simulation Parcel Stacking	Automatic Monitoring Simulation	Integrity Inspection
Line-Hual Transportation	Demand Forecast Time Efficiency Estimation Simulation Automatic Measurement Vehicle Routing	Vehicle Routing Autonomous Driving Simulation Intelligent Loading	Automatic Monitoring Simulation	-
Distribution	Demand Forecast Time Efficiency Estimation Simulation	Facility Location Selection Simulation	Automatic Monitoring Simulation	-
Delivery	Time Efficiency Estimation Vehicle Routing Simulation Demand Forecast	Vehicle Routing Intelligent Loading Simulation Autonomous Driving	Simulation	-

The intersections of component and challenge not yet covered by existing literature are filled using the symbol "-".

each component (e.g., a warehouse, a transportation rout, a distribution center or a delivery network) can be treated as an individual CPS since it can make decisions independently based on the local collected information. However, the entire logistics network can be regarded as a CPS globally as well due to the logical connections between the components, induced by which the decision in a component may need the information collected from other parts and lead to global impact. For instance, the location selection of distribution centers will depend on the demand of up/down stream and impact the time efficiency of the entire logistics network. In the logistics network, different components may share common need of functionalities, as depicted in Fig. 1 and Table I. Among the categories of functionalities, resource allocation can be applied in all components to predict the future demand and facilitate appropriately usage of resources, thereby addressing the challenges on time efficiency and cost. Similar to resource allocation, the planning and scheduling functionalities tackle the challenges on time efficiency and cost of all components. The major difference is that the focus of planning and scheduling narrows down to the combinatorial optimization problems such as vehicle routing, bin packing and facility location selection. Automatic measurement and monitoring help improve the time efficiency and safety through collecting the identities, physical properties and health conditions of goods and equipment in the warehousing, transportation and distribution scenarios. Autonomous driving helps reduce the labor cost in transportation and delivery steps. Simulation provides a useful tool to validate the decisions in the logistics network both globally and locally to improve the time efficiency and safety, and reduce the cost. As cyber-security is a relatively new challenge in the logistics CPS, the techniques to improve the cyber-security is discussed in Section VIII.

As AI is a very broad field containing a wide variety of specific technologies, we mainly focus on the regression, reinforcement learning, computer vision and clustering techniques that have great potential to be utilized to address the challenges in logistics scenarios. It is worth noting that the reviewed AI-based solutions are not limited to applying existing techniques to solve the problems in logistics systems. In fact, they have made theoretic innovations to better tackle the specific difficulties in real-world scenarios. Among these techniques, regression has been widely utilized for the prediction of demand value (demand forecast), time-of-arrival (time efficiency estimation) and input/output values of simulation systems. Based on the needs of specific scenarios, innovative model architectures have been developed to identify the contribution of different factors in time series [11], [12]. Furthermore, sophisticated neural network architectures are designed to effectively extract complex spatial-temporal correlations trained using customized loss functions for time efficiency estimation [13], [14], [15]. Reinforcement learning is mainly used for inventory optimization, control of autonomous driving systems and developing efficient solutions of combinatorial optimization problems (logistics planning and scheduling). It is worth noting that the reinforcement learning-based solutions point the recent trends for solving combinatorial optimization, and hence, considerable efforts have been devoted to construct innovative model architectures to learn the characteristics of the problems [16], [17], [18], [19], [20], [21], [22]. Computer vision is crucial for monitoring & measurement in logistics systems (e.g.warehouses) and perception of autonomous driving. Unlike general computer vision models, the models used in this direction are usually customized to resolve the specific issues in logistics scenarios, such as the large rotation angles of vehicle license plates [23], [24]. The perception of autonomous driving relies on both 2-dimensional (2-D) and 3-dimensional (3-D) computer vision techniques. Thus, a recent trend is to construct fusion frameworks to combine the advantages of both 2-D and 3-D vision techniques for accurate recognition of traffic environment [25]. Clustering techniques are mainly employed for facility location selection since that problem naturally involve clustering patterns. In this line of research, the clustering techniques considering constraints is investigated to accommodate the challenges in practical scenarios [26]. In the following sections, the applications of AI technologies will be discussed from the technical category perspective. In order to provide a clear guideline, the representative works reviewed in this survey are summarized in Table II and analyzed associated with their specific technical contributions.

TABLE II
THE SUMMARY OF REPRESENTATIVE WORKS ON THE APPLICATIONS OF AI IN LOGISTICS SCENARIOS

Category	Technical Domain	Approaches & Literature
Resource Allocation	Demand Forecast	Data-Driven: [27], [28], [29], [30], [31], [32] Hybrid: [11], [12], [33] Ensemble: [34], [35]
	Inventory Optimization	Deep Reinforcement Learning: [36], [37], [38], [39], [40], [41] Forecast Free: [42], [43], [44], [45]
	Time Efficiency Estimation	Travel Time Estimation: [13], [46], [14], [15], [47] Delay Prediction: [1] Root Cause Analysis: [48]
Planning & Scheduling	Vehicle Routing Problem	Pointer Network: [16] Deep Reinforcement Learning: [49], [50], [51], [17], [18], [52] Multi-Agent Deep Reinforcement Learning: [53], [54]
	Bin Packing Problem	Offline Bin Packing: [55], [19], [20], [56] Online Bin Packing: [21], [22]
	Facility Location Selection	Deep Learning: [57] Clustering: [58], [59], [60], [26]
	General MIP	Graph Neural Network: [61]
Automatic Measurement & Monitoring	Measurement	Image-Based: [62], [63] Point Cloud-Based: [64], [65], [66], [67]
	Monitoring	Licence Plate Detection: [68], [69], [23], [24] Licence Plate Recognition: [70], [71], [68], [72], [73] Conveyor Belt Monitoring: [74], [75]
Autonomous Driving	Last Mile Delivery	Perception: [76], [77], [78], [25] Localization: [79], [80], [81], [82], [83], [84], [85] Planning & Control: [86], [87], [88]
	Warehouse Robotics	Task Prediction & Selection: [89], [90]
Logistics Simulation	Simulation	Input Parameter Analysis: [9] Surrogate Model: [91], [92] Simulation Model Reuse: [93], [94], [95] Digital Twin: [96], [97]

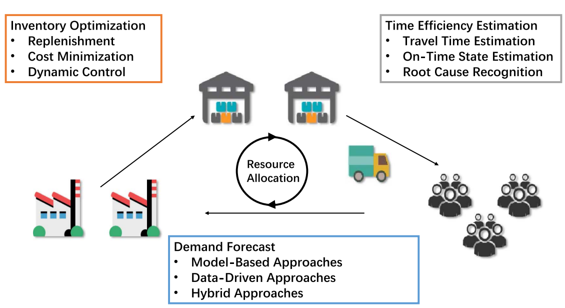

Fig. 2. Demand forecast, inventory management and time efficiency estimation are important basis for resource allocation in the logistics system that cooperate to ensure the quality of logistics service.

