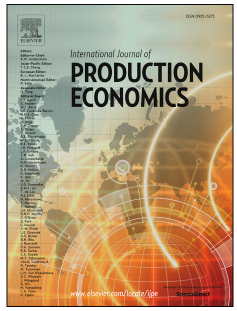

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PII: S0925-5273(21)00329-7

DOI: https://doi.org/10.1016/j.ijpe.2021.108353

Reference: PROECO 108353

To appear in: *International Journal of Production Economics*

Received Date: 22 June 2021

Revised Date: 1 November 2021

Accepted Date: 8 November 2021

Please cite this article as: Leung, E.K.H., Hang Lee, C.K., Ouyang, Z., From traditional warehouses to Physical Internet hubs: A digital twin-based inbound synchronization framework for PI-order management, *International Journal of Production Economics* (2021), doi: https://doi.org/10.1016/j.ijpe.2021.108353.

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From Traditional Warehouses to Physical Internet Hubs: a digital twin-based inbound synchronization framework for PI-order management

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From Traditional Warehouses to Physical Internet Hubs: a digital twin-based inbound synchronization framework for PI-order management

ABSTRACT

Physical Internet (PI) is a new concept to ensure global mobility of physical objects. Conventionally, logistics networks are closed and independent. Under the concept of PI, they are transformed into an open logistics network, providing an efficient way to relocate physical goods to a given place in a short period of time. A hyperconnected city logistics system is conceptualized as the final segment of a PI-network. It uses regional and city hubs as the final leg of last-mile delivery. Inventory at PI-hubs has to be managed efficiently so as to maximize the benefits of PI. This paper proposes a digital twin-based inbound synchronization framework to streamline the operations of a PI-hub in a hyperconnected city logistics system. Digital twins and Internet of Things technologies are proposed for data acquisition and virtualization of real conditions of physical objects, followed by machine learning-integrated models to optimize a joint order fulfillment and replenishment operation in the PI-hubs. Adopting the proposed framework can formulate a Total Inbound Synchronization at three levels: order synchronization, process synchronization and information synchronization. Simulation results show a significant reduction of traveling distance in PI-hubs if the interdependent order fulfillment and replenishment operations are considered as a joint operation. In addition, this paper provides practical implications for logistics service providers to manage information flows within a PI-network driven by digital twins.

Keywords Hyperconnected City Logistics, Physical Internet, Synchronization, Joint Order Fulfillment and Replenishment, Digital Twins, Internet of Things

1. Introduction

Physical Internet (PI) is a new solution to unsustainable operations of production and freight transport by interconnecting heterogeneous and independent logistic networks and leveraging them toward a common open logistics network (Ambra et al., 2019; Pan et al., 2015). Under the PI paradigm, Hyperconnected City Logistics (HCL) utilizes the multitude of existing urban logistics facilities in supply chains, including distribution centers, warehouses, and vehicle depots (Crainic & Montreuil, 2016). Amongst all facilities in HCL, regional and city distribution centers are the final leg of the distribution of goods (Pan et al., 2017). In addition, to facilitate an efficient flow of goods in HCL, goods are encapsulated in modularly dimensioned easy-to-interlock smart containers, called PI-containers (Montreuil et al., 2014; Landschützer et al., 2015). As defined by Sallez et al. (2016), PI-containers are composed of a three-layer hierarchy of container management – Transport container (T-container), Handling container (H-container) and Packaging container (P-container). Physical goods are stored in these PI-containers in their logistics cycle. With modularized dimensions, PI-containers are easily transported by PI-movers (e.g., delivery service providers including crowdsourced delivery fleet and third-party delivery couriers), stored and handled by PI-handlers (e.g., material handling equipment including conveying systems, lifts and belts) in PI-hubs. Fig. 1 illustrates the PI-container flow in a HCL system which consists of a set of facilities such as factories, regional hubs, and city hubs, represented as PI-nodes. Regional PI-hubs receive T-containers from factories or other regional PI-hubs, and then deliver them to city PI-hubs. Upon arrivals of T-containers, city PI-hubs decompose them into H- and P-containers for storage.

One of the existing challenges faced by city PI-hubs is the high throughput rate brought by e-commerce businesses. To improve the efficiency of warehouse processing, configuring a PI-hub with a forward area and a reserve area is increasingly popular. The purpose of a forward-reserve (FR) hub is to store items, such as stock keeping units (SKUs) or PI-containers, in small quantities in the forward area and leave bulk storage in the reserve area. Such a configuration has been recognized as effective in speeding up the last-mile order fulfillment process in e-commerce (Yu & de Koster, 2010). Therefore, it is understandable that distribution centres or warehouses at the final leg of a supply chain, e.g. city PI-hubs, but not those at the middle mile of the supply chain which process transhipment orders in a much larger lot size, usually adopts a forward-reserve configuration. Fig. 2 depicts the operations involved in a city PI-hub with a forward area and a reserve area. After a city PI-hub receives T-containers from its upstream PI-hubs, put-away operations for storage in forms of H- and P-containers are performed in the reserve area, followed by internal replenishment of H- and P-containers from the reserve area to the forward area. Next, to fulfill downstream last-mile demand, H- and P-containers are picked up from the forward area. If H- and P-containers are absent from the forward area, they are picked up from the reserve area.

While internal replenishment between forward and reserve areas are allowed, the effectiveness of a FR PI-hub lies in whether the benefits gained from picking up in the forward area outweigh the additional cost of internal replenishment (Jiang et al., 2020). Current literature addressed this issue by determining the appropriate size or ratio of forward and reserve areas (Van den Berg et al., 1998; Gu, 2005), the static set of SKUs and their storage quantity in the forward area (Walter et al., 2013; Gu et al., 2010), and replenishment policies in the forward area (Bahrami et al., 2019; Emde, 2017). In addition, despite the importance and interdependence of order fulfillment and stock replenishment operations in FR hubs, prior studies considered the operations independently. Yet, optimizing order fulfillment and replenishment operations as two individual problems could be a significant drawback in the PI context because modularized PI-containers are designed for ease of handling and processing in a batch mode. Hence, order fulfilment and replenishment operations should be tackled together as a joint operation. This paper investigates a joint optimization of order fulfillment and replenishment operations in PI-hubs, synchronizing the inbound PI-container management operations within the hubs. This addresses the research call made by Yu et al. (2020) who identified an urgent need to synchronize internal operations, owing to the benefits of cost-saving and order transhipment efficiency improvement in the distribution center (Yu et al., 2020). Jiang et al. (2020) presented a synchronization approach to streamline order picking and replenishment operations in e-commerce robotic warehouses. Though their approach is limited only to SKUs in the robotic forward area experiencing frequent stock-outs, it provides a foundation to this study in designing the optimization model. This study is different from Jiang et al. (2020) in twofold. First, the warehouse configuration considered in this study is a traditional warehouse, which is different from the robotic one considered in Jiang et al. (2020). The motivation to consider a traditional warehouse instead of a robotic one is to increase the employability of our framework in industry, where not all warehouses are using robots transporting movable shelves. Second, this study addresses the inbound order fulfilment problem in PI hubs while there are no PI elements considered in Jiang et al. (2020). In view of the advancement in PI development, this study is amongst the first to propose synchronization of internal order fulfilment operations at PI-hubs.

This study promotes the development of PI in traditional, manual warehouses. To introduce PI elements and terminologies into these warehouses, we develop internal synchronization strategies into managing material flows at manual warehouses, which serve as an effective mean of facilitating the transformation of traditional warehouses into city PI-hubs. A digital twin-based inbound synchronization framework (DTIS) is proposed, allowing logistics service providers to identify the essential configurations of a PI-hub. These configurations facilitate logistics service providers under the hyperconnected Physical Internet network to minimize the PI-container processing lead time, thereby maximizing the synergetic flow of PI-containers between PI-nodes. A Total Inbound Synchronization (TIS) strategy is designed to coordinate replenishment (i.e., Operation 3 in Fig. 2) and picking operations (i.e., Operations 4 and 5 in Fig. 2), achieving synchronization at three levels:

(i) *Order synchronization* – postponement of last-mile delivery orders for consolidated order fulfillment at FR PI-hubs;
(ii) *Process synchronization* – joint optimization of order fulfillment and replenishment operations within forward and reserve areas; and
(iii) *Information synchronization* – real-time update and monitoring of all relevant operations and stock levels.

This paper, to the best of our knowledge, is amongst the first to introduce synchronization strategies at inbound distribution hubs under the PI paradigm with both soft computing optimization, i.e., the joint PI-order fulfillment and replenishment optimization, and hardware technology integration, i.e., digital twin (DT) with Internet of Things (IoT) tracking functionalities. The rest of this paper is organized as follows. Section 2 reviews the recent development of PI, DT and IoT. Section 3 presents the three inbound synchronisation areas considered in the TIS strategy. Section 4 describes the DTIS framework for implementing the TIS strategy. Section 5 presents the simulation results. Section 6 is the discussion of results. Section 7 concludes this study.

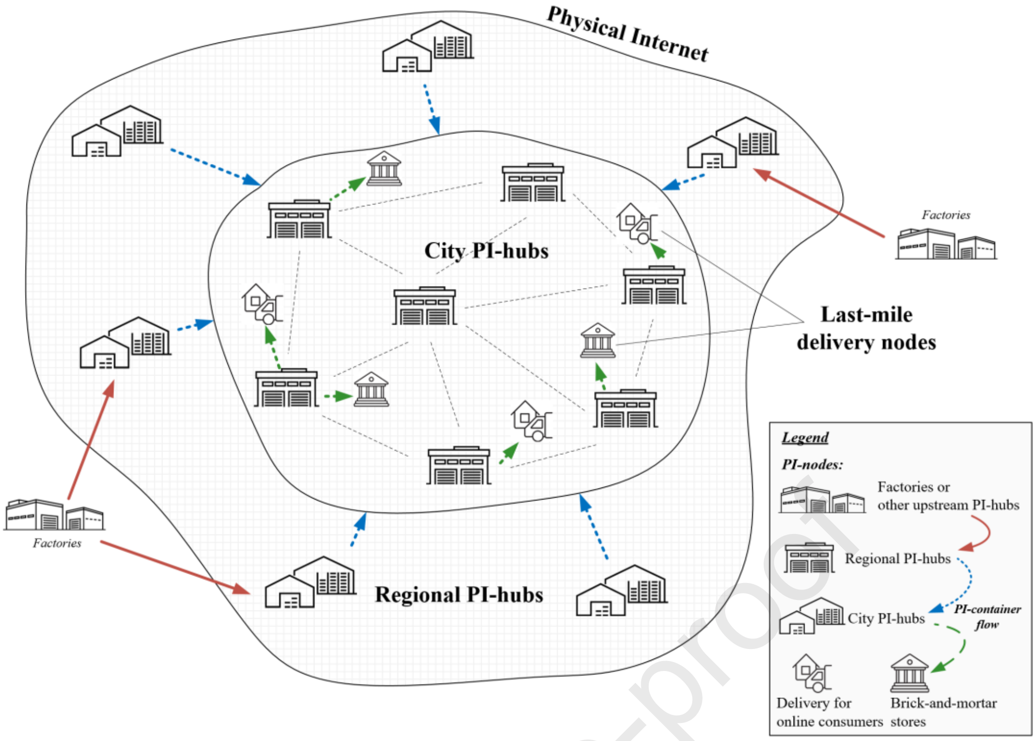

Fig. 1. Logistics network of the Physical Internet concerning Regional and City PI-hubs

