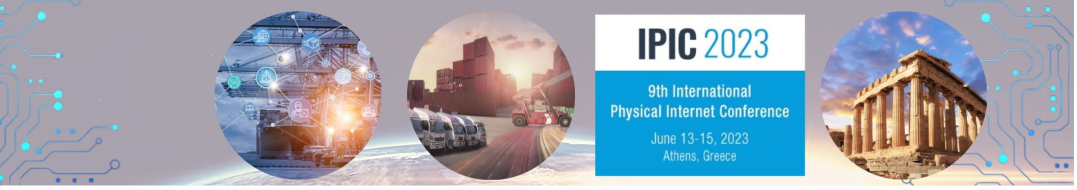

A Proposal and Evaluation of a Digital Twin Framework for PI-Hubs using Re-enforcement Learning based Multi-Agent Systems Model

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Abstract: *The Physical Internet (PI) provides a way to enhance logistic network performance spanning the social, financial, and environmental domains. Hyperconnected City Logistics (HCL) encompasses logistic activities arising within PI across the greater metropolitan region. To enable PI to operate as an open, collaborative network, a standard form of data exchange amongst network participants is required.*

GS1 Scan 4 Transport's Digital Link (GS1DL) is a data sharing standard enabling tracking of products through the supply chain. This includes the realization of shorter and more consistent processing times at goods transfer points within facilities. The potential impact of utilizing the GS1DL within a collaborative environment is yet to be investigated. Digital Twin (DT) enables real-time monitoring of assets' statuses and tracking of containers, leading to a real-time virtual representation of the physical facility, integrating the various computer network systems.

This study proposes a novel Digital Twin framework for PI-Hubs, integrating a re-enforcement learning based multi-agent system (MAS). Real-time location of goods flowing through the facility will be used by machine learning to predict the likelihood of containers arriving at the outbound docks, to be subsequently re-allocated to outbound vehicles via a reallocation optimization algorithm. The evaluation of the DT framework on PI-Hub's operational performance will include the assessment of Scan4Transport's Digital Link standard.

Keywords: *PI-Hubs, Data Standards, Automation, Collaboration, Operational Planning, Digital Twin, Hyperconnected City Logistics, Goods to Vehicle Allocation Problem*

Conference Topic(s): *autonomous systems and logistics operations (robotic process automation, autonomous transport/drones/AGVs); distributed intelligence last mile & city logistics; material handling; Modularization; omnichannel & e-commerce logistics; PI modelling and simulation; hubs; technologies for interconnected logistics (Artificial Intelligence, IoT, machine learning, digital twins); vehicles and transshipment technologies.*

Physical Internet Roadmap *(Link): Select the most relevant area(s) for your paper:* ☒ *PI Nodes,* ☐ *PI Networks,* ☐ *System of Logistics Networks,* ☒ *Access and Adoption,* ☐ *Governance.*

1 Introduction

The Physical Internet (PI) provides a way to enhance logistic network performance spanning the social, financial, and environmental domains. PI-Hubs are key components for PI's functional performance, serving as goods transshipment facilities among numerous carriers, where goods are transshipped between vehicles operating across the network (Ballot et al., 2021).

Hyperconnected City Logistics (HCL) embodies logistic activities arising within PI across the greater metropolitan region. This includes servicing of ecommerce based last mile deliveries (LMD) to homes via a nearby PI-Hub, such as an access or local hub (Crainic & Montreuil, 2016).

To enable PI to operate as an open, collaborative network, a standard form of data exchange amongst network participants is required. Currently, majority of logistic service providers (LSPs) utilise their own standards for data encoding and sharing, such as: the final destination, handling requirements and status updates. Upon receipt of inbound goods from various carriers each operating with their own proprietary standards & methods for sharing information, a PI-hub will face significant variability in processing times. This uncertainty may lead to adverse impacts on proceeding operations such as sorting, consolidating and loading of outbound vehicles.

Moreover, in the absence of a unified data standard, a PI-Hub may be forced to adopt its own approach, resulting in additional processing times for carriers operating outbound vehicles who will need to decode PI-Hub's data standard to extract the relevant information. Without the utilization of a unified data standard, collaboration within PI networks will be significantly impeded.