III. Resource Allocation

The resource allocation in a logistics system relies on the prediction of system states, including the market demand and quality of service. As logistics system is always closely bounded to the supply chain, accurate estimation of the demand in supply chain is the foundation to appropriately allocate the resources in logistics systems in advance. Generally, the demand of logistics service can be predicted directly or obtained through inventory optimization given the prediction of sales. Furthermore, expected time efficiency is another important basis for resource allocation such that more resources can be invested to reduce the anticipated delay. Thus, in this section, we discuss the intelligent demand forecast, inventory optimization and time efficiency estimation techniques as well as the new challenges posed by the development of logistics industry in these fields. Refer to Fig. 2. From technical perspective, we mainly focus on the regression techniques for demand forecast and time efficiency estimation, as well as the reinforcement learning techniques for inventory optimization.

A. Demand Forecast

In practice, demand forecast in the supply chain field is usually modeled as a time series forecasting problem, which aims to predict the future variations of a time series based on the past time-dependent observations and available external variables [98], [99]. While time series forecasting has been extensively studied in both academia and industry, the existing approaches can be generally classified into three categories including quantitative model-based approaches, data-driven approaches and hybrid approaches [12]. As a specific type of time series, the demand in supply chain suffers from complex pattern due to the impact of multiple complicated factors such as promotion, whether, market trends, customer behavior and competition products [29], [100], [101]. These difficulties are usually tackled through investigating the pattern of the time series itself and modeling the impact of external variables. Thus, accuracy and explainability are two vital issues for the forecast of time series in practice, which are usually addressed through breaking a time series into several components and investigating the prediction of each component individually [12]. Great efforts have been devoted to reach this target in existing works. The details of the representative time series forecasting approaches are summarized as follows.

- *Quantitative Model-Based Approaches:* Quantitative model-based approaches refer to the methods that predict the future time series based on their statistical characteristics. Within this range, the representative methods such as

Exponential Smoothing [102] and Auto-Regressive Integrated Moving Average (ARIMA) [103] have been widely adopted in the industrial solutions due to the reliability. These approaches employ various components to capture the effects of multiple factors such as trend, seasonality and auto-regression. However, the techniques in this category usually suffer from the limitations induced by their restrictive assumptions, which requires deep domain knowledge and sophisticated modeling skills of the analysts to tackle these challenges and adapt to complicated real-world scenarios [12].

- *Data-Driven Approaches:* Compared with the general time series forecasting problems, the accurate demand forecast in logistics and supply chain scenarios needs to take into account the impact of various factors including economic development, industrial structure, commercial trade, residents consumption level, capital investment, macroeconomic policies, external environment, etc., apart from the historical records of demand [104]. The strong capability of machine learning techniques on extracting informative data patterns enables them to capture the correlations between these external factors and the demand of logistics service. In contrast to the quantitative model-based approaches that fit predictive models of individual sequences, the data-driven approaches allow to learn from substantial amount of similar/related time series [27]. Hence, machine learning techniques have been widely used for time series forecast in recent works. Among the various types of machine learning models, recurrent neural network (RNN) is commonly adopted due to the auto-regressive nature of demand sequences [105]. Based on this framework, various other mechanisms such as attention have been incorporated to improve the accuracy and interpretability [106]. The recent advances of deep learning further enhanced the capability on learning the complicated correlations and long-term dependency, thereby promoting the development of high-performance models for time series forecasting such as DeepAR [27] and Informer [28]. In addition to neural networks, other machine learning techniques such as support vector machine and decision tree have also been utilized for time series forecasting [31], [104]. When predicting the demand of a product, the information of competing products/sellers should be considered apart from its own historical records and features. In order to accommodate the spatial-temporal correlations between products and time points, graph neural network (GNN) has been popularly employed to construct the forecasting framework in recent research [29]. The data-driven demand forecast approaches have gained significant popularity in recent years as the increasing availability of data can provide sufficient information for the training of machine learning models, especially neural network-based models, to achieve high accuracy. Experimental study has been conducted in [27], where the DeepAR model outperforms the state-of-the-art baselines including a few model-based ones taking advantages of the strong representation capability. However, these models often suffer from weak interpretability and strong need of engineering skills, which can only be appropriately handled by experts with both data science and domain-specific background [12].
- *Hybrid Approaches:* As is known, the demand in supply chain and logistics system usually suffers from several issues such as the rapid increase on special holidays [98]. Although these issues have been considered in other types of forecasting approaches by being treated individually in the pre-pocessing steps [98], they usually require the analysts to be proficient in both domain-specific knowledge and time series modeling. In order to tackle these challenges, Prophet, which is the precursor of hybrid approaches, decomposes the time series into three components to represent trend, seasonality and holidays, respectively [11]. In each component, flexible models with interpretable parameters are utilized to accommodate different assumptions. It provides an automated framework such that a domain expert can easily optimize the model without deep prior knowledge on time series [11]. Based on these advances, the neuralprophet model further strengthens prophet by incorporating neural network-based auto-regression and covariate modules to adapt to non-linear dynamics [12]. In the other line of research on hybrid approaches, the deep learning-based time series forecasting techniques are facilitated by classic approaches (e.g., exponential smoothing) such that the classic approaches are used in the pre-processing steps to mitigate the variations, which allows the deep learning models to learn across different time series more efficiently [33].

Despite these achievements for demand forecast, a single model can hardly fully capture the characteristics of the demand trend in all scenarios at all times [107]. This makes ensemble approaches a natural option to improve the robustness of forecast through optimizing the weight of each individual model in the final forecast output. Recently, reinforcement learning has been employed to automatically explore the weighting strategies [34], [35], [107]. In [34], the model selection action is generated based on the demand pattern through optimizing the expected inventory cost. In [35], the reinforcement learning framework outputs the weights of forecast models as action based on the prediction patterns and their historical performance.

While some existing works are devoted to the forecast of the total demand of logistics service such as [98] and [104], another common approach is to predict the sales/demand of specific stock keeping units (SKU)s, thereby aiding the appropriate inventory management strategies correspondingly. A major challenge for the SKU-based forecast is the demand forecast of new products since no explicit data of them can be drawn from historical records. A common practice to resolve this issue is to extract useful data pattern from existing SKUs for the prediction of new products. This is usually implemented by dividing the products into groups using clustering techniques (e.g., k-means and self-organizing map) such that each group of products share the same forecasting model and a new product can be assigned to a cluster with the strongest similarity [30], [31], [108]. The recent development of deep learning and multi-modal techniques have also been incorporated for the demand forecast of new products through investigating their correlations with product images and multiple other external attributes [32].

B. Inventory Optimization

Inventory optimization is a vitally important task in supply chain, which aims to maintain a reasonable stock level through a series of actions such as replenishment considering the estimated market demand and various practical constraints to minimize the expected cost induced by understocking, overstocking and operations [41], [44]. Due to the aforementioned nature, inventory optimization is usually formulated as a dynamic control problem, the conventional solutions of which intend to generate a sequence of decisions under uncertainty using dynamic programming, heuristics or rules [40], [41], [109], [110], [111]. The conventional solutions can usually be limited by several issues such as generalization and scalability especially when the variability of the demand is high or the dimension of the problem (e.g., the number of SKUs and stores) is huge. In contrast, the recent advances of machine learning techniques have been employed to provide data-driven solutions to tackle the aforementioned difficulties and multiple other constraints.