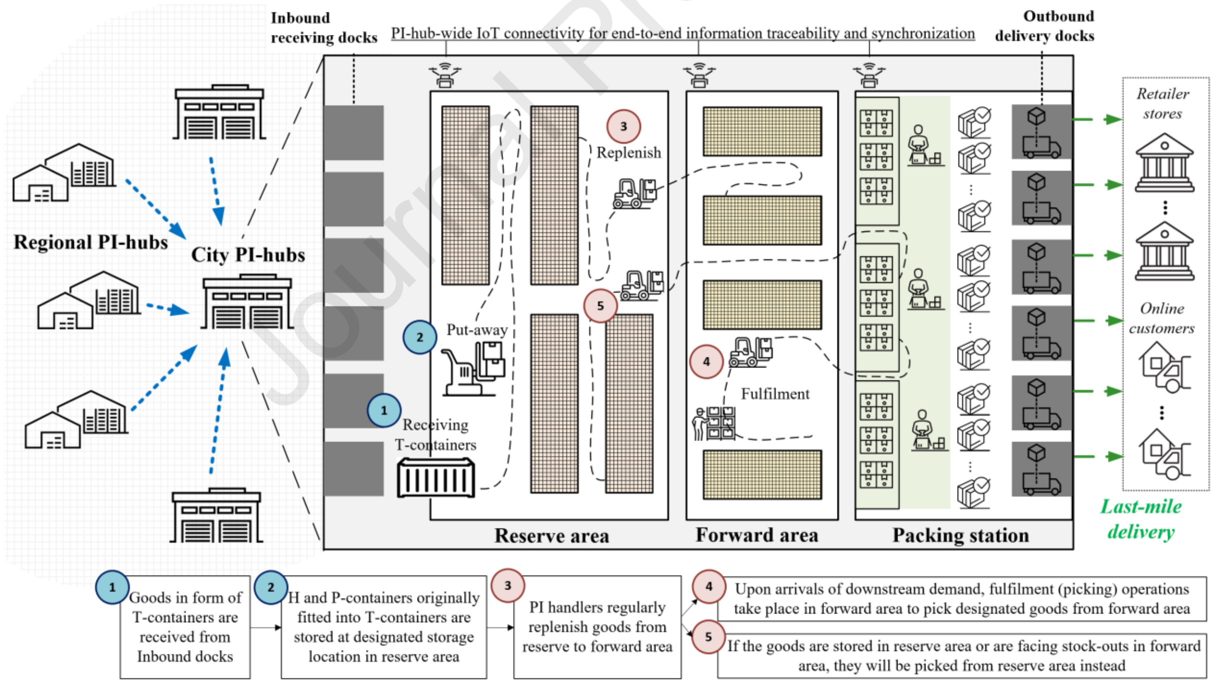

Fig. 2. PI-container management in city PI-hubs

2. Literature Review

To provide a better understanding of the terminologies discussed in this paper, this section reviews the relevant literature in three major aspects: developments associated with the PI paradigm, cyber-physical and IoT systems in supply chains.

2.1 Physical Internet

The sharing economy is a socio-economic system built around the sharing of resources (Cheng, 2016). PI extends beyond the concept of sharing ecosystems into managing global supply chains. It serves as a solution to global sustainability issues (Montreuil, 2011). By analogizing to digital internet where messages are split into different pieces (packets) that travel over the internet via various routes to reach the receiver's side, PI refers to a concept where physical objects are routed via different links from their origins to destinations (Ambra et al., 2019). In the logistics context, PI refers to encapsulating physical objects in modularly-dimensioned smart containers flowing in an open global logistics web (Montreuil, 2009). Modularity enables containers to complement each other and allows a better use of the means of transportation (Sallez et al., 2016). Under the concept of PI, conventionally closed and independent logistics networks are transformed into a HCL system. An HCL system is conceptualized as the final segment of the PI logistics and transport networks. It allows physical goods to be delivered in an openly consolidated way, improving the efficiency of urban freight movements and their environmental footprint (Benjelloun et al., 2010).

The infrastructure of an open logistics network consists of three assets, namely PI-containers, PI-movers and PI nodes (Montreuil, Meller, & Ballot, 2010). PI-containers are the unit loads to be manipulated within the infrastructure of PI. PI-movers, such as vehicles and carriers, are responsible for transporting, handling and storing the PI-containers. PI-nodes are locations that are interconnected to the logistics activities for managing PI-containers. In the city logistics context, PI-nodes can be the city or regional distribution centers that offer crossdocking, consolidation and short-term storage functionalities for inventories (Crainic & Montreuil, 2016).

In an openly shared network, however, inventory management is complex because replenishments between PI-nodes are allowed. In response to this, prior studies have been conducted to address the production and inventory management challenges brought by PI. Yang, Pan, and Ballot (2017) introduced PI focused inventory management models and assessed their impact on resilience. Marcotte et al. (2015) developed a deterministic optimisation model for planning make-to-order production operations and production module transhipment. Pan et al. (2015) defined new replenishment policies in the PI context. Their analysis considered multiple criteria for selecting sourcing points to fulfill a PI-order and their results show that source substitution was the most efficient and stable criterion according to various scenarios. In addition to operations between PI-nodes, operations within a PI-node are important topics in the field of PI because they directly affect logistics costs. To the best of our knowledge, there have not been any studies addressing the operations within a PI-node. Further, as proposed by Montreuil, Ballot and Tremblay (2015) and Pan et al. (2017), more smart crossbreeding with complementary game-changing threads such as the IoT and blockchain are expected to develop. This study thus makes an attempt to focus on synchronizing operations within a PI-node with the use of advanced technologies including IoT and DT, details of which are given in Section 2.2.

The PI-node considered in this study is a forward-reserve warehouse (hereafter FR PI-hub) that is a type of warehouses gaining popularity in the era of e-commerce due to its effectiveness in order fulfillment (Yu & de Koster, 2010). The storage area of a FR warehouse is subdivided into a reserve area and a forward area. The forward area is designed to store products in small quantities that can be easily retrieved while the reserve area stores products in bulk to replenish the forward area (Walter et al., 2013). In a FR PI-hub, T-containers arrived at the PI-hub are decomposed into H-containers (i.e., PI boxes) and P-containers (i.e., PI packs), before being stored in the reserve area. The operations within the PI-hub considered in this study are the inbound flows of H- and P-containers. The inbound operations involved in a FR PI-hub include internal replenishment (i.e., moving PI containers from reserve areas to forward areas) and order fulfillment (i.e., picking PI containers up from forward areas). In the current literature, a majority of studies deal with forward-reserve allocation problems, which determine the SKUs to be stored in forward area, the space allocated to each SKU, and the overall size of the forward area (Walter et al., 2013). Kübler, Glock and Bauernhansl (2020) presented a new iterative method for solving the joint dynamic storage location assignment, order batching and picker routing problem in manual picker-to-parts warehouses. Their results indicate that solving these problems jointly yields a significant improvement in terms of traveling distance of pickers, which proves the essence of optimizing highly interdependent warehouse operations jointly. In FR PI-hubs, models optimizing continuous flows of SKUs between reserve and forward areas for replenishment and order picking have been rare, hence the focus of this study.

2.2 Digital twin and Internet of Things

DT and IoT technologies are new emerging technologies for transforming logistics operations into the era of Industry 4.0. A DT is a digital replica of a physical object (Lu et al., 2020). It has been widely adopted as the core technology for realizing the functions of a cyber-physical system (CPS) through creating the virtual presentation of the physical asset (Zhao et al., 2021). A CPS can be described as a set of physical objects that interact with a virtual cyberspace through a communication network (Leng et al., 2019). As a DT cannot live without its twining asset in the physical space, it can also be viewed as a prerequisite for the development of a CPS (Uhlemann et al., 2017). Lim et al. (2020) reviewed digital twin in terms of the associated techniques, engineering product lifecycle management and business innovation perspectives. Bao et al. (2018) presented an approach of modelling and operations for the digital twin in the context of manufacturing. Tao et al. (2018) provided detailed application methods and frameworks of using DTs in product lifecycle management, covering product design, manufacturing, and service. From these applications, it can be seen that various activities in the entire product lifecycle can be simulated, monitored, optimized and verified in the virtual space of DTs. In a similar vein, Ding et al. (2019) adopted CPS and DT to build the interconnection and interoperability of a physical shop floor and corresponding cybershop floor to realize real-time monitoring, simulation and optimization of manufacturing operations. From a practical point of view, DTs not only enable virtualization of real conditions of objects on a real-time basis, but also allow simulation of many options before taking real actions in the physical world (White et al., 2021). The use of DT is useful in PI-hubs because there could be a number of possible alternatives to choose from in a decision-making process, and fast and accurate decisions are demanded.

In addition, IoT refers to connections between a network of physical assets through which data can flow between themselves. IoT technologies can be integrated into CPS to enable communication and data acquisition. Under an IoT environment, smart objects with integrating wireless communication technologies, sensors and actuators can connect to the internet and share their data, facilitating the real-time acquisition of data in logistics and supply chain management (Yan et al., 2016). Tu et al. (2018) proposed an IoT-based CPS architecture framework for production logistics applications. Keung et al. (2020) proposed a cloud-based CPS architecture, providing a comprehensive understanding on conflict avoidance strategy in the multi-layers multi-deeps warehouse layout. Although the advancement of the IoT has streamlined the collection of data, the question remains if the data can be processed properly in order to provide the right information for the right purpose at the right time (Lee et al., 2013). Thus, machine learning models should be embedded in an IoT-based CPS to process such data. Leung et al. (2020) proposed machine learning models based on adaptive neuro-fuzzy inference systems. The prediction accuracy of their models in forecasting near-real-time arrivals of orders in warehouses and distribution centers was validated. Backed by their implementation results, this study designs a machine learning model to predict arrivals of PI-orders at PI-hubs under the HCL network.