GS1 Scan 4 Transport's Digital Link (GS1DL) is a data sharing standard enabling tracking of products through the supply chain. This includes the realization of shorter and more consistent processing times at goods transfer points within facilities. The potential impact of utilizing the GS1DL within a collaborative environment is yet to be investigated (*Scan4Transport Pilot Report*, 2021). Therefore, this research seeks to investigate its role in facilitating efficient operations within PI-Hubs.

To enable optimal operational decision making amidst high volume of goods expected to flow through PI-Hub facilities, autonomous real-time decision making is necessary. There has been significant advancement of computational capabilities to process large amounts of data via sensors attached to the assets such as: identification & tracking sensors (eg: radio frequency identification tags (RFID) & 2D-QR); & environmental sensors (eg: temperature, vibration, gas, light & humidity) (Taniguchi et al., 2020; Tran-Dang et al., 2020). Further, with advancement in geographic information systems (GIS), it is possible to visualise, on a real-time basis, the data captured and the resulting analysis.

Digital Twin (DT) enables real-time monitoring of assets' statuses and tracking of containers, leading to a real-time virtual representation of the physical facility, integrating the various computer network systems such as: the Warehouse Management Systems (WMS), Transportation Management Systems (TMS), & Enterprise Resource Planning (ERP) (Taniguchi et al., 2020). This can assist in making more optimized operational decisions. There has been limited investigation of DT within PI-hubs.

Thus, this study proposes a novel Digital Twin framework for PI-Hubs, utilising a re-enforcement learning based multi-agent system (MAS). Real-time location of goods flowing through the facility will be used by machine learning to predict the likelihood of containers arriving at the outbound docks, to be subsequently re-allocated to outbound vehicles. The evaluation of the DT framework on PI-Hub's operational performance will include the assessment of Scan4Transport's Digital Link standard.

1.1 PI-Based Collaboration Focused Studies

There have been a number of studies investigating ways of enhancing collaboration within PI networks. For example, ICONET sought to develop a cloud-based PI-framework and platform, building communications hub software enabling collaboration amongst various parties within the SCN (*New ICT Infrastructure and Reference Architecture to Support Operations in Future PI Logistics Networks*, 2019). Similarly, CO-GISTICS was an European project leveraging cooperative intelligent transport systems to enhance sustainability performance of networks within seven European logistics hubs. Further, PLANET, an EU project, designed a platform for collaborative planning called the Symbiotic Digital Clone. It serviced TENT-T Corridor participants (Zuidwijk et al., 2022).

Scan4Transport, a subsidiary of Global Standards One (GS1) has developed a novel 2D QR code called the Digital Link (GS1DL). This technology can foster collaboration amongst network participants along with enabling digital twin applications via its tracking and traceability functionality. The QR code can be encoded in a standardized way, critical product & delivery information including: origin, destination, & delivery handling requirements (*Encoding Transport Process Information - GS1 Implementation Guideline*, 2021). Furthermore, each time the code is scanned, the location of the scan (and thus the associated goods) is logged, enabling real-time spatial and temporal updates. This updated data can aid digital twin applications including data visualization and real-time operational decision making.

To date, no studies have been conducted towards assessing its suitability for operationalizing collaborative SCNs and its role in enabling digital twin functionalities (*Scan4Transport Pilot Report*, 2021). Its ease of adoption amongst users and enabling functionalities makes it a powerful candidate for assisting in the manifestation of PI. Thus, this research will focus on GS1DL's role in enhancing PI-Hub operations, both with respect to data transmission between carriers and the PI-Hub operator, and in enabling digital twin functionality via real-time operational decision making.

2 Problem Definition

A PI-Hub facility has its own outbound vehicles that services deliveries. It receives orders that it fulfills via its storage facility along with serving as a transhipment hub for goods incoming from inbound vehicles. Located within an urban area, thus constrained by size, it is likely to experience congestion and variable travel times of containers flowing through its facility and variability in inbound vehicle schedules due to urban traffic (McKinnon, 2015). Further, bottlenecks arise in crossdocks during loading of the vehicles at the outbound docks (Pach et al., 2014).