As the distributions of external attributes such as market demand can usually be assumed to follow Markovian transitions [112], [113], the optimization of inventory management policy can naturally be modeled using Markov Decision Process (MDP) [36], [39], [113]. Theoretically, an MDP model can usually be solved using analytical&exact, analytical & approximate, numerical & exact and numerical & approximate methods [113]. Recently, researchers tend to solve MDP using deep reinforcement learning, a numerical & approximation method, due to the scalibility and the strong representation capabilities [36], [113]. Based on these advances, a natural option for solving a MDP is deep reinforcement learning in modern research, which generates the replenishment actions based on the expected reward [36], the optimal policy [37], or a combination of both [113] computed by the model. A difficulty of inventory optimization is the uncertain environment (e.g., future demand, lead time), which is induced by multiple factors such as market changes, customers' behavior, price fluctuations and extreme events [38], [113], [114], [115]. Conventional optimization-based approaches rely on the assumptions on the distribution of uncertainty, which can hardly be available to decision makers in real-world scenarios [43], [113]. In contrast, the deep reinforcement learning-based approaches can directly model the approximation of the uncertainty taking advantage of the rich state space in a data-driven fashion [38], [113].

This framework enables learning specific policies for individual problem setups based on a generic set of features as well as accommodating the complex combinatorial issues [41]. Hence, the reinforcement learning-based methods have gained considerable popularity in modern inventory management solutions. In [39], the complete procedure for reinforcement learning-based replenishment policy optimization under lost sales inventory models including formulation and parameter tuning is studied in details, where the performance of reinforcement learning-based modeling can match the state-of-the-art heuristics in three classic intractable scenarios. In [37], a reinforcement learning formulation is developed using semi-Markov decision process to accommodate multiple types of costs such as transportation cost, holding cost and stock-out penalty cost. In [40], deep reinforcement learning with continuous action space is applied to solve inventory optimization problems with different configurations and earned superior results compared with the baselines in all cases. In [41], a multi-agent reinforcement learning approach is utilized to solve the inventory optimization problem with multi-product constraint, where it effectively achieved the coordination between warehouses and stores.

The prediction of market demand is the basis for inventory optimization. However, a majority of existing methods for inventory optimization usually follow a prediction-then-optimization framework, which separate the demand forecast and inventory policy optimization as two individual steps. This can potentially induce the lost of information and result in sub-optimal solutions [44], [45]. In order to resolve this issue, the single-step methods have been developed in recent works to generate the decision based on the historical demand and related features directly. In [42], the mapping from external features to the inventory optimization decision is learned through minimizing the empirical risk on historical demand. In [43], a quantile regression framework is employed to optimize the inventory decision based on the assumed relation between the replenish order quantity and demand forecast. While both [42] and [43] focus on single-product newsvendor problem, [44] applied the machine learning-based solution to multi-product scenarios. Furthermore, an end-to-end deep learning framework is developed in [45] to generate multi-period inventory replenishment decisions. In summary, the one-step methods can circumvent the demand forecast step, which is usually impacted by multiple complex factors, and can be trained in an end-to-end fashion, thereby improving the convenience and quality of inventory optimization.

Scalibility is a major concern for inventory optimization since there can exist a huge number (e.g., up to millions) of SKUs to manage in logistics warehouses, and hence, numerous historical records and the corresponding external features need to be processed for the computing of replenishment operations. In the industrial data systems, the processing of huge amount of data is usually supported by distributed computing frameworks such Hadoop, Spark and Flink. The modern distributed computing frameworks have been sophisticatedly optimized to support in-memory computing and stream data, thereby enabling efficient machine learning workflows. Apart from the employment of advanced data processing frameworks, it is also important to keep only informative data to avoid unnecessary computing overhead [2].

C. Time Efficiency Estimation

Apart from the future demand, time efficiency is another important basis to allocate the resources in the logistics system that benefits both logistics corporations and customers. As the end-to-end time efficiency of logistics is impacted by those of each processing step including packaging, sorting, transportation and delivery, the accurate estimation can enable better plans to allocate resources to the critical processing steps, thereby improving both time efficiency and the satisfactory of customers [116]. Generally, one desires to estimate the total on-route time of goods given the complete origin-to-destination (O-D) path, which can contain the routes for transportation/delivery and the facilities for packaging/sorting operations, and external attributes such as time and weather. However, the estimation of time efficiency is usually non-trivial in practice due to multiple challenges such as the impact of various complicated temporal and spatial factors. This motivates the appropriate quantification of their impacts in recent works, where the advances of modern neural network architectures are investigated to learn the representations of these factors. For instance, the benefits of multiple wide linear models, deep models and recurrent networks are combined in [13] to utilize the information from multiple sources such as spatial information, temporal information, traffic information and personalized information for accurate route-based travel time estimation.

As the complete O-D path for transportation/delivery consists of several individual segments, a natural approach to estimate the travel time is to estimate those of each individual road segment and sum them up to that of the whole route while considering the inter-segment variations [13], [46]. However, a drawback of this framework is that it can hardly take into account the impact of transitions between the segments (e.g., road intersections, traffic lights and direction turns), and can easily induce the accumulation of errors for the estimation of each segment [14], [15]. For this reason, recent works tend to estimate the travel time of the entire route directly [13], [14], [15]. In these works, sophisticatedly crafted neural network architectures are designed to extract complex spatial and temporal correlations between data attributes and auxiliary losses are utilized to supervise the estimation of end-to-end travel times through incorporating the penalty for the estimation of each local path.

Another challenge for practical time efficiency estimation is the high uncertainty due to the impact of various complicated and random factors. In specific, there are two major difficulties including 1) it is very hard to obtain all the detailed information of the routs or processing steps and 2) the future dynamics cannot be known in advance [1], [47], [116]. A common approach to tackle these difficulties is to regard the unknown information as missing values and implicitly learn their expected impact using specific model architectures. For instance, [1] predicts the on-time state of on-route parcels while considering the future dynamic information of unreached processing steps as missing values, which are handled simultaneously when modeling taking advantages of the decision tree structures. Furthermore, [47] predicts the travel time without knowing the specific routs for transportation. In contrast, it utilizes specific neural network architectures to extract the underlying correlations between travel time and road network topology.

Apart from directly estimating the metrics of time efficiency, another important task is to identify the components/steps with critical impacts to time efficiency, thereby aiding the resource allocation to improve the overall performance of logistics service. This can usually be accomplished by root cause analysis techniques. A specific solution is provided by [48], where explainable machine learning is utilized to recognize the root causes inducing delays in delivery through considering both global statistics and the local characteristics of each event.

In summary, the challenges of resource allocation in logistics systems lie in the dynamics of the real world, such as the uncertainty in market trend, user interests, special events, complex traffic/weather conditions and multiple other types of unknowns. These challenges significantly impact a broad variety of tasks in logistics scenarios such as the demand forecast associated with new/long-tail products, inventory optimization under uncertainty, which further affect the quality of logistics service. Thus, the appropriate strategies to accommodate these issues will remain attracting the research efforts in the future investigation of this domain.