In summary, this study focuses on synchronizing operations within a FR PI-hub under a HCL network. In particular, a Total Inbound Synchronization strategy is designed to manage order fulfillment and replenishment as a joint process. A digital twin-based inbound synchronization framework is proposed to illustrate how PI data can be captured and used for prediction, formulating the TIS strategy.

3. Total Inbound Synchronization Strategy

Synchronization, firstly introduced at supply chain distribution networks and freight transportation level, aims to coordinates the production-logistics process chain. It helps to increase the overall throughput rate in a distribution center, thereby achieving a reduction of operating costs associated with storage and retrieval of goods (Xu et al., 2019; Baptiste & Maknoon, 2007). In logistics and manufacturing literature, Giusti et al. (2019, p.92) defined synchromodality as "*the provision of efficient, reliable, flexible, and sustainable services through the coordination and cooperation of stakeholders and the synchronization of operations within one or more supply chains driven by information and communication technologies (ICT) and intelligent transportation system (ITS) technologies*". There has been an increasing trend in the application of synchronization models. However, they are often generalized for production logistics. For example, Qu et al. (2016) developed a synchronization system integrating cloud manufacturing and IoT for managing the logistics operations in production and manufacturing. Pan et al. (2021) presented a multi-level cloud computing enabled digital twin system for the real-time monitor, decision and control of a synchronized production logistics system. In distribution and transportation sector, Yu et al. (2020) developed an operation synchronization model tailored for scheduling operations in e-commerce distribution centers. Apparently, optimizing sequential operations through synchronization is proven to be one of the research directions for obtaining an optional solution for operations in warehouses and distribution centers. Nevertheless, synchronization models in managing internal coordinated flows of PI-containers have not been developed yet to date.

In this study, the TIS strategy is defined as *the integration of cyber-physical systems and internet of things for digitally visualizing and sharing all relevant internal information and decisions among stakeholders in a warehouse with operational decision support enabled by machine learning-based optimizations*. In the PI-based logistics network, hereinafter referred to as PI-network, demand-driven order fulfillment operations, which are initiated from any city or regional PI-hubs, have revamped the entire processing and material flows within a PI-hub. To minimize the possibility of order delay and ensure the PI-network performs well as a whole, each PI-hub has the responsibility to maintain an adequate level of throughput. To achieve this, we introduce a three-dimensional synchronization in PI-hubs – order synchronization, process synchronization and information synchronization.

3.1 Order Synchronization

Order synchronization is a concept of consolidating fragmented orders through intended postponement of actual processing. In Leung et al. (2018), they introduced a Warehouse Postponement Strategy (WPS) to proactively postpone the processing of logistics orders in a standard warehouse. One of the key operational benefits of executing the WPS in e-commerce distribution centers is streamlining order fulfillment operations through consolidation of small lot-sized orders. In this study, the idea of WPS is integrated into the proposed TIS strategy. Without order synchronization, as depicted in Fig. 3, a typical FR PI-hub performs order picking in the forward area once a PI-order is received. The absence of intended postponement implies that the storage locations in forward and reserve areas have to be repetitively visited every time when an order arrives. Order synchronization fits well in FR PI-hubs due to the fact that the forward area is designed to store popular, fast-moving PI-SKUs. In other words, these PI-SKUs are being ordered frequently throughout the operating hours. With order synchronization, PI-orders are composed (aggregated) to reflect the total quantity of each PI-SKU required by the aggregated set of PI-orders from the PI-network. To evenly distribute the subsequent order picking operations, the aggregated PI-SKU set is decomposed into several order picking lists according to the storage location proximity among the PI-SKUs.

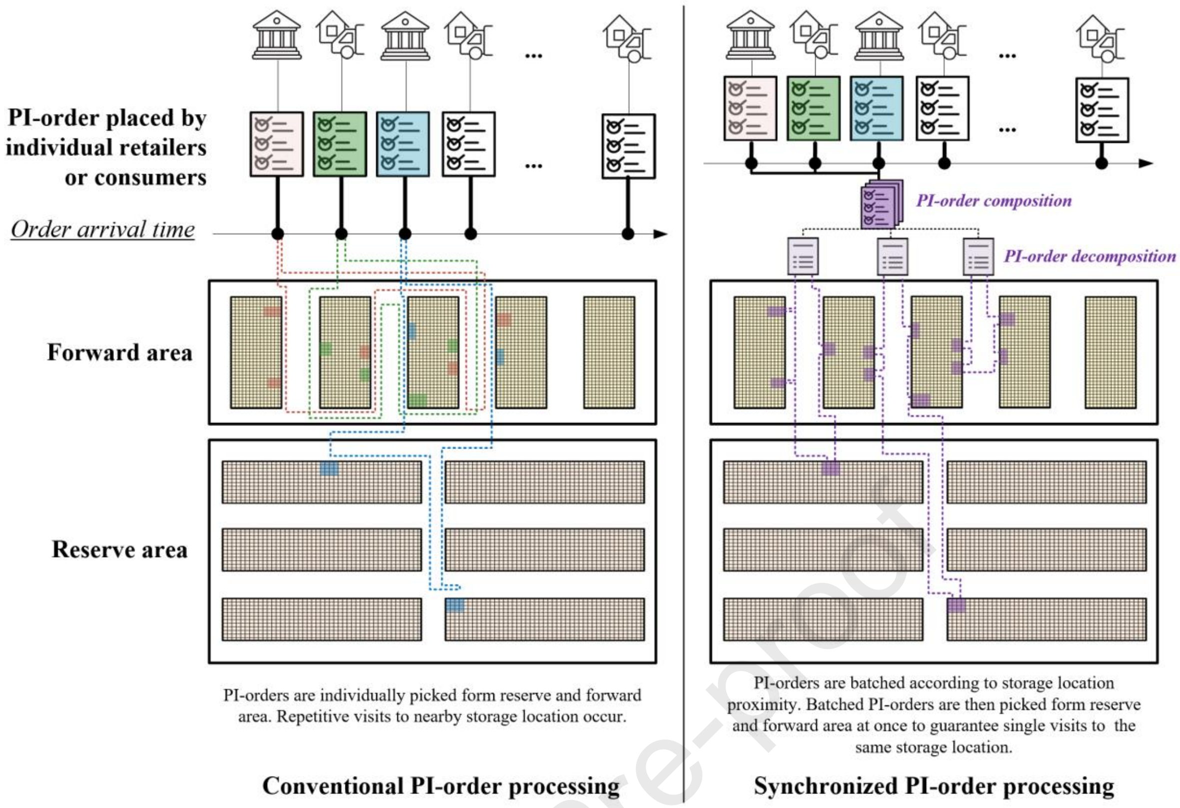

Fig. 3. PI-order synchronization

3.2 Process Synchronization

Order synchronization emphasizes the aggregation of PI-orders for batch processing, which only streamlines order fulfillment (picking) operations in FR PI-hubs. To maximize the value of FR PI-hubs, process synchronization is introduced, which further synchronizes order fulfillment and stock replenishment operations. The "process synchronization" is inspired by recent developments of internal synchronization at production houses and distribution centres. Li and Huang (2021) presented a production-intralogistics synchronization, which demonstrate the merits of joint production and intralogistics optimization in production facilities. In the context of distribution centres, Jiang et al. (2020) validated the essence of jointly considering picking and replenishment operations. Although integrating two or more internal operations increase optimization complexity, both of the above literature confirms the need to synchronize in inter-related operations in facilities where heavy material flows exist inside the plant.

Conventionally, replenishment operations are triggered to perform: (i) when the stock level of a particular SKU reaches the pre-assigned replenishment point, or (ii) when regular replenishment cycles are introduced. As order fulfillment and replenishment operations take place respectively in the forward and reserve areas, it is a common phenomenon to optimize these operations separately (Emde, 2017). However, although the forward area should sufficiently meet the demand of popular SKUs, there is still a chance of visiting the reserve area to complete orders that cannot be fully fulfilled in the forward area. In light of such circumstances of partial order fulfillment by visiting the reserve area, the TIS introduces process synchronization for performing order fulfillment and replenishment operations in the reserve area at once. By so doing, the process synchronization avoids repetitive visits to the same storage location in reserve area, as demonstrated in Fig. 4. Instead of visiting the same location separately for order fulfillment and replenishment to the forward area, each order fulfillment batch takes into the consideration of the set of PI-SKUs and their respective quantities that need replenishment from the reserve area. A joint order fulfillment and replenishment (OFR) problem is therefore introduced and to be tackled by a machine learning-enabled OFR model discussed in Section 4.