Within such a turbulent environment, real-time operational decisions need to be made including the allocation of goods to their respective outbound vehicles. Without real-time tracking of the goods, enabling real-time decision making, goods delayed due to congestion or late arrival at inbound docks, may result in sub-optimal loading factors for outbound vehicles and longer dwell times. Tracking can arise with the use of GS1DL, whereby the QR codes are scanned as the goods enter/exit through the facility at key junctures, including but not limited to: inbound & outbound docks; sortation area; & storage areas. A re-enforcement learning based algorithm can then be utilised to determine the likelihood of the containers arriving at the outbound docks, which in turn informs the goods to vehicle re-allocation model. Further discussion is provided below.

3 Methodology

Figure 1 provides an overview of the proposed conceptual framework integrating the re-enforcement learning (RL) based predictive algorithm and the container to vehicle re-allocation algorithm. The RL algorithm is trained on past historical data, based on real operational data to be gathered from a large logistics company. It can also be simulated via discreet event simulation.

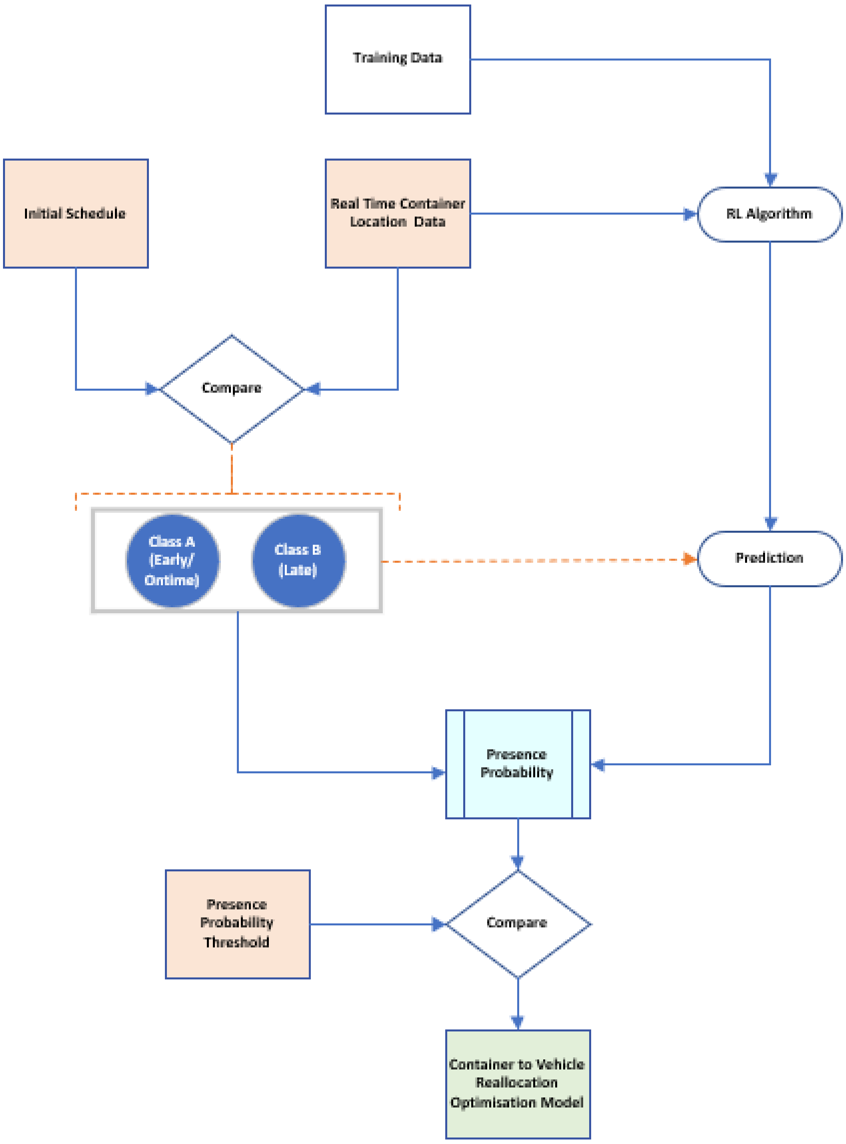

Figure 1 - Conceptual Framework of Re-enforcement Learning based Predictive Model and Container to Vehicle Reallocation Optimisation Model. Adapted from Prakoso et al. (2022).