IV. Logistics Planning and Scheduling

Combinatorial optimization is a widely studied topic in operations research that intends to find the optimal solution of a problem defined in a discrete space, which plays a critical role in logistics industry [117], [118]. In the real-world operations of logistics and supply chain, many practical problems such as vehicle routing problem (VRP) [119], [120], bin packing problem [55] and facility location selection [26], can be formulated using combinatorial optimization. As combinatorial optimization is a typical NP-hard problem, existing techniques can hardly find the optimal solution in a highly efficient manner. In order to seek a reasonable tradeoff between solution quality and efficiency, approximate algorithms, heuristic algorithms and meta-heuristic algorithms have been adopted for industrial applications. However, these methods suffer from their specific shortcomings despite the advantages. Although approximate algorithms can obtain near-optimal solutions, their applications in practical scenarios are still limited by the high time complexity [118], [121]. The meta-heuristic and heuristic algorithms usually cannot guarantee a theoretical bound of the solution quality despite the superior time efficiency [118]. Furthermore, the heuristic algorithms are often task-specified such that a high-quality heuristic algorithm usually needs to be designed by a domain expert through leveraging the special structure of the problem [117], [118].

In recent years, machine learning has been utilized to solve combinatorial optimization problems due to multiple advantages. The advances in its sub-domains such as deep learning and reinforcement learning allow it to investigate the complex problem structures through vast amount of data and adapt across a family of problems without extra handcrafted effort [117], [118], [122]. In order to achieve high-quality solutions for combinatorial optimization problems, an important task is to catch the representative features of the problem formulation. Hence, great efforts have been devoted to extracting appropriate representations from the underlying structures of the problem using sophisticatedly optimized model architectures. In this section, we conduct the survey on the machine learning-based solutions on VRP, bin packing and facility location selection problems due

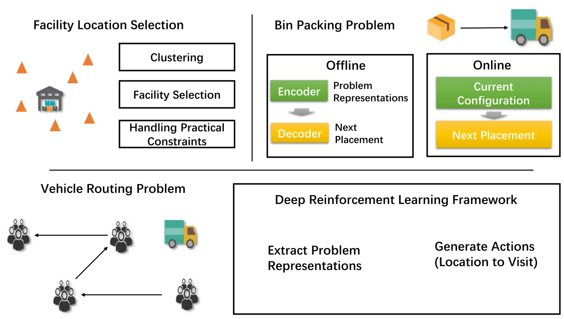

Fig. 3. Combinatoral optimization plays an important role in the operations of logistics. In practice, a large number of planning and scheduling problems can be formulated using combinatoral optimization such as facility location selection, vehicle routing problems and bin packing problems. In contrast to conventional solutions, the AI-based techniques extract the appropriate representations from the problem formulations using specific model architectures, thereby aiding the decision making.

to their importance in the logistics domain, as depicted in Fig. 3. We will discuss the rationalities of the solutions associated with the characteristics of each specific problem. From technical perspective, we mainly focus on the reinforcement learning and clustering techniques for solving the combinatorial optimization problems in logistics scenarios.

A. Vehicle Routing Problem

In the VRP problem, a fleet of vehicles have a set of road-networked locations to serve, where the vehicles aim to minimize the transportation cost subject to a set of operational constraints while satisfying the need of customers [17], [18]. Thus, a solution of the VRP problem needs to specify a sequence of locations to visit for each vehicle. Due to this reason, a majority of the existing works formulate VRP as a specific sequence-to-sequence learning problem, where the model is trained to generate the most probable sequences of locations to visit given the set of visited ones. However, in contrast to the standard sequence-to-sequence learning task, each location can only be visited once in VRP, which means that the visited locations need to be removed from the output dictionary. In order to achieve high-quality solutions, another challenge is to draw appropriate representations of the problem setup, i.e., the available locations to visit, to aid the final decision-making.

To tackle the aforementioned challenges, a precursor in this research field is [16], which invents a pointer network architecture to solve the travelling sales man problem (TSP), a simplified version of VRP such that only one agent (vehicle or person) is considered. It established the model using two RNN architectures, where the encoder network learns the embedding of available locations and the decoder generates next location to visit given the pre-visited ones. Furthermore, it incorporates content-based input attention as a mask over the inputs, thereby removing the visited locations from the output dictionary. Due to the offered advantages, the encoder-decoder architecture and the pointer mechanism are extensively adopted by subsequent research. However, the pointer network in [16] relies on the labeled data for training, which is expensive to obtain and can potentially limit the model to explore solutions superior to the quality of labeling. In contrast, [49] employs the deep reinforcement learning framework trained using policy gradient, which receives the reward as feedback signal to discover the best action (a permutation of locations) proactively. This provides another standard framework for machine learning-based solutions of combinatorial optimization problems. In succeeding research, significant efforts has been devoted to the further optimization of encoder architectures in recent research to extract important information and handle specific constraints [122]. For instance, multi-head attention is utilized in [50] to accommodate the time window and rejection constraints. Graph embedding techniques are employed in [51] to learn a superior strategy for the optimization problems over graphs including TSP.

As VRP is basically a generalized form of TSP, the deep reinforcement learning framework, encoder-decoder architecture and pointer-network mechanism that have been successful for solving TSP are adopted to fit VRP as well. A challenge to adapt pointer network to the VRP scenario is that the output dictionary needs to be updated dynamically due to the changing of demands after a location is visited. In order to tackle this difficulty, [17] replaced pointer network using RNN decoder, which involves the visited locations as part of the input. Furthermore, it also discards the RNN module in the encoder architecture to improve the time efficiency since the order of visited locations is not meaningful in the considered setup. Compared with RNN architectures, attention-based networks are proven to be highly effective and flexible, which are adopted in recent research to learn representative problem embeddings across multiple contexts [17], [18]. Apart from model architectures, formulating the action space of the reinforcement learning framework is another major challenge especially for the highly complicated problems such as capacitated VRP. A solution is proposed in [52], which improves the policy approximation accuracy by fitting the value function given each starting state using a neural network.

While a solution of VRP is expected to return multiple routes beginning and ending at the depot, a broad variety of existing works [17], [18], [52] generate each route one after another. A major limitation of this type of approaches is that they do not scale well in the complicated scenarios with dynamic and stochastic events [53], [54], [123]. This motivates the succeeding research to investigate the application of multi-agent reinforcement learning techniques to improve the flexibility and ability for generalization. Based on the characteristics of VRP, a natural multi-agent formulation is to model each vehicle as an agent such that each vehicle makes sequential decisions on the locations to visit individually given the shared environment information. Therefore, appropriate definition of state to represent the environment information is a critical issue in the multi-agent scenario. In [53], the state is defined to enable the sharing of remaining capacity among agencies to address the on-demand delivery issue. In [54], the encodings of the global environment and each vehicle are combined to obtain the intermediate state of each vehicle in real-time for accurate decision making.

B. Bin Packing Problem

Bin packing problem is another combinatorial optimization problem commonly encountered in the logistics scenarios such as box packaging, vehicle loading and warehouse stacking [56]. While there exists multiple types of bin packing problems, we focus on the 3-dimensional (3-D) bin packing problem, which has great significance in logistics scenarios, such that the sequence, orientation and location of each item to be loaded/packed are determined in order to optimize various targets, thereby making best usage of resources [124]. In a box packing scenario, one may desire to minimize the surface area of the package bin given a set of cuboid-shaped items to reduce the usage of material [19]. In a vehicle loading problem, one may desire to maximize the number of cuboid boxes loaded into the container of the truck in order to save the transportation cost [125]. Based on the specific need of application scenarios, the bin packing problem can be further categorized into offline and online versions, where the formulation of each version can be quite different due to the variations on the availability of information. The details are discussed as follows.