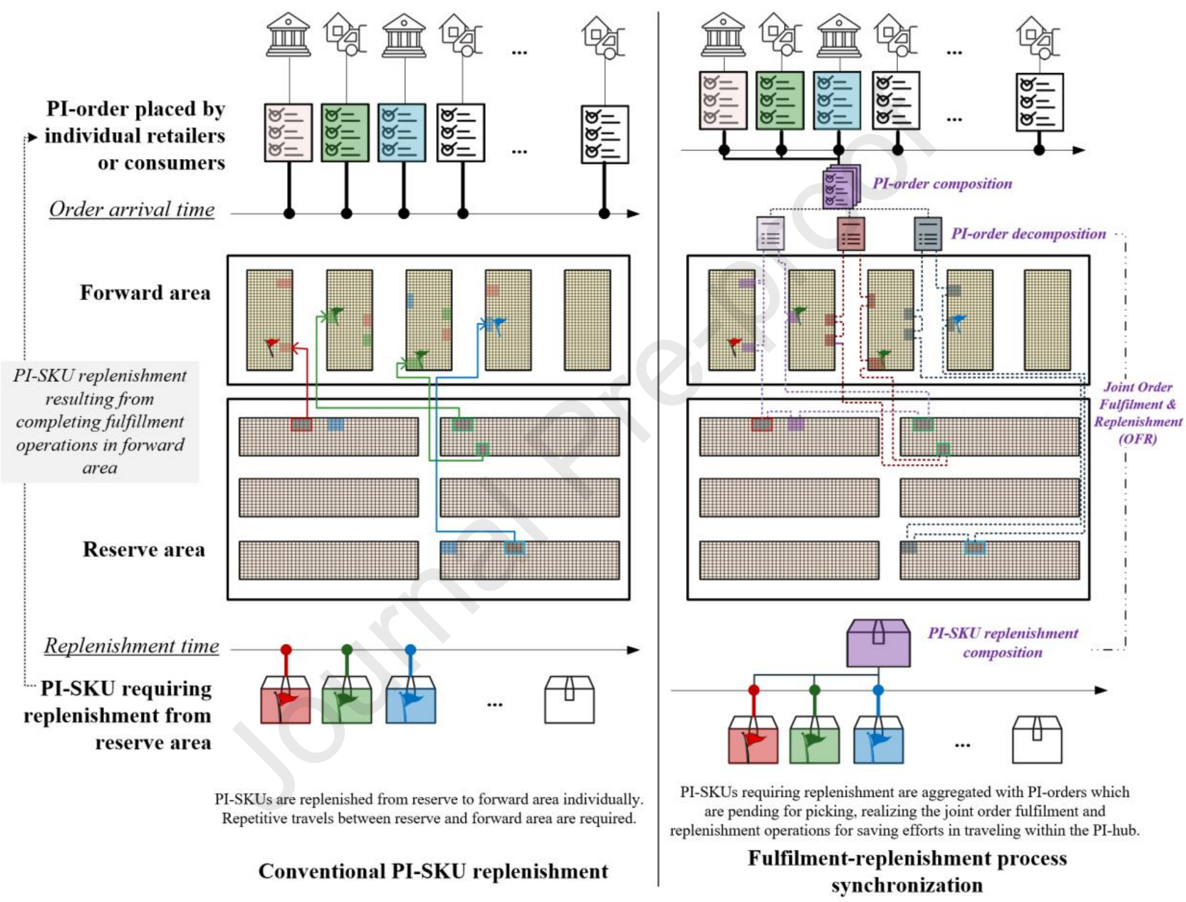

Fig. 4. Fulfillment-replenishment process synchronization

3.3 Information Synchronization

The deployment of order synchronization and process synchronization requires synchronized information in a digital platform for decision-making. Without real-time resource availability and PI-network demand information, PI-order and fulfillment-replenishment process synchronization are not possible. Therefore, the TIS strategy introduces information synchronization to facilitate order and process synchronization. In the era of Industry 4.0, digital twin and cyber physical systems play a vital role in visualizing physical activities in production and logistics facilities (Mörth et al., 2020). With state-of-the-art IoT devices capable of capturing and processing information, cyber physical systems also utilize the real time operational data to support daily decision-making (Lee et al., 2015). In the logistics and warehousing sector, warehouse operations and resource allocation are managed through dedicated management systems, such as Warehouse Management Systems (WMS), Transportation Management System (TMS) and Order Management System (OMS). However, their track and trace of real-time resource and demand arrival mostly depend on human input or IoT automatic retrieval. In this regard, blockchain technology can further be integrated to enhance the traceability and trackability for order management (Ho et al., 2021). To fully reflect the physical environment and uncover more relevant information related to, for example, the current availability of resources, we develop a digital-twin-based synchronization framework which integrates digital-twin and IoT technologies into synchronizing all in-house data and information, as discussed in the next section.

4. A Digital Twin-based Inbound Synchronization Framework

This section proposes a digital twin-based inbound synchronization (DTIS) framework, as shown in Fig. 5, which facilitates the deployment of TIS strategy proposed in Section 3. Like most CPS, there are the physical space (PS) and the cyberspace (CS). First, data from the PS are collected using IoT technologies and transformed to the CS where DTs are created to represent the physical entities. The DTs are operationally dynamic because their status is based on the near-real-time data coming from the physical counterpart in the PS. As such, they are living models that are useful for monitoring, controlling, diagnosing, and predicting the actual status in the PS. Prescriptive analytics is embedded in the framework to determine the course of actions to be taken in the PS for (OFR) based on PI-order arrival prediction. Details of the framework are presented in the following sections.

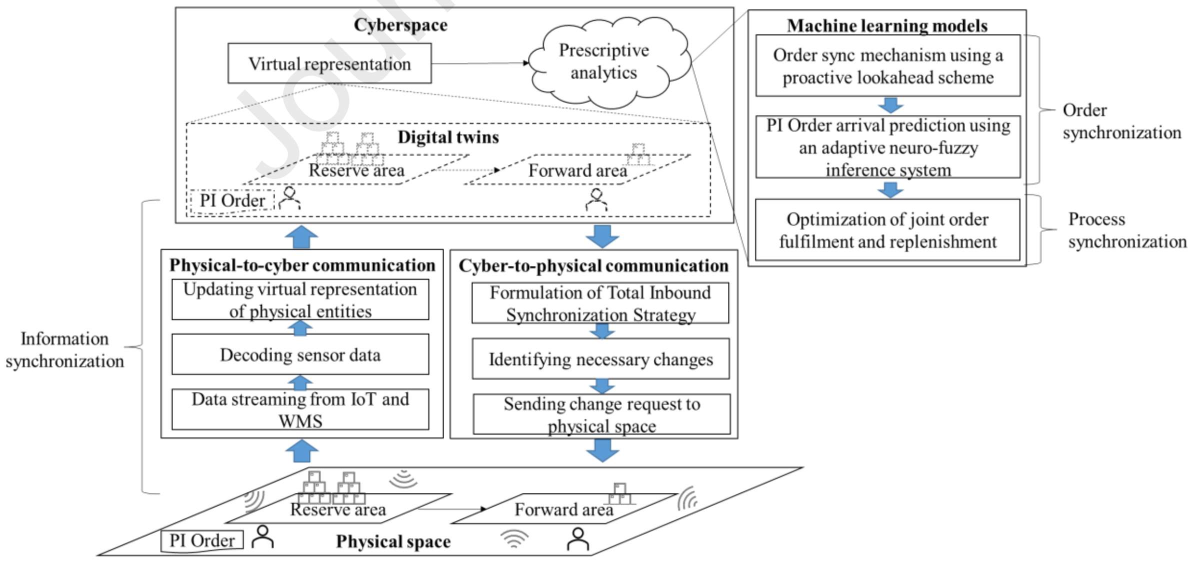

Fig. 5. A digital twin-based inbound synchronization framework

4.1 Physical Space

The PS consists of a physical environment, a physical system and physical processes. In this study, the physical environment is a PI-hub with a storage area subdivided into a forward area and a reserve area. The physical system that resides in the physical environment is the order picking system. In general, there are two types of order picking systems: picker-to-parts and parts-to-picker systems. The former one requires workers to get the PI containers from the storage area to fulfill an order while the latter one uses mobile robots to bring the PI containers to the workers. This study focuses on a picker-to-parts system because it is more commonly used in the industry due to its low costs, compared to parts-to-picker systems. The physical processes that performed in a FR PI-hub include (i) order consolidation, (ii) internal replenishment and (iii) order fulfillment. Order consolidation refers to the aggregation of PI-orders in terms of T-containers and the determination of the required quantities per container for internal replenishment. It takes place at the reserve area where the T-containers are unpacked into H-containers and P-containers for storage. Internal replenishment refers to replenishment from the reserve area to the forward area within the same warehouse. During order fulfillment, workers pick the containers up from the storage locations and bring them to the packing station where workers pack them into boxes for delivery. In a joint OFR process, requirements should be fulfilled using the minimum number of shelf visits.

In the PS, IoT-enabling technologies are used to capture data from the warehouse. A wireless sensor network is established to collect three types of data: environmental data, product data, and handler data. Environmental data include temperature, humidity and light intensity of the PI hub. These data could be useful in decision making, depending on the types of PI containers stored in the warehouse. For instance, SensorTag CC2650 can be used to capture environmental data when perishable items are stored. Product data include the inventory levels and storage locations of the PI containers. For instance, Radio Frequency Identification (RFID) technologies can be used to keep track with the storage locations and quantities of PI containers. If the inventory level reaches the reorder point, an alert can be sent to the WMS for replenishment. Handler data include data related to both equipment and workers, such as their real-time locations. For instance, workers can be given with handheld devices that communicate with the sensors so that their locations can be captured. Besides, workers can indicate the start and end of each of their assigned tasks via the devices so that their workloads and productivities can be monitored.

After the data are captured using IoT, they have to transfer to the CS where optimization is performed to formulate strategies for joint OFR. In the physical-to-cyber communication, they need to be decoded, otherwise they will lose the meaning and context. As such, the specifications of the physical entities including PI containers and workers have to be defined. In addition, changes to a physical entity are detected by sensors and transmitted to its digital twin in the CS. In this regard, industrial transmission protocols can help collect data from physical devices. Apart from the near real-time data collected by IoT, static data such as PI-orders are extracted from the WMS and sent to the CS. The virtual PI-orders contain necessary information for order consolidation. In this study, a dynamic-time window batching approach is used for order consolidation.

4.2 Digital Twins in Cyberspace

DTs in the CS are the virtual representations of the physical entities such as PI containers. They abstract the features of a physical entity based on the heterogeneous IoT data streamed from the PS and PI-orders from WMS. Enabled by near real-time synchronization between the CS and the PS, a DT is a live representation of its physical counterpart. Depending on the chosen level of abstraction, the component of the virtual representations can be the virtual environment, the virtual system, or the virtual process.

In the DTIS framework, an important feature of the cyber-to-physical communication is to allow direct feedback fed from the CS to the PS to achieve the TIS strategy. In particular, the TIS strategy supports the following decisions:

- A set of PI-orders that should be consolidated for batch processing
- The estimation of future PI-SKUs arrival
- The joint OFR operations

To formulate the TIS strategy effectively, machine learning-based models are constructed for three tasks: (i) order synchronization mechanism using a proactive lookahead scheme, (ii) order arrival prediction using an adaptive neuro-fuzzy inference system and (iii) optimization of joint OFR based on predicted order arrival. They can be performed on a cloud platform such as IBM Watson Studio, Microsoft Azure, Google Cloud Platform and Amazon Web Services. Cloud platforms are preferred in this framework because they offer infinitely scalable provisioning of computational and storage resources and users can thus scale up and down according to demand.

Based on the TIS strategy, there can be necessary changes to be made in the PS. By comparing the optimal parameters and the near-real-time parameters in the PS, change requests are sent to the PS to reconfigure the parameters of the physical system (e.g., storage locations assigned to PI containers) or the parameters of physical processes (e.g., replenishment quantities of PI containers) if required. For instance, workers can receive notifications from their handheld devices about new order picking tasks assigned to them. Instructions of the tasks include the amounts of PI containers to be picked up from the reserve area, the amounts of PI containers to be put at various storage locations at the forward area, and the travelling route within the warehouse. The devices can record the time where the workers start a particular task, and the data are transmitted to the CS. As a result, the progress of the workers is digitalized in the CS on a near real-time basis.