Initial schedules of the inbound and outbound vehicles are used to allocate containers to respective outbound vehicles. Once at the facility, the containers' real time location is logged via scanning of the GS1DL code attached to each container. The captured real-time location is used to predict the estimated time of arrival at the outbound dock where the container is to be loaded onto the allocated outbound vehicle. This enables a comparison with the initial schedule, and helps classify the container into one of two categories: Class A – where the container is expected to arrive earlier or on time as per initial schedule; or Class B – where the container is expected to arrive later than initial schedule. Subsequently, trained on historical data, RL algorithm assigns a presence probability for that container, reflecting the likelihood of it being in the class specified. Only those classified as late, ie in class B, and above a pre-defined presence probability threshold will be considered for the container to vehicle reallocation algorithm.

Prakoso et al. (2022) implemented a similar methodology for a chemical plant, dealing with the slot reallocation problem, where vehicles were reassigned to docks based on their ETA at the facility. Inspired by Prakoso et al. (2022), this study seeks to utilise presence probabilities for optimally allocating goods to vehicles based on their real-time location within the facility.

Further, Figure 2 provides an overview of how the RL based predictive model and reallocation optimization models are integrated with the multi-agent system. Real data is used to train the machine learning model that predicts the presence probability of the arriving goods at the outbound docks. Based on the presence probability of the arriving containers, the goods are (re)allocated to vehicles. Furthermore, in between these optimal reallocations, there may be perturbances that arise, including equipment breakdown within the facility or dock malfunction, resulting in inaccessibility to the respective outbound vehicle. This may mean that the containers may need to be re-allocated to other vehicles.

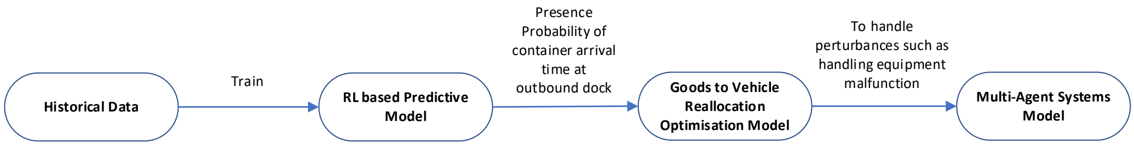

Figure 2 - Overview for integrating re-enforcement learning based Predictive Model, Goods to Vehicle Reallocation Optimisation Model, and the Multi Agent Systems Model

Figure 3 outlines the proposed multi-agent systems framework for handling such perturbances. Containers provide their real-time location data via the periodic scanning of the GS1DL QR code, which gets shared with the Physical Internet Management System (PIMS, as introduced by Tran-Dang & Kim (2018)). PIMS also receives operational status updates for the outbound docks and the AGV transporters, enabling optimal reallocation of the containers to the outbound vehicles under perturbances.

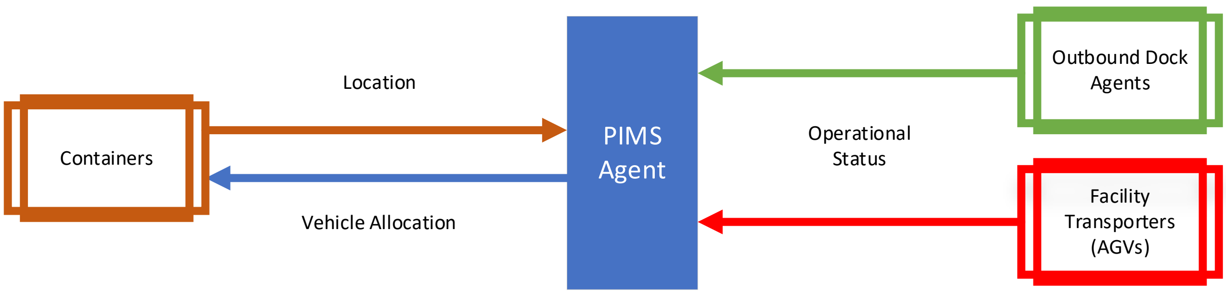

Figure 3 - MAS Architecture for handling perturbances

Three scenarios will be considered. The base case will be compared against two scenarios. The base case encompasses non-digitised, manual operations within the hub, including unique electronic data interchange (EDI) between each carrier & hub operator. Such characteristics may result in delayed loading/unloading times & sub-optimal vehicle scheduling, consolidation, routing and loading of containers. The process is summarised in Figure 4.