- *Offline Bin Packing Problem:* In the offline bin packing problems, the information of all items to be packed are known in advance. Therefore, the approaches developed in this line of research can determine the packing/loading of all items at once. In this scenario, a solution aims to generate a sequence of box IDs with the corresponding orientations and locations. Hence, deep reinforcement learning with encoder-decoder architecture that is commonly used for solving VRP is also a natural option to formulate the offline bin packing problem. For instance, the pointer network architecture that has been used to solve TSP is adapted to minimize the surface area of the bin through optimizing the sequence of items to be packed [55]. Under this framework, various types of encoders such as convolutional neural network (CNN)s and transformers have been explored to improve the quality, flexibility and scalability of the generated solutions [19], [20]. Apart from the common deep reinforcement learning-based solutions, another plausible approach is to involve machine learning techniques in the classic bin packing frameworks to help improve the solution quality and efficiency. This has been investigated in [56], where the computational complexity of the conventional tree-search method is reduced through predicting and pruning the redundant paths using a neural network. In contrast to these methods that search the positions and orientations of items in the entire container space, the clustering strategy have also been adopted to decompose the bin packing problem into several sub-problems, where the stacking of a single layer is investigated in each sub-problem. Subsequently, the individual layers are further sorted to form the packed structure. This leads to the development of hierarchical bin packing methods, among which a representative is the tree-search method that decomposes the bin packing problem into constructing multiple x-layers and y-layers [125], [126], [127].
- *Online Bin Packing Problem:* In contrast to the offline bin packing problem, the information of all items cannot be known in advance in many practical scenarios. This motivates the researches to consider the bin packing problem in the online scenarios, where the items for packing arrive continuously and the decision for each item needs to be made within limited time period based on the observation of limited number of items [21]. Although one can attempt to determine the positions and orientations of currently observable items using offline bin packing techniques, they will usually lead to inferior performance since they do not account the future dynamics. Thus, an appropriate online bin packing algorithm should consider both the current state and future uncertainties. While deep reinforcement learning framework is still a feasible choice, a critical issue is to appropriately represent the current configuration of the bin and the item to be placed in order to overcome these difficulties. The heat map and tree-based representations have been investigated in [21] and [22], respectively, where convolutional neural network and graph neural network are utilized correspondingly to extract informative features from these structures. Note that an online bin packing algorithm is feasible in the offline scenario as well. However, the quality of solution will be inferior to the offline bin packing algorithms since they cannot consider the global information of all items. A comparison study has been conducted in [128], which demonstrates that the solution achieved using online bin packing algorithm results in 27% more resource consumption compared with offline bin packing algorithm in the considered problem.

C. Facility Location Selection

Facility location selection aims to select a subset of locations from a large candidate set to build facility nodes of the logistics network, such as warehouses, distribution centers and terminal stations, to serve the demand of other locations [26]. In the real-world applications, one intends to select appropriate facility locations for various targets such as improving the quality-of-service and reducing operational cost. Similar to VRP and bin packing problem, facility location selection can also be formulated as a combinatorial optimization problem. Although deep learning-based solutions have been developed for facility location selection [57], most research in this field tend to solve this problem using clustering techniques since the locations served by a facility naturally forms a cluster. Although the classic clustering algorithms such as k-means clustering can be efficiently implemented to solve the facility location selection problems [58], [59], strategical modifications need to be applied to accommodate the practical challenges. In order to avoid converging to locally optimal solutions, heuristic search mechanisms have been combined with k-means and hierarchical clustering in [60] and [26], respectively. Furthermore, the combinations of multiple practical constraints are handled through incorporating initial conditions and dynamically updating the measurement of clustering distances in [26].

While most of the existing works concentrate on specific types of combinatorial optimization problems, researchers are also dedicated to investigating the generic characteristics among them and mitigating the domain specific limitations. As a combinatorial optimization problem can usually be formulated using

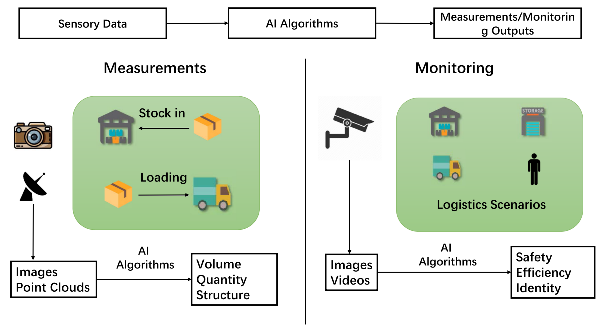

Fig. 4. Multiple sensoring devices, such as video camera and LiDAR have been adopted for the automatic measurements and monitoring in logistics scenarios, thereby ensuring the efficiency and safety. In this process, the data collected using sensory approaches are analyzed using AI algorithms to generate the measurements and states of system.

mixed integer programming and solved using branch-and-bound approach, [61] explores the graphic representation of mixed integer programming formulations to estimate a subset of variables, which is subsequently used to restrict the regions of branch-and-bound search for the computation of the rest variables, thereby accelerating the problem solving. Although the AI-based solutions have demonstrated great potential for efficiently solving complicated combinatorial optimization problems, the generalization of the widely adopted deep reinforcement learning-based solutions is still a challenging task [117], which requires further efforts to develop more powerful algorithms to explore the knowledge transfer across different distributions of problem configurations.

V. Automatic Measurements and Monitoring

Keeping track of the states of goods, equipment, vehicles and employees is always strongly desired in logistics industry to ensure a high productivity and safety. Conventionally, these observations are usually obtained through manual efforts, which suffers from intensive labor cost, low efficiency and potential safety risks. Taking advantage of the rapid development of sensoring techniques in nowadays, AI-based solutions have been extensively employed, which enables the automatic analysis of the sensory data and allows the efficient management of large-scale logistics systems. Due to the aforementioned importance of the automatic measurement and monitoring techniques, we review the applications of them for the management of goods, equipment and vehicles in this section. The specific techniques discussed in this section mainly fall in the computer vision domain. Refer to Fig. 4 for details.

A. Automatic Measurements

The measurements of goods such as volume, weight, structure and quantity are primary information for logistics operations, which facilitate the resource allocation for the storing and transportation of goods as well as allowing the identity verification at different network points [62], [64]. Volume and weight are fundamental attributes of goods in logistics industry. While the weights of goods can be easy to obtain, the accurate and efficient measurement of volume is still an open problem although existing solutions have been developed based on the sensoring data collected using either camera or LiDAR [64], [66], [67], [129]. As most of those existing works focus on the truck load scenarios and need calibration to remove the impact of the redundant parts, generic algorithms executed on potable devices with low cost is in urgent need since volume should be measured in a wide variety of scenarios in logistics industry. For this purpose, a global competition on intelligent volume measurement was hold by Cainiao in 2019 to collect the smartphone-based volume measurement solutions, which attracted attentions from both academia and industry [130].