4.3 Prescriptive Analytics in Cyberspace

Performing prescriptive analytics in the CS of the DTIS framework aims to generate informed decisions for managing PI-containers in the PS of a city PI-hub. A machine learning-based model is developed and integrated for optimizing the joint OFR in PI-hubs. A lookahead functionality is developed for PI-hub decision makers to plan for OFR operations ahead of the actual arrival of network demand. The model is comprised of three modules: PI-network order sync module, PI-network order arrival prediction module and Joint OFR optimization module. Each of which serves a particular purpose like how PI components collectively operate for each other.

4.3.1 PI-network order synchronization (sync) module

This module is responsible for the retrieval and pre-processing of PI-orders received at city PI-hubs, which realized order synchronization suggested in Section 3.1. Order synchronization involves order decomposition and composition. Within the HCL network in PI, all PI-orders are submitted in the form of PI-containers. First, the order sync mechanism digitally decomposes PI-orders from H-containers to P-container level. Each P-container consists of only one PI-SKU. At the end of each order fulfillment cycle, the mechanism calculates the demand of each PI-SKU from all the arrived PI-orders during the current cycle, as depicted in Table 1. The mechanism identifies if the PI-SKUs are stored in the forward area. PI-SKUs that are in the forward area are to be picked up from the reserve area directly. For PI-SKUs that are stored in the forward area, the mechanism provides a proactive lookahead feature by predicting their future arrivals in the next order fulfillment cycle *t+1*, i.e., column D in Table 1. The predicted demand of each PI-SKU in the forward area during the *t+1* cycle is determined by the neuro-fuzzy-based PI-network order arrival prediction module, hereafter the prediction module. Hence, the PI-network order sync module identifies the set of PI-SKUs that need future demand prediction and triggers the prediction module for forecasting. Then, by identifying the current stock level (column E) in physical space, the actual picking quantity of each PI-SKU in the forward (column F) and reserve area (column G) is determined. It is worth noting that the picking quantity in the reserve area should satisfy both the current and the future demand, so as to reduce future efforts in visiting the reserve areas again in the next cycle.

The above computations in the order sync module identifies the picking quantities of PI-SKUs in the forward and reserve area only. To save efforts in visiting the reserve area, replenishment operations are also integrated into considerations. The mechanism identifies the stock levels of each PI-SKU after satisfying current demand (column H). PI-SKUs are required to be replenished at their specified quantity denoted in column J should their remaining stock level after satisfying the current demand (column H) is below the point of replenishment (column I). Therefore, by summing up the picking quantity for order fulfillment and replenishment, respectively computed in column G and column K, the order sync mechanism determines: (i) the set of PI-SKUs and their corresponding quantity to be picked from the forward area for order fulfillment, (ii) the set of PI-SKUs and their corresponding quantity to be picked from the reserve area for satisfying current and future demand, as well as for replenishment.

Table 1. PI-order decomposition in the order sync module

Real-time PI-order retrieval at fulfillment cycle t with lookahead functionality:

A	***B***	***C***	***D***	***E***	***F***	***G***	***H***	***I***	***J***	***K***
Stored in forward area?	**PI-SKU #**	**Aggregated demand**	**Predicted demand in *t+1***	**Current Stock level**	**Picking Qty in forward area**	**Picking Qty in reserve area for satisfying *t* and *t*+1 demand**	**Stock level after order fulfillment**	**Replenish point**	**Preferred Stock level**	**Additional Qty for replenishment from reserve area**
Y	001	20	10	30	20	0	0	5	40	40
Y	003	30	7	5	5	32	0	5	40	40
Y	011	35	20	10	10	45	0	3	30	30
Y	015	21	20	57	21	0	16	10	50	0
N	032	22	0	0	0	22	0	0	0	0

4.3.2 PI-network order arrival prediction module

The joint OFR optimization is able to streamline material flows by combining the order fulfillment operation in the forward area and replenishment operation between the reserve and forward areas. However, to further maximize utilization of resources when performing the joint OFR operation, the proposed proactive lookahead scheme replenishes SKUs to the forward area at a quantity exceeding actual demand. Prior to the start of each OFR cycle *t*, a tailored neuro-fuzzy prediction model is used to predict the SKUs' future demand during *t* and *t+1*. By so doing, the actual OFR operation performed in cycle *t* replenish SKU *i* at a quantity $Q_{i,t}$ given by:

$$Q_{i,t} = D_{i,t} + F_{i,t+1} \tag{1}$$

where $D_{i,t}$ is the actual demand of SKU *i* aggregated from the order synchronization mechanism and $F_{i,t+1}$ is the predicted demand of SKU *i* during period *t* and *t+1*. To determine the $F_{i,t+1}$, a forecasting method with a high level of accuracy for e-commerce order arrival prediction is required. This study adopts and tailors the neuro-fuzzy model developed by Leung et al. (2020) to forecast the future arrivals of PI-SKUs. A standard five-layer network architecture of two inputs *a* and *b*, and one output *f*, is shown in *Appendix A*.

- *Tailored inputs and output of the neuro-fuzzy model integrated in the DTIS framework*

There are three inputs and one output for the predictive model introduced in this study. As the order sync mechanism aggregates the pending demand retrieved from downstream customers, such as retailers and online customer orders, the mechanism provides the actual demand figures of the aggregated SKUs. Therefore, for *n* aggregated SKUs exist in the order sync mechanism, *n* neuro-fuzzy models are used to individually forecast the future demand of these SKUs. In other words, demand for SKUs not existed in the current order sync pool will not be forecasted. In practice, this approach makes sense because the joint OFR governs how the aggregated SKUs are to be replenished in form of H- and P-containers from the reserve area and picked at the forward area. By only forecasting the future arrivals of the aggregated SKUs, PI-movers, typically the order pickers with the aid of material handling equipment, are not required to visit other storage locations at reserve and forward area which store SKUs not demanded at this moment. Instead, they are only required to visit the storage locations of the aggregated SKUs for replenishing to the forward area at a quantity the computation procedures presented in the order sync mechanism with the support of the predictive model. This approach practically aligns with our theoretical proactive lookahead scheme and rationale of "replenish only when it is needed" in FR warehouse management.

For the predictive models of each aggregated SKU, the single output *f* is their corresponding predicted demand during *t* and *t+1*. The three inputs are:

(i) *Actual arrival figures of the current period t* – In time-series study, lag variables, i.e., previous actual figures, are one of the primary indicators for forecasting the next figure. A least square method is required to statistically identify the optimal number of lag variables to be used as inputs. One lag variable, i.e., the current arrival figure, Q_t, is required for forecasting the future demand of an SKU.

(ii) *Momentum of order arrival between t and t-1* – The volatility of previous demand figures of SKUs is considered as another indicator studying the trend of the time-series-based arrivals of orders in warehouses. A one-order momentum, M_t, is proved to be necessary for forecasting the future demand of an SKU, which is calculated by:

$$\boldsymbol{M_t = Q_t - Q_{t-1}} \quad (2)$$

(iii) *Average arrival figures at t, t-1 and t-2* – Simple moving average (SMA) is another understandable factor for inclusion of a prediction model. Study by Leung et al. (2020) confirmed the suitability of choosing a three-period SMA, Q_{avg}, as one of the inputs in future SKU demand arrival prediction, which can be computed by:

$$\boldsymbol{Q_{avg} = \frac{1}{3}(Q_t + Q_{t-1} + Q_{t-2})} \quad (3)$$

An illustrative example is shown in Fig. 6 to demonstrate the prediction of future demand of a set of SKUs.

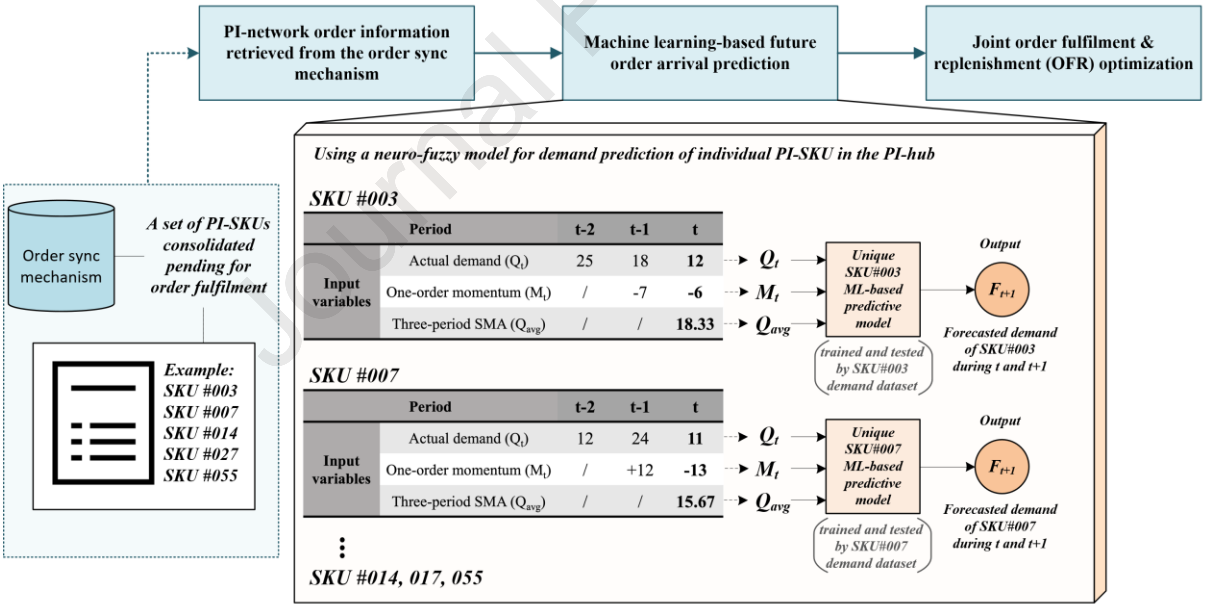

Fig. 6. Predicting future demand of a set of SKUs using the neuro-fuzzy model

4.3.3 *Joint OFR optimization module*

The objective of the joint OFR optimization model is to minimize the total traveling distance of visiting storage locations in both reserve and forward areas during fulfillment and replenishment operations. The model is described as follows.

Assuming that there are n SKUs in the depot indexed by i and the first m SKUs are stored in both forward and reserve areas. The associated inventory storage locations of SKU i in reserve and forward areas are denoted as i and $n+i$, respectively. Following the pick-to-parts systems, the PI-handlers performing the joint PI-order OFR considered in this study are standardized multi-tier picking trolleys. These PI-handlers has a centralized, dedicated storage space denoted as 0. Next to the forward area, there is a packing station for SKU i denoted as $2n+i$ for packing and consolidating them so that they are ready for outbound delivery. Hence, $N=\{0,1,2,...n,n+1,...,2n,2n+1,...,3n\}$ is the set of all locations that PI-workers and PI-handlers can visit. It is noted that the actual size of a forward area is smaller than the reserve area, so that only places from $n+1$ to $n+m$ really exist in the depot. Additionally, since all SKUs are packed at the same place, locations from $2n+1$ to $3n$ indicate an identical physical place. We further define a set $Pr=\{1,2,...,n\}$, $Pf=\{n+1,n+2,...,2n\}$, $Pk=\{2n+1,2n+2,...,3n\}$ containing all PI-handlers visiting locations in the reserve area, forward area and packing area, respectively, and $P=Pr\cup Pf\cup Pk$.