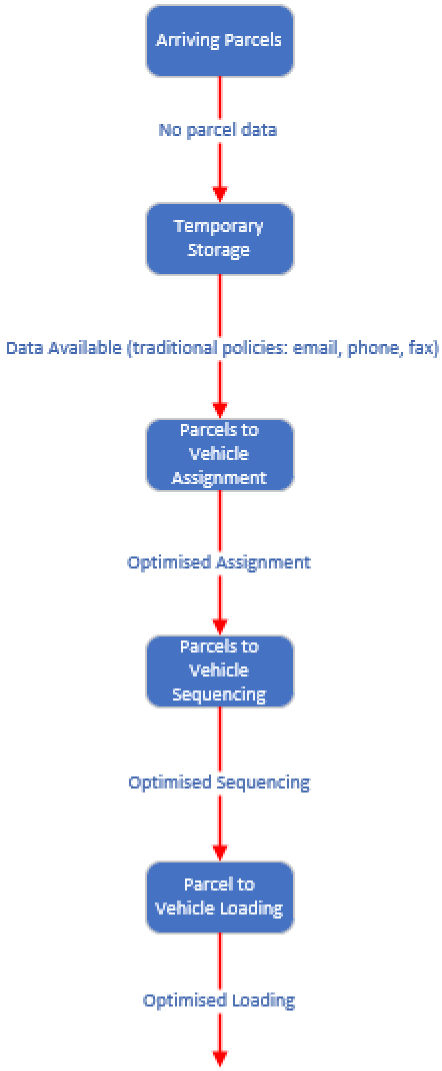

Figure 4 - Base Case: Facility without GS1DL, using preestablished electronic data inter-exchange with carriers and shippers to exchange data (Optimisation Model) and no real-time tracking through facility to enable parcel to vehicle reassignment.

The first scenario will be where GS1DL is utilised for EDI between carriers and hub operators The shorter and more consistent handling times during the product transfer between the vehicle and the hub should enable lower storage and personnel costs. Furthermore, the first scenario will include the utilisation and assessment of the Digital Twin framework for container tracking and the monitoring of assets operating within the PI-hub. DT is enabled via the scanning of the GS1DL QR code at key processing points within the facility. Figure 5 encapsulates this process.

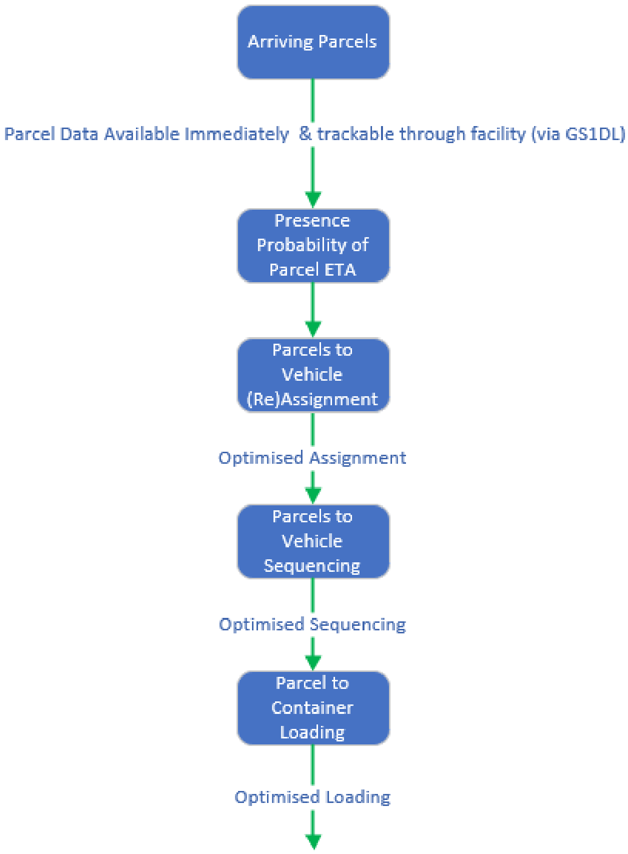

Figure 5 - Carriers and facility are GS1DL enabled with location tracking of goods, utilising the DT framework. Thus, presence probability of container ETA at outbound dock can be formulated via RL model, informing the container to vehicle assignment model.