The need of volume measurement using potable devices motivates the subsequent research to establish solutions based on 2-dimensional (2-D) cameras due to the extensive availability. Yet, as volume cannot be computed without 3-dimensional (3-D) information, a major challenge for volume estimation using 2-D images is the lack of depth. In order to tackle this challenge, there are generally two types of methods in practice. A natural method is to construct the 3-D architecture of the target object using structure from motion (SfM) techniques and compute the volume based on the point cloud [65]. In this type of approaches, the 3-D structure needs to be constructed using images taken from multiple angles facilitated by the computational intensive matching of landmarks. The other way is to estimate the depth information from a single image, where the relative positional relations between planes in the image are extracted using segmentation techniques and the absolute measurements are further computed based on reference information [63]. The advances of computer vision makes it a common option to construct the AI-based solutions for automatic measurement even beyond volume in recent years. The measurement of structure and quantity of logistics packages in the transport units are presented in [62], where instance segmentation is employed to recognize the packages within each unit, and the segmentation results are further refined to estimate the structure and quantity.

B. Automatic Monitoring

As efficiency and safety are crucial targets of logistics operation, it is an increasing trend to employ smart monitoring techniques in logistics industry to improve the management efficiency and identify the potential threats [131], [132]. The monitoring task in logistics scenarios intends to capture the states (e.g., structure health and working condition) of equipment [132]. In this survey, we focus on the identification of vehicles and damage recognition of warehousing equipment due to their importance to the smooth and safe management of logistics operations.

The scheduling of vehicle loading/unloading plays a fundamental role due to its importance to time efficiency. This motivates to keep track of the identifications of vehicles through recognizing the license plate numbers since they are the most important identification information of vehicles. The modern license plate recognition techniques usually contain two steps including license plate detection and character recognition. The license plate detection step aims to localize the pixel region corresponding to the license plate in the input image for further recognition, and hence, it is usually formulated as an object detection problem [23], [24], [68], [69], [133]. A straightforward way for this task is directly adopting the state-of-the-art objective detection algorithms with limited customerization [68], [69]. However, the license plates may suffer from large rotation angles, which poses challenges to the character recognition step. In order to address this issue, the rotation angle of license plate has been considered as an output of the detection model [23]. Furthermore, specific neural network architecture is proposed in [24] that learns an affine transformation to project the detected license plate to a rectangular area. The license plate detection techniques considering rotation angles [23], [24] can return a license plate image in an unwrapped angle to improve the ability of generalization and reduce the character recognition error in following steps. In terms of character recognition, the existing approaches can be categorized into segmentation-based ones and segmentation-free ones [70]. The segmentation-based approaches usually employ detection or segmentation methods to extract and recognize each single character [68], [71], which are then sorted to generate the license plate number. In contrast, the segmentation-free methods model this task using sequence-to-sequence learning and solve it through RNN or CNN architectures [72], [73]. While the sequence-to-sequence-based approaches do not need complex post-processing, segmentation-based ones can offer more flexibility to easily generalize to different formats of license plates.

Conveyor belt is one of the most important equipment for logistics operation that is massively employed in the logistics warehouses and distribution centers to help sort and transport the parcels [75]. Therefore, the safety and health of the conveyor belts significantly impact the logistics efficiency, and hence, efforts have been devoted to monitoring the states of conveyor belts. The common problems that impact the safety and health of conveyor belts are defects and congestion. Although surveillance cameras can be utilized to collect the images of conveyor belts in real time, the anomaly discovery and analysis can potentially be limited by high computational cost considering the large number of surveillance cameras needed to cover all the critical regions. Therefore, the light-weighted algorithms are usually preferred for these tasks. Examples have been shown in [74] and [75], where clustering and Canny-based edge detection techniques have been employed to detect the defects and congestion on conveyor belts, respectively. In summary, the measurement and monitoring significantly rely on computer vision (both 2-D and 3-D) techniques, a majority of which are constructed using computation intensive deep neural networks. On the other hand, the measurement and monitoring functionalities are massively applied on terminal devices such as surveillance cameras and portable devices. Thus, a great challenge in this domain is to develop light-weighted algorithms to fit the capacity of the terminal and edge computing components.

VI. Autonomous Driving

As autonomous driving is gaining popularity from a wide variety of domains, its usage in logistics scenarios mainly focuses on last-mile delivery (LMD), which refers to the logistics activities of delivering parcels to customers' pickup location. In recent years, LMD grows rapidly promoted by the flourishing of e-commerce. Despite the offered convenience, last-mile logistics service needs large amount of workforce to support the rapidly growing volume of parcels. The labor shortage caused by the aging population and rising labor prices induced by the increasing demands of last-mile delivery service have brought huge operating pressure to enterprises [134]. In addition, contactless delivery is urgently needed during the COVID-19 epidemic, which puts forward higher requirements for last-mile delivery. Compared with the traditional human-based logistics services, autonomous LMD service provides a promising solution to reduce the delivery cost, complement human deliveries, diversify services and fill labor shortages during busy periods and at night. It is shown in literature that the incorporation of an autonomous vehicle will reduce the completion time of delivery to all customers by 0%–33% without parking scene and 30%–77% when considering the time to find a parking space [135].

Fig. 5. The 5-th generation of autonomous LMD vehicles developed by JD Logistics.

Motivated by the aforementioned advantages, autonomous driving technologies have been extensively studied in the past few years. Apart from the massively emerging research works in academia, commercial products have been taken into usage by the leading enterprises. With the development of AI technologies such as deep learning, rapid breakthroughs have been made in the core technologies of autonomous LMD vehicle. Refer to Fig. 5 for the autonomous LMD vehicle developed by JD Logistics Corporation in China. Unlike the autonomous vehicles for passenger transportation, the autonomous LMD vehicles are usually featured by relatively lower speed and smaller size. Therefore, they usually need to share the lanes with bicycles and possible pedestrians, which can be more complex compared to the regular driveways. This motivates the development of accurate scene perception, path planning, behavior arbitration and motion control based on the AI architectures [76], majorly in the domain of computer vision and reinforcement learning. The details are summarized as follows.

- *Perception:* Perception refers to the recognition of the objects including drivable area of road, vehicles, pedestrians and traffic light/signs that can impact the decision making of driving. In the autonomous driving system, this is usually enabled by deep learning-based detection and recognition techniques, which analyze the 2-D images from video cameras and 3-D point clouds from LiDAR to establish the estimation of complex traffic condition [76], [77]. Recent research develops various object detection methods, which can support the effective perception of autonomous driving [25], [78].

- *Localization:* Although the localization of autonomous LMD vehicles can be accomplished using navigation technologies, the accuracy is usually limited in the complicated city scenarios. Therefore, simultaneous localization and mapping (SLAM) is employed as a powerful complement to improve the accuracy of localization. The recent advances in this domain usually employ deep learning techniques to construct the driving scene based on LiDAR sweeps and intensity maps [79]. A specific utilization of AI in this line of research is to promote the performance of visual odometry (VO) [80] through improving the accuracy of key points detection using deep neural networks such as PoseNet [81] and VLocNet++ [82].
  While the conventional SLAM techniques usually explore the environment following a pre-defined strategy, the SLAM in a large and complex unknown environment requires more intelligent exploration for reconstruction maps given a limited time budget, which motivates the active SLAM research that learns an efficient exploration policy based on current observation and historical actions [83], [85]. In this direction, deep reinforcement learning is becoming a popular choice to construct the model due to the strong capability on representing the environment features for effective decision making [84], [85], which creates an open problem for the high quality SLAM strategies.
- *Planning, decision and control:* Path planning, trajectory planning and decision for LMD vehicles were usually developed using rule-based methods in conventional autonomous driving. In nowadays, imitation learning [86] and deep reinforcement learning [87] have been introduced for the planning, decision and control of autonomous LMD vehicle due to the offered advantages. This allows the automatic optimization of policy based on the inputs of environmental parameters, thereby offering sufficient flexibility. A survey in [88] presents the novel deep reinforcement learning techniques for motion planning and autonomous vehicle control, which shows a promising research trend in this domain.