At the start of each fixed fulfillment cycle, a pickup request with quantity pq_i or a delivery request with quantity dq_i is placed for each SKU $i\in P$. A set of PI-handlers in the depot with identical capacity Q, which is denoted as $K=\{1,2,...,|K|\}$, is used to fulfill these requests. One SKU i captures a deterministic volume q_i and the traveling distance between place $i\in N$ with $j\in N$ is also deterministic and denoted as $d_{i,j}$.

There are three types of variables are considered in this joint OFR decision model, including binary variables $x_{i,j,k}$ ($i,j\in N$, $i\neq j$, $k\in K$), PI-handlers loading variables $y_{i,k}$ ($i\in N$, $k\in K$), and visiting sequence variable $z_{i,k}$ ($i\in N$, $k\in K$). Overall, the problem is how to determine $x_{i,j,k}$, $y_{i,k}$ and $z_{i,k}$ to minimize the overall PI-handlers traveling distance while the PI-SKU replenishment and PI-order fulfillment tasks are accomplished all at once in a same cycle. The model is presented as follows.

Objective

$$\min \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} x_{i,j,k}\cdot d_{i,j} \tag{4}$$

Subject to

$$\sum_{k\in K}\sum_{j\in N} x_{i,j,k} \le 1,\ i\in P \tag{5}$$

$$M\cdot\sum_{k\in K}\sum_{j\in N} x_{i,j,k} \ge (pq_i+dq_i),\ i\in P \tag{6}$$

$$\sum_{j\in P} x_{0,j,k} = 1,\ k\in K \tag{7}$$

$$\sum_{i\in P}\sum_{j\in Pk} x_{i,j,k} = 1,\ k\in K \tag{8}$$

$$\sum_{k\in K} f^{+}\Big(\sum_{i\in P} x_{i,j,k} + \sum_{i\in P} x_{i,n+j,k} + \sum_{i\in P} x_{i,2n+j,k}\Big) \le 1,\ j\in Pr \tag{9}$$

$$x_{i,j,k} = 1 \Rightarrow y_{j,k} = y_{i,k} + \left(pq_j - dq_j\right)\cdot q_j,\ i\in P,\ j\in P,\ k\in K \tag{10}$$

$$x_{i,j,k} = 0 \Rightarrow y_{j,k} = y_{i,k},\ i\in P,\ j\in P,\ k\in K \tag{11}$$

$$x_{0,j,k} = 1 \Rightarrow y_{j,k} = y_{0,k} + \left(pq_j - dq_j\right)\cdot q_j,\ j\in P,\ k\in K \tag{12}$$

$$x_{0,j,k} = 0 \Rightarrow y_{j,k} = y_{0,k},\ j\in P,\ k\in K \tag{13}$$

$$y_{0,k} = 0,\ k\in K \tag{14}$$

$$y_{i,k} \le Q,\ i\in N,\ k\in K \tag{15}$$

$$x_{i,j,k} = 1 \Rightarrow z_{j,k} = z_{i,k} + 1,\ i\in P,\ j\in P,\ k\in K \tag{16}$$

$$x_{i,j,k} = 0 \Rightarrow z_{j,k} = z_{i,k},\ i\in P,\ j\in P,\ k\in K \tag{17}$$

$$x_{0,j,k} = 1 \Rightarrow z_{j,k} = z_{0,k} + 1,\ j\in P,\ k\in K \tag{18}$$

$$x_{0,j,k} = 0 \Rightarrow z_{j,k} = z_{0,k},\ j\in P,\ k\in K \tag{19}$$

$$z_{0,k} = 1,\ k\in K \tag{20}$$

$$z_{i,k} \le z_{n+i,k},\ i\in Pr \tag{21}$$

$$z_{n+i,k} \le z_{2n+i,k},\ i\in Pr \tag{22}$$

$$z_{i,k} \le z_{j,k},\ i\in Pr \cup Pf,\ j\in Pk \tag{23}$$

where M is a big number and function $f^{+}(x)$ is formulated as follows:

$$f^{+}(x) = \begin{cases} 1 & \text{if } x \ge 1 \\ 0 & \text{else} \end{cases} \tag{24}$$

Constraint (5) and (6) ensure that one and only one PI-handler is assigned to SKU i if a pickup or delivery demand is required on SKU i. Constraint (7) and (8) mean that all used PI-handlers begin their trips from their origin, that is, dedicated storage space denoted as 0, and finish their at the packing station. Constraint (9) guarantee that the place of one type of SKU, i.e., $i, n+i, 2n+i$, is visited by the same PI-handler. Constraint (10) – (15) describe that the volume of loaded SKUs shall not surpass the PI-handler capacity. Constraint (16) – (22) force that, for one type of SKU, its inventory storage location in the reserve area is visited before that in the forward area and its storage location in the forward area is visited before visiting the packing station. Constraint (23) forbids PI-handlers to return to the reserve or forward area when they complete the assigned, joint fulfillment and replenishment tasks.

5. Simulated Experiments

Simulations are conducted to evaluate the performance of the proposed model in optimizing the joint OFR operations. The benchmarking of the joint OFR operations with respect to replenishment and fulfillment operations performed separately is made through measuring the traveling distance and the number of repetitive visits to the reserve area. In this section, the parameter setting for simulations, the set of KPIs, and simulation results are presented.

5.1 Experimental design and data sets

A city distribution hub considered in the simulation manages PI-orders within its HCL network received from other regional and city PI-hubs. In a city PI-hub, orders received are initiated either by other city PI-hubs within the network, or retailers and end consumers. The section simulates the fulfillment operations of retailers' and consumers' orders, as well as the internal replenishment operations of transporting PI-SKUs from the reserve to forward areas. Due to the nature of these orders, SKUs are picked at piece level, rather than pallet level. In other words, the city PI-hub stores and transports PI-SKUs at the P-container level, not the H-container level. Assuming that there is a total of 600 PI-SKUs in the PI-hub, based on the Pareto principle, 20% of them, i.e. 120 PI-SKUs, are fast-moving, popular SKUs. Hence, the standard, rectangular-shaped forward-reserve city PI-hub considered in this study has dedicated storage locations for the 600 PI-SKUs in the reserve area, of which 120 PI-SKUs are also stored in the forward area, as illustrated in Fig. 7. To maintain the designated stock levels of each popular PI-SKU in the forward area, PI-SKU replenishment operations are performed by replenishing stocks from the reserve area. The proposed joint OFR operations are regularly performed at a fixed 60-minute cycle, implying that PI-orders are consolidated for 60 minutes and are to be picked from either the reserve or forward area to the packing station in batch mode under the picker-to-parts system. Simultaneously, the trip of each PI-handler to visit the reserve, forward area and packing station under each cycle also takes care of replenishment tasks. To effectively evaluate the performance of the joint OFR operations against OFR operations performed in a standalone manner, parameters for the simulation study are defined, as summarized in Table 2.

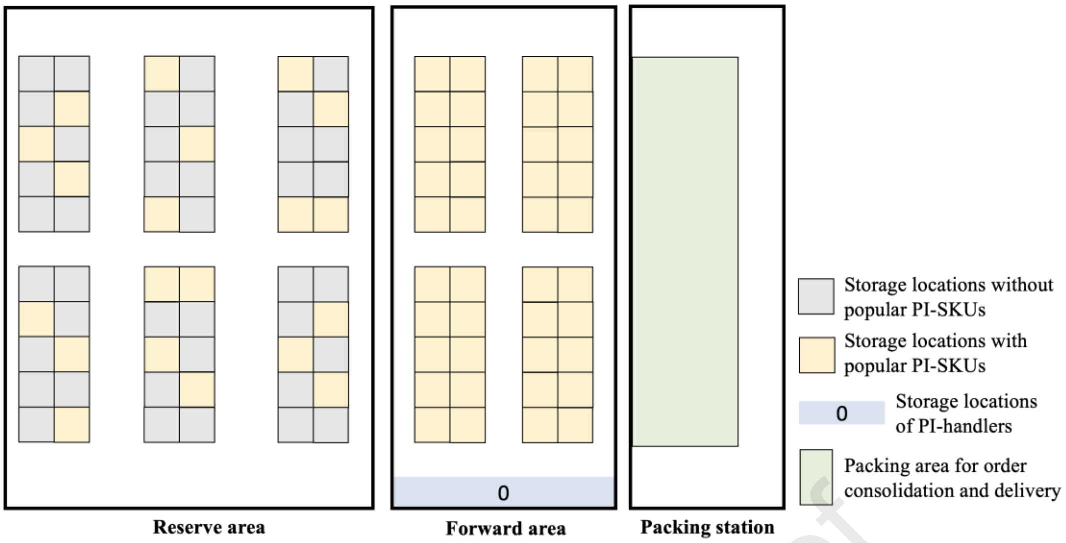

Fig. 7. A standard, rectangular-shaped facility layout of a FR city PI-hub for simulation

Table 2. A summary of the parameter setting for the simulation

Parameter	Configuration
PI-SKU attributes	
Number of PI-SKUs stored in reserve area	600 PI-SKUs
Number of PI-SKUs stored in forward area	120 PI-SKUs
PI-SKU replenishment point and quantity	Each PI-SKU has its pre-defined replenishment point and quantity
PI-SKU storage location in reserve area	Dedicated storage system
PI-SKU storage location in forward area	Dedicated storage system
PI-handler attributes	
Number of PI-handlers	20
PI-handler capacity	600 kg
PI-order attributes	
PI-order arrival rate	0.5 min per order
Number of PI-SKUs in each PI-order	Average: 2 (min: 1, max: 3)
Quantity of each PI-SKU required by a PI-order	Average: 2 (min:1, max: 3)
Weight of each PI-SKU	Average: 0.7 kg (min: 0.1 – 3 kg)
Experiment attributes	
OFR cycle time	Every 60 minutes
Opening hours of the city PI-hub	8:00 – 20:00
Simulation duration	20 days

5.2 Simulation results

To facilitate the actual deployment of proposed joint OFR operations in city PI-hubs in real business environment, comprehensive decision flows of the conventional practice and the proposed joint OFR operations are presented in Fig. 8 and 9 respectively. The conventional order fulfillment (i.e., order picking) operation in a typical FR distribution hub does not feature order lookahead functionality. In other words, at each order batching cycle, i.e. decision epoch in this simulation study, SKUs are picked for to exactly fulfill the existing orders only. In a FR warehouse, popular SKUs are to be picked from forward area. However, they will also be picked together with non-popular SKUs in the reserve area if stock-out of these SKUs in the forward area occurs. To compare the performance of the joint OFR against the conventional practice, we assume that stock replenishment operations are also initiated at each decision epoch. As depicted in Fig. 8, at each decision epoch, SKUs stored in the forward area will be assessed to identify if they require replenishment from the reserve area. Any SKUs requiring replenishment will be summarized into a stock replenishment list, which serves as the input of the decision algorithm in the simulation to generate trips for PI-handlers to pick the required PI-SKUs from the reserve area to the forward area.