The second scenario will consider internal perturbations including facility transporter and dock malfunctions. The objectives of the model will be to minimise makespan and maximise the volumetric capacity utilisation of outbound vehicles.

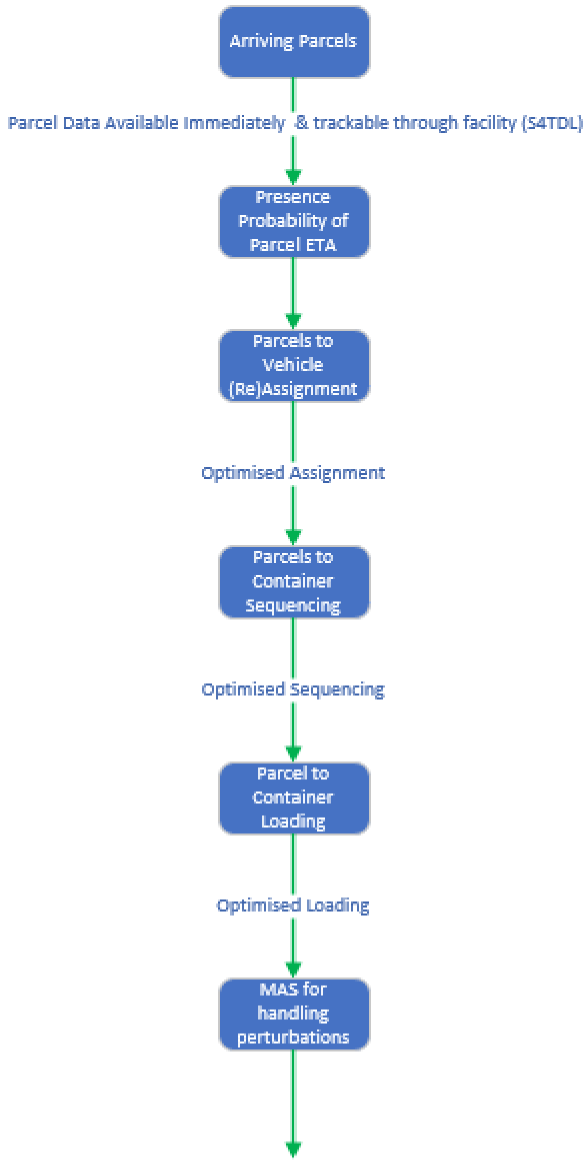

Figure 6 - Carriers and facility are S4TDL enabled with internal perturbations of facility transporter and dock malfunctions (Multi-Agent-System).

4 Conclusion

Harnessing the potential of Digital Twin technology, PI-Hubs can be greatly benefited. GS1DL is a strong candidate for enabling the use of such technology within the fast paced urban environments that PI-Hubs are expected to face. A novel DT framework integrating re-enforcement learning and optimization models has been proposed. Real-time location of goods flowing through the facility are used by machine learning to predict the likelihood of containers arriving at the outbound docks, to be subsequently re-allocated to outbound vehicles using the reallocation optimization model. Perturbances such as equipment and dock malfunctions are handled via the proposed multi-agent system.

It is expected that with real-time temporal & spatial monitoring of the assets within the facility, coupled with a common data standard enabling shorter and more consistent processing times at transfer points, greater accuracy of predicting container ETAs at the loading docks should arise. This in turn is expected to enable the attainment of greater outbound vehicle loading factors with lower dwell times. Hub operators will be the primary beneficiaries of this study, coming to understand the operational impact of integrating Digital Twin technology & GS1DL into their facility's operations.

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