Autonomous LMD vehicle has a broad market space and rich AI-based research scenarios, which has attracted widespread attention from large global technology companies. The global unmanned delivery industry is mainly dominated by American unmanned delivery vehicle startups Nuro and Starship Technologies, as well as Chinese technology companies such as Ali, JD Logistics, and Meituan, which have invested a lot in research and development for 2-4 years. Despite the recent advances and achievements in autonomous driving for LMD, there still exists open problems for better application in real-world scenarios. As a participant of the public traffic, the interaction with other vehicles and pedestrians is critical to guarantee the safety. Thus, predicting the behavior of pedestrians and other vehicles is another important task beyond merely recognizing these objects in order to make appropriate decisions, which points the future improvement directions of autonomous driving for LMD.

Apart from LMD, warehouse robotics is another important application scenario of autonomous driving, where intelligent robots, such as forklifts, six-axis robots and automatic packaging robots, usually summarized as autonomous guided vehicle (AGV)s, are commonly used in the unmanned warehouses for the transportation, sorting and loading/unloading of goods instead of human labor [136], [137]. Similar to the LMD scenario, perception, localization and path planning/scheduling/control are the critical tasks for AGV as well. Hence, a large number of AI-based solutions for LMD are also applicable for AGV. For instance, deep reinforcement learning has been investigated for the positioning of AGV based on LiDAR sweeps and AGV routing in [138] and [139]. As the warehouse environment is usually semi-closed with pre-planned entrance and exit points, the locations of AGVs can also be identified through recognizing the fixed positioning makers [136].

In contrast to LMD, where each individual autonomous vehicle prefers to make its own decision independently, the tasks of AGVs are closely bounded to the whole manufacturing process in the warehouse. Therefore, a decision maker usually desires to manage a feet of AGVs in a centralized fashion for better dispatching and coordination [136], [140], [141]. The control of AGV fleets raises new challenges on congestion and collision avoidance, especially when the distribution of tasks is uneven [136]. To tackle these difficulties, deep learning and reinforcement learning solutions have been developed to optimize the control of AGVs [141], which output the sequence of nodes visited by an AGV given the encoded format of the environment. Apart from the widely studied path planning techniques, control strategies are also investigated associated with task prediction and selection to appropriately allocate the AGV resources [89], [90].

VII. Logistics Systems Simulation

While vast techniques have been utilized to facilitate the decision making in logistics systems in every aspect, the efficacy of the decisions can be difficult to predict due to the large scale and high complexity of the logistics system [142]. For this reason, the impact of an operational action usually needs to be evaluated before applying it to the logistics system. However, the on-site evaluation can be difficult, expensive or dangerous, which can potentially cause irreversible consequences [143]. In order to tackle these difficulties, simulation is a powerful tool that defines a digital representation of the physical world and emulates the reactions to the operational actions, thereby gaining useful insights and provide valuable feedback to the decision makers on optimizing the logistics systems [144], [145]. Refer to Fig. 6. In order to manage a modern logistics system, employing simulation techniques such as discrete event simulation

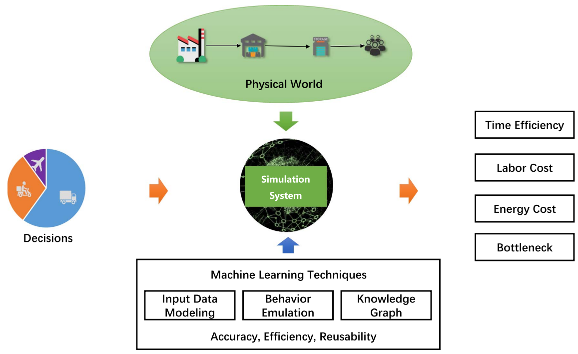

Fig. 6. The simulation system emulates the behavior of physical world in reaction to the input policies. It helps to evaluate the impact given the input policies instead of on-site evaluation, which may not be feasible due to multiple difficulties. In recent research, machine learning techniques have been massively employed in the logistics system simulation to improve the accuracy, efficiency, and reusability.

to emulate the global state on how each parcel is processed is an indispensable step. However, developing a high-quality and efficient simulation framework is not a trivial task due to the various challenges.

In nowadays, artificial intelligence and machine learning have been massively adopted to enhance the simulation models due to the wide popularity. Generally, these technologies have mainly been incorporated to improve the accuracy, efficiency and reusability of simulation systems. From technical perspective, these works mainly focus in regression and reinforcement learning techniques. The accuracy of simulation highly depends on the modeling of input data, which helps capture the characteristics of the physical world [9]. A major challenge on input data modeling is that some key dimensions of the input data may suffer from process shift due to the dynamic nature, thereby violating the previously learned model. While predicting and adapting to future data distribution may incorporate propagative errors, a relatively robust approach is to extract the time-invariant features from the dynamic data for modeling [9]. In some applications, simulation needs to be executed iteratively in a highly-frequent fashion to help improve the quality of actions. In this scenario, the "simulation" targeting the simulation system is usually conducted through emulating the behavior of the simulation system using a machine learning model, thereby efficiently generating the simulation output without intensive computations [91], [92]. In recent research, knowledge graph is utilized to improve the reusability of simulation models [93]. While a simulation model for logistics system is usually nontrivial to implement, the knowledge graph-based representations of logistics simulation models have been investigated to ease the adaption across application scenarios and automatic simulation flow generation [94], [95].

In the modern logistics systems, the growing integration of IoT techniques enhanced the two-way connectivity between the simulation system and the physical world, such that the simulation system is enabled to capture the update of the physical world in real-time and build a virtual replica correspondingly, which is referred to as "digital twin" [96]. Taking advantages of the CPS architecture, the digital twin can conveniently converge to the dynamics of the real world compared with a static simulation model [97], [146], which allows the approximation of the future, simulation of "what-if" scenarios and decision making to facilitate the operations in the physical world [96], [97], [147]. The nature of a digital twin model as the virtual mirror of physical entities enables the applications of almost all AI techniques that can be used in real logistics systems, such as emulating the output of simulation subroutines and generating intelligent decisions (e.g., the schedules of vehicles) [96]. Furthermore, a specific usage of AI in digital twin is to build a data-driven simulation model through converting the un-structural data collected by sensors and cameras into time-stamped data [97]. Despite the offered advances, the penetration of digital twin in logistics also poses new challenges on the efficiency and scalability of logistics system simulation to accommodate the rapid updates and generate simulation results in real-time.

VIII. New Challenges and Perspectives

Although the AI techniques have already brought significant advances to the logistics systems, the rapid development of the global world is continuously posing new challenges in the research and applications of this domain. In this section, we discuss the new challenges that will have significant impact to the logistics systems and the potential AI-based solutions in four perspectives including efficiency, cost, safety, and cyber-security of AI models.