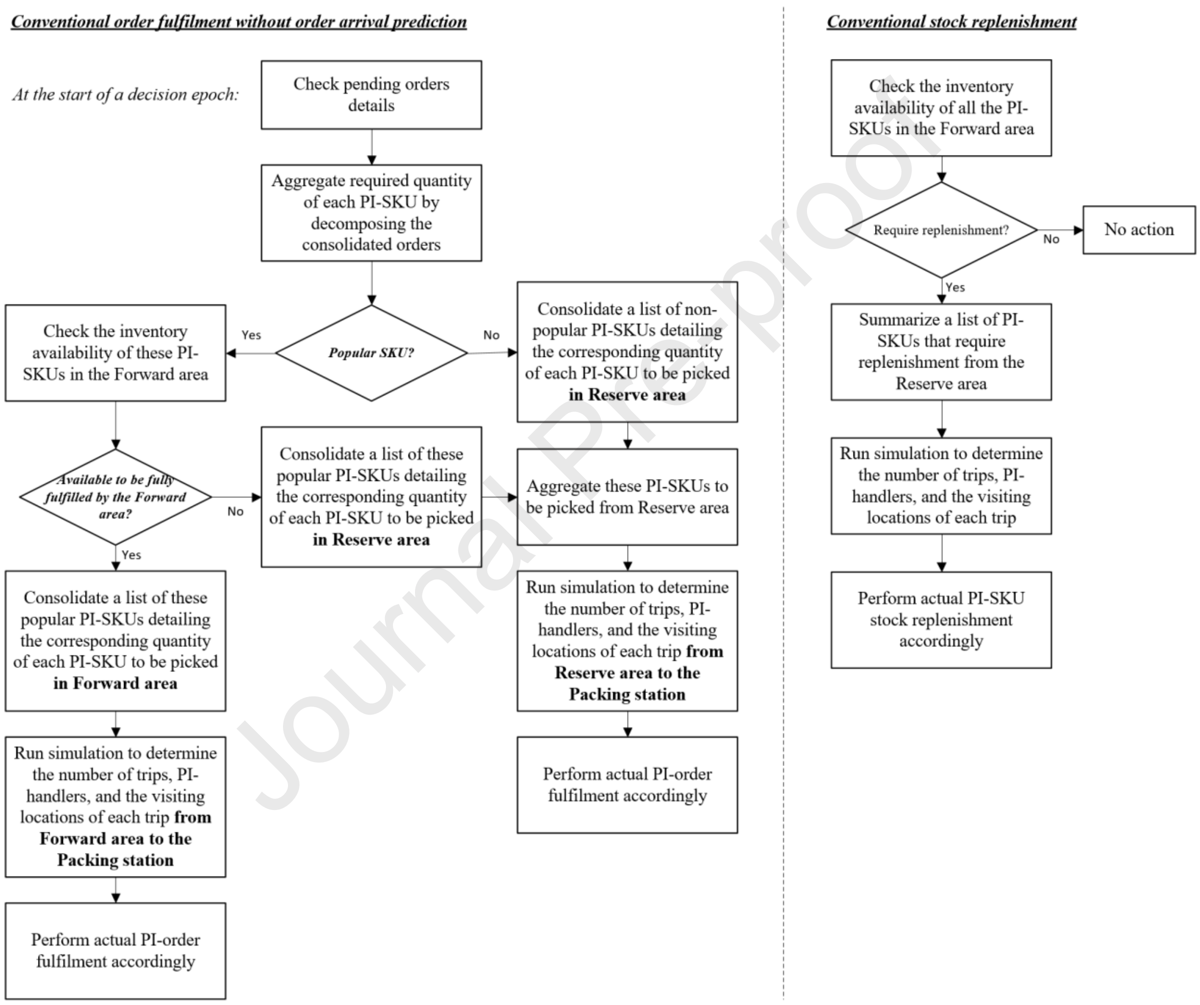

Fig. 8. Conventional order fulfillment and stock replenishment operations in forward-reserve PI-hubs

For the joint OFR operations, the simulation also integrates the proposed PI-order lookahead scheme by adding a function that forecasts the quantity of the popular PI-SKUs possibly to be arrived in the next decision epoch. The stock replenishment quantities of PI-SKUs are aggregated with the quantity to be picked from the reserve area, as depicted in Fig. 9. In this sense, repetitive visits to the reserve area would potentially be reduced. It is therefore suggested to deploy the joint OFR DT and IoT technologies proposed in Section 4 to re-engineer the operational flow in FR PI-hubs for streamlining the handling procedures of PI-containers in PI-hubs.

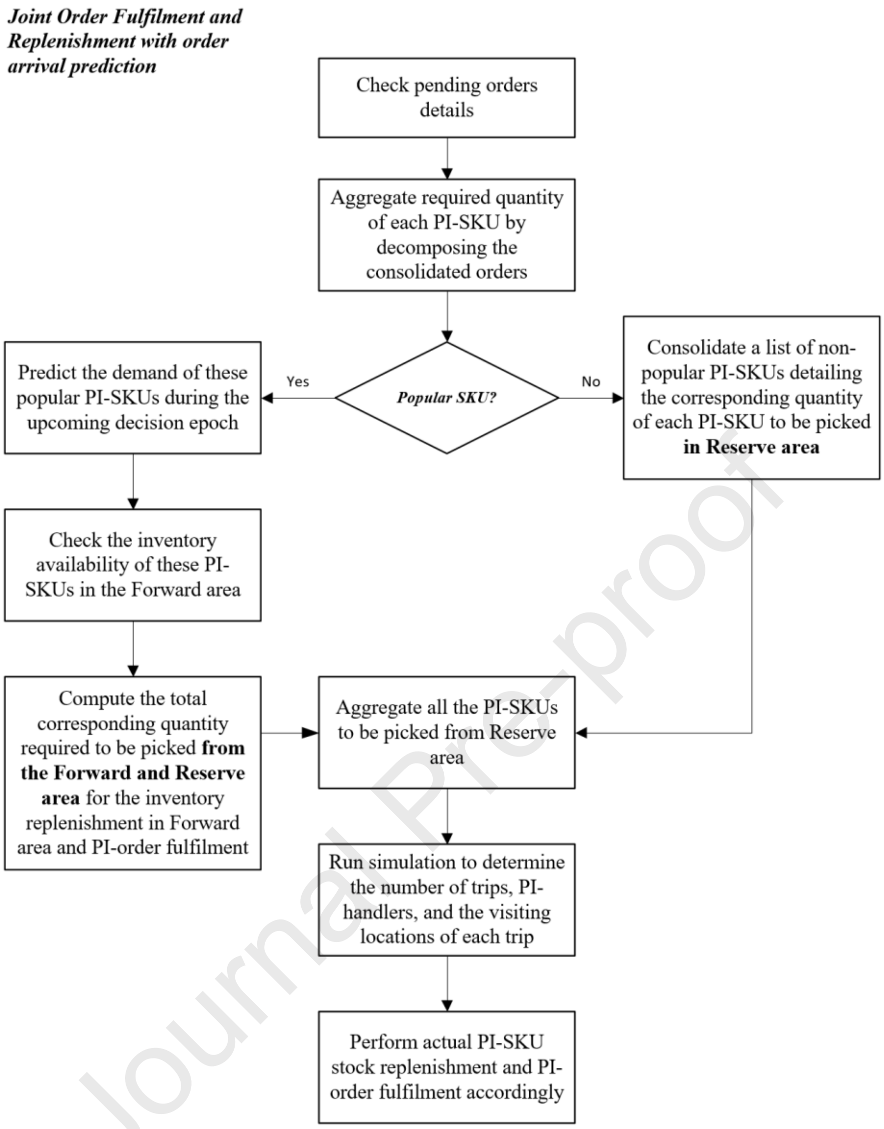

Fig. 9. Joint order fulfillment and replenishment operations in forward-reserve PI-hubs

5.2.1 Traveling distance reduction

The potentials of the joint OFR with order arrival lookahead functionality is evaluated in terms of the traveling distance and the number of repetitive visits to reserve areas. Table 3 summarizes the traveling distance reductions with our joint OFR operations taken place in city PI-hubs. Even without the lookahead functionality, the standalone PI-order fulfillment and PI-SKU stock replenishment operations require in total 27.61 km per day for the PI-handlers to transport PI-SKUs from one storage area to another. A drastic reduction (80.9%) of traveling distance is achieved with the introduction the joint OFR operations, which gives only 5.27 km of traveling distance on a daily basis. To further evaluate the operational efficiency of the joint OFR approach, the daily required number of trips is also measured during the simulation study. With the 60-minute OFR cycle in place, each working day has a total of 12 cycles for order fulfillment and replenishment. Results reveal that our synchronized approach yields over 85% of the reduction in terms of the number of trips per cycle. When receiving a large number of orders on a minute-and-minute basis as configured in this experiment, our approach only generated on average 9.36 trips in each cycle, not to mention that these trips are formulated to pick PI-SKUs for fulfilling both the existing and future PI-orders due to the inclusion of the order arrival lookahead scheme powered by the machine learning algorithm. Such drastic reduction allows practitioners to save huge manpower to repetitively travel between the reserve, forward area and packing station. Nevertheless, since the number of trips under the deployment of the TIS has been drastically minimized, the average traveling distance of a trip is increased by 34%, from 35.03 to 46.96 metre. However, such slight increase, i.e., around 10m per trip is totally worthwhile considering the impressive reduction of the number of trips per cycle.

Table 3. Simulation results in terms of traveling distance

	Standalone OFR *(Without order arrival prediction)*	**Joint OFR** *(With order arrival prediction)*	
	20-day mean value	*20-day mean value*	*Improvement*
Total daily traveling distance	27.61 km	5.27 km	80.9%
Average daily number of trips	788	112	
Average number of trips per cycle	61.78	9.36	85.5%
Average traveling distance per trip	35.03 m	46.96 m	-34%

5.2.2 Number of visits to the reserve area

The simulation, also compares the number of visits to the reserve area with and without deployment of the joint operations. Results summarized in Table 4 reveal that on average the total number of visits per day has been reduced from 461 to 93 times. In other words, statistically the reserve area is visited by the PI-handlers for 7.75 times in each cycle, experiencing a 79.8% improvement as compared to the standalone OFR. Moreover, considering the average number of trips in a cycle, this figure indicates that 7.75 out of 9.36 trips have to visit the reserve area. There is a 20.6% increase in the percentage of trips required to visit the reserve area. However, such 20% rise in the chance to visit the reserve aera in fact only increase 10m of the traveling distance.

Table 4. Simulation results in terms of the number of repetitive visits to reserve area

	Standalone OFR *(Without order arrival prediction)*	**Joint OFR** *(With order arrival prediction)*	
	20-day mean value	*20-day mean value*	*Improvement*
Total daily no. of visits	461	93	79.8%
No. of visits per cycle	38.42	7.75	79.8%
			Differences
% of trips visiting reserve area	62.2%	82.8%	+20.6%

6. Implications

A joint OFR operation performed in the reserve area and forward area is modelled in this study. Integrated with DT technologies, an inbound synchronization framework is designed to achieve a multi-dimensional synchronization for synergizing the inbound processing of PI-containers at city PI-hubs. Simulation results revealed three underlying problems brought by optimizing replenishment operations without taking order fulfillment into account: waste of replenishment efforts, ineffectively use of forward area space, and diminishing the value of forward reserve warehouse configuration. Yet, these problems can be alleviated through the optimization of the joint problem defined in this study. The significance of managing the interdependencies of the operations of OFR can be observed in strategic, methodological and practical perspective:

(i) *Strategically maximizing the value of forward-reserve configuration in Physical Internet* – This study realizes internal synchronization in terms of order, process and information synchronization. The combinational benefit of the three-dimensional synchronization lies in the potentials of maximizing the value of configuring a traditional warehouse into a FR PI-hub. The underlying concept of "replenish only when it is needed", realized in the proposed joint OFR optimization, replenishes an SKU from the reserve area to the forward area in the current replenishment cycle only if the PI-hub receives real-time demand from last-mile end customers. This strengthens the coordination among the forward area and the reserve area as replenishment efforts are saved for actual needs.

(ii) *Methodologically integrating soft and hard technology for a streamlined PI-hub environment* – The proposed methodology not only facilitates the deployment of TIS, but also serves as a generic, conceptual architecture of how ML, DT and IoT collectively operate to build a smarter, streamlined, and more favourable PI environment in the era of Industry 4.0. Further, a novel perspective of how synchronization could be made possible in the interdependent internal operations among reserve, forward and order packing area is presented. The TIS streamlines material flows in FR PI-hubs, particularly among reserve, forward and packing area when fulfilling orders and replenishing SKUs in the forward area. Essentially, streamlined processing of PI-containers allows re-allocation of idle resources to handle PI-operations others than PI-order fulfillment and replenishment (Roy et al., 2019; Leung et al., 2018), such as PI-order receiving and inspection activities at the inbound dock, put-away operations for bulk storage of H-and P-container at the reserve area, and etc. This study motivates future research in the field of forward reserve warehouse management to explore the potentials of synchronizing warehouse operations with high levels of interdependency and interrelationship, given a vast amount of operational data being available for improved decision-making in the era of Industry 4.0 (Witkowski, 2017).

(iii) *Practically minimizing repetitive visits to reserve area* – In the absence of the proposed operational synchronization, repetitive visits to reserve area for replenishment and direct order fulfillment are anticipatable. In the face of frequent arrivals of fragmented, time-sensitive orders within the PI-network, effort in monotonous order picking and replenishment from reserve area, a huge storage area storing large number of SKUs, is tedious and time-consuming (Bahrami, Aghezzaf, and Limère, 2019). The proposed mechanism is therefore designed to reduce replenishment efforts by minimizing the number of traveling trips of PI-handlers. In other words, the operating efficiencies for both operations are improved. In long run, even a minimal improvement in terms of operating efficiencies is able to strengthen the core competence of a firm in terms of internal order handling, as the travelling trips undertaken during the entire working hours governs the material flows within the reserve area and the forward area.

7. Conclusion and Directions for Future Research

The COVID-19 pandemic has made many consumers switch to e-commerce. It is expected that such a paradigm change in consumer behaviour will continue affect the retail environment. In the delivery sector, there have been innovations such as air drones and driverless cars for last-mile delivery, to minimise human-to-human contact. However, their adoption is in the infancy stage. Human still plays a leading role in the management and execution of both the inbound and outbound order fulfillment process in the coming decade (Pasparakis, de Vries, & de Koster, 2021). It is of prime importance to continuing the assessment of the potential integration of the state-of-the-art technologies in warehouses, such as DT and IoT technologies, in order to minimize human efforts in the OFR while maintaining an adequate level of throughput for satisfying the ever-increasing demand for last-mile delivery in e-commerce.

This paper studies the internal operations in manual picker-to-parts systems, which account for a majority of order picking systems in warehouses worldwide (De Koster et al., 2007). The proposed TIS Strategy supports the picker-to-parts material handling system in city PI-hubs by synchronizing: the actual and predictive arrivals of last-mile PI-orders, internal order fulfillment and replenishment operations, and relevant internal information and decisions among stakeholders under the PI framework. After all, streamlining the internal flows of PI-orders within a PI-hub improves the throughput of not only a single PI-node, but the entire hyperconnected PI logistics network. To extend the applicability of the proposed synchronization in a wider spectrum, there are several avenues for future research. First, some assumptions in this work could be relaxed, such as order fulfillment cycle time, replenishment policy, and others. Another research direction would be to deploy the TIS strategy in a robotic parts-to-picker warehouse environment under the era of PI. This could further validate the essence of integrating DT, ML and IoT for synergized OFR operations in Industry 4.0.

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Appendices

Appendix A – *Network structure of a standard neural network model*

The network structure of ANFIS consists of two parts – premise and consequence parts. For a typical first-order two-rule Takagi-Sugeno type fuzzy inference system, the two fuzzy if-then rules are expressed as follows (Takagi-Sugeno, 1983).

$$\text{Rule 1: If } a \text{ is } J_1\text{, and } b \text{ is } K_1\text{, then } f_1 = p_1 a + q_1 b + r_1$$

$$\text{Rule 2: If } a \text{ is } J_2\text{, and } b \text{ is } K_2\text{, then } f_2 = p_2 a + q_2 b + r_2$$

where J_i and K_i are the fuzzy sets, f_i is the output set within the fuzzy region specified by the fuzzy rule, and p, q and r are linear output parameters determined during the training process.

Layer 1. This is a fuzzification layer, in which $O_{1,i}$ represents the output of the ith node from this layer, an input to node i is denoted as x, J_i is the linguistic label for the input, and $\mu_{Ji}(x)$ is the membership function in a particular shape. For a membership function with a given parameter set $\{x_i, y_i, z_i\}$, each node i in this layer is a square node with a function of:

$$O_{1,i} = \mu_{Ji}(a) = \frac{1}{1+(\frac{a-z_i}{x_i})^{2yi}} \quad \text{for } i = 1, 2$$

Layer 2. Every node in this layer is a circle node labelled Π so as to multiply the incoming signals and send the product out. ω_i serves as the output of this layer, which denotes the firing strength of each rule. It is calculated by:

$$O_{2,i} = \omega_i = \mu_{Ji}(a)\ \mu_{Ki}(b) \quad \text{for } i = 1, 2$$

Layer 3. Symbolized by an N notation, each fixed node in this layer is a circle node. The output of this layer, $\overline{\omega}_i$, denotes the ratio of the i^{th} node firing strength to the sum of the firing strength of all rules. The output of this layer is known as normalized firing strength, which is expressed as:

$$O_{3,i} = \overline{\omega}_i = \frac{\omega_i}{\sum \omega_i} = \frac{\omega_i}{\omega_1+\omega_2} \quad \text{for } i = 1, 2$$

Layer 4. Each adaptive node in this layer is a square node calculating the contribution of the i^{th} node towards the overall output. Parameters in this layer are referred to as consequent parameters, f_i represents the fuzzy if-then rules with $\{p_i, q_i, r_i\}$ being the parameter set. It is represented as:

$$O_{4,i} = \overline{\omega}_i f_i = \overline{\omega}_i (p_i a + q_i b + r_i) \quad \text{for } i = 1, 2$$

Layer 5. The final layer has a single fixed circle node symbolized by a Σ notation. It computes the overall output of the network by calculating the summation of the contribution of all rules:

$$O_{5,i} = \sum \overline{\omega}_i f_i = \frac{\sum \omega_i f_i}{\sum \omega_i} = f = \textit{final output} \quad \text{for } i = 1, 2$$

Appendix B – *List of abbreviations used in this paper*

Abbreviation	Definition
CPS	Cyber-Physical System
CS	Cyber Space
DT	Digital Twin
DTIS framework	Digital twin-based inbound synchronization framework
FR	Forward-reserve
H-container	Handling Container in Physical Internet
HCL	Hyperconnected City Logistics
ICT	Information and Communication Technologies
IoT	Internet-of-things
ITS	Intelligent Transportation System
ML	Machine learning
P-container	Packaging Container in Physical Internet
PI	Physical Internet
PI-container	Containers handled in Physical Internet
PI-handler	Material handlers in Physical Internet
PI-hub	Distribution hubs in Physical Internet

PI-mover	Vehicles and carriers responsible for transporting, handling and storing the PI-containers
PI-order	Orders in Physical Internet
PI-network	Logistics network of the Physical Internet
PI-node	A node in the logistics network of the Physical Internet
PI-SKU	Stock Keeping Units handled in Physical Internet
PS	Physical Space
RFID	Radio Frequency Identification
SKU	Stock Keeping Units
T-container	Transportation Container in Physical Internet
TIS	Total Inbound Synchronization
TMS	Transportation Management System
OFR	Order fulfillment and replenishment
OMS	Order Management System
WMS	Warehouse Management System
WPS	Warehouse Postponement Strategy

Highlights

- This is the first study to develop operating strategies streamlining PI-container handling
- A Total Inbound Synchronization Strategy is proposed for multi-level synchronizations
- A joint PI-SKU replenishment and PI-order fulfilment problem at city PI-hubs is formulated
- Digital-twin, IoT and machine learning algorithms are integrated into the proposed framework
- Results reveal significant reduction in traveling distance and number of visits to storage areas