A. Efficiency

Apart from the time efficiency have been discussed in Section III, energy efficiency is another critical targets of AI-based solutions in the industry. As road traffic is a major contributor to energy consumption [148], the utilization of alternative fuel vehicles is gaining increasing popularity in the logistics domain. In fact, large quantity of electric vehicles, a specific type of alternative fuel vehicle, have already been adopted by the premier logistics corporations. However, alternative fuel vehicles are often limited by the energy capacity and rely on refueling stations to extend the driving range [149]. Hence, the routing of alternative fuel vehicles must take the locations of refueling stations and the refueling delay into consideration, which is known as green vehicle routing problem (G-VRP) [149]. While the AI techniques can provide high-quality solutions to a bench of combinatorial optimization problems, an highly effective approach to solve G-VRP is needed to build the green logistics system. Furthermore, the penetration of electric vehicles also poses grand challenges to the power grid operation since the charging of electric vehicles can easily cause peak energy usage [150]. Therefore, the coordination between logistics system and power system will become an important research topic in the future.

It is also worth noting that handling unexpected emergencies can usually induce extra energy consumption in the logistics systems [151]. In order to tackle this issue, prediction of the emergencies can be made based on the environmental data obtained through real-time monitoring, thereby facilitating the management of the logistics system to make timely decisions and reduce the uncontrollable costs [151].

B. Cost

A press of the modern AI algorithms, especially computer vision algorithms, are based on deep learning, which are usually computational intensive. Although the high-performance computing devices such as GPU have been deployed in both cloud and edge sides that allow most algorithms to be executed in a highly efficient manner during inference, they are often associated with high economic cost, which prevents the very large-scale utilization in practice. For instance, a logistics warehouse can have thousands of surveillance cameras, and it will induce huge cost if a deep learning model is applied on each camera. A plausible approach to overcome this difficult is to develop light-weighted models based on the specific characteristics of the application scenarios. This idea is adopted in [75], where the visual features of parcels on the conveyor belts are extracted using edge detection techniques. Subsequently, statistical approaches are leveraged to help recognize the congestion. The recent advances of knowledge distilling has provided another option to help deploy AI models in practical scenarios. It transfers the experience encoded by the original model to a light-weighted student model without excessively decreasing the accuracy [152], which can substantially reduce the usage of computation resources. Apart from economic cost, the environmental cost of AI during its whole life cycle is attracting increasing attentions from both researchers and policy makers [153]. As shown in recent research, training deep learning models using GPU will lead to considerable amount of carbon dioxide emission (approximately 600,000 lb for natural language processing) [154]. While AI is becoming an indispensable component in the modern logistics CPS, the sustainability issue will open up vast research opportunities on the optimizations of data utilization, algorithm development, software/hardware design and carbon footprint [155].

C. Safety

In order to guarantee the safety of logistics operations, proactively assessment of the potential risk is preferred, such that actions can be taken to avoid the consequential losses before their occurrence. It means that a safe logistics system is expected to be predictive. Although the prediction of vehicles and pedestrians in the public areas have already been explored to facilitate the decision in autonomous driving [156], [157], the application in logistics scenarios will face even more challenges posed by the high complexity and uncertainty. Generally, the applications of predictive recognition approaches can be categorized into two parts including autonomous driving for LMD and the monitoring of logistics operations. In contrast to the general autonomous driving, the LMD vehicles usually need to share the lanes with bicycles and pedestrians due to the small size and low speed. Thus, the behavior prediction of the traffic participants suffers from much higher difficulty induced by their crowd and dynamic nature. In the logistics operation monitoring scenario, the decision maker desires to predict the behavior of vehicles, equipment and workers. Furthermore, the potential interaction between these roles is an important basis for risk assessment. As this direction has not been considered in existing literature, it will open up vast opportunities for both academic practical research for establishing a safer logistics system.

Another challenge of these scenarios is the distribution uncertainty due to the high complexity in real world, such that a large amount of data need to be annotated to cover the long-tail cases and guarantee the robustness to interference. In order to alleviate the labor cost for data annotation, a recent trend is to incorporate the human-in-loop strategy, which involves human efforts to mine the data with high potential to improve the modelling accuracy for labelling [158].

D. Cyber-Security

The management of the modern logistics system significantly relies on the information systems such as warehouse management system (WMS) and transportation management system (TMS). Furthermore, the monitoring and control in the logistics system are enabled by the communications infrastructure. Although these advances brought by the development of information technology have offered considerable convenience to the logistics operations, they also raise new security concerns in the mean time. The weakness of those architectures can potentially be leveraged by the malicious hackers to launch cyber-attacks and induce losses to the logistics systems. Examples are been shown in [159], where the malicious hacker can use jamming and eavesdropping techniques to attack the transportation system to impact the traffic conditions. Therefore, detecting the cyber-attacks and mitigating their impact are critical targets for the maintenance of logistics systems. For this target, the AI and machine learning techniques have great potentials to examine the anomaly through analyzing the system-state data, thereby detecting the cyber-attacks. In [160], a real-world example in e-commerce industry is studied, where the malicious merchants can gain profit and induce losses to the e-commerce corporations through manipulating attacks. In specific, a malicious merchant can manipulate the goods information on the retailing platform to achieve a high ranking in searching result while bringing confusion to the customers. The manipulation can also be applied on the goods information on the logistics platform, where the malicious merchant can store the wrong item in the warehouse simultaneously such that it will be shipped to the customer when an order is placed. While the manipulation attack can significantly impact the customer experience, an inspection architecture is proposed using deep neural network and natural language processing techniques to identify the consistency between the goods information on different platforms, thereby recognizing the manipulating attacks.

In fact, the AI models are targets of cyber-attacks themselves. As the AI models rely on the sensors and communication infrastructures for data acquisition and transmission, the malicious hacker can launch data poisoning attacks to impact the model outputs by injecting poisoned data [161]. While the defense of data poisoning attacks has already been deeply studied in the machine learning domain, the impact of them to the logistics systems and their corresponding defense strategies will be important topics for research and application to guarantee the cyber-security of logistics. In this direction, the attacking on the license plate recognition model has been studied in [162], where poisoning attack is applied on the feature extraction layers of the model such that it will mis-classify a pre-selected digit to a target one. Through this attacking strategy, a malicious hacker can take control over the entrance and platform management of a warehouse, such that the appointed vehicle cannot smoothly accomplish the loading/unloading tasks. In the logistics scenarios, this type of cyber-attacks can potentially be detected and conquered from data, model and system levels, which will motivate more domain specific research on the security of AI.

IX. Conclusion

In this article, a comprehensive survey on the application of AI technologies in logistics cyber-physical systems is conducted. We started from the high-level architecture of the logistics system and subsequently move to the critical problems of each component, including resource allocation, logistics planning & scheduling, automatic measurements & monitoring, autonomous driving and logistics system simulation. For each part, we discussed the targets to be optimized and the critical problems to be addressed. Examples from both academia and industry are studied in details to illustrate how AI techniques are utilized to provide high-quality solutions and tackle the grand challenges in the logistics systems. Finally, a prospective view is provided on the new challenges posed by the development of the society and industry as well as the new opportunities of AI in logistics research and applications. Through this survey, we intend to benefit both researchers and practitioners by providing a guideline of how AI can help improve the quality of logistics, thereby promoting the intelligentization of logistics industry.

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