RESEARCH PAPER

Towards Automated Physical Internet System: Simulations of Two Privacy-Protecting Routing Protocols

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ABSTRACT

The Physical Internet (PI) is an innovative logistics framework designed to improve the efficiency and sustainability of logistics systems through extensive collaboration. In this paper, we introduce two decentralised routing protocols in PI, focusing on their performance and impact on privacy by minimising data sharing. We use Agent-Based Modelling (ABM) and Monte Carlo (MC) simulations to evaluate the effectiveness of the protocols in optimising route quality, monetary costs and external costs in a realistic business setup at the Belgian scale. In addition, a sensitivity analysis was performed to assess the impact of response delays in a logistics network. We find that at our problem scale, trucks are the preferred mode when only monetary costs are considered. Our findings also illustrate the significant impact of response delays on the efficiency of route planning and the need for automation in improving the reliability of PI systems. We further suggest that trust issues should be one of the primary focuses for the current stage of PI research.

KEYWORDS
Physical Internet; Agent-based modelling; Shortest-path algorithm; Automation; Privacy

1. Introduction

Physical Internet (PI) is a visionary logistics concept. First proposed by Montreuil, Meller, and Ballot (2010), PI aims at building an open and interconnected network to make the logistics system more efficient and sustainable. Similar to the other concepts of smart logistics like synchromodality, PI also relies on collaboration, but even more extensively. In synchromodal transport, for instance, a majority of previous studies focus on optimisation (Ambra, Caris, and Macharis, 2019), i.e., utilising the data, where data availability is naturally assumed. However, with decades of research, businesses have not reached the level of collaboration as assumed, and the theoretically proven benefits are far yet to be achieved in reality.

On the other hand, in PI, the information system and architecture that facilitates the interconnection have become one of the fundamental building blocks. In a comprehensive review of PI, Treiblmaier *et al.* (2020) conduct a thematic analysis, in which

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two of the seven themes (data exchange and cooperation model) are closely related to this issue.

Many studies have shown the distinctive features of PI and its solutions. Sun, Cassan, and Macharis (2023) summarise the two most prominent features of the PI information system: interconnection and decentralisation. By this design, at the individual level, more devices with a higher activeness level are to be employed (Sallez *et al.*, 2016; Tran-Dang and Kim, 2021), while at the network level, the PI system is expected to be more integrated and service-oriented (Kubek and Więcek, 2019; Pan, Zhong, and Qu, 2019).

Such a high level of interconnectivity and automation challenges the trust among the participants. Actually, the trust issue has been gaining increasing attention in PI (Ballot, Montreuil, and Zacharia, 2021). It is quite likely that stakeholders will be imminently confronted with the situation of entrusting an automated agent that has access to the company data to make decisions and collaborate with other entities on their behalf. Therefore, it is important to depict the characteristics and effects of PI. Many previous studies have investigated this aspect, but in this paper, the analysis is carried out from a different angle in order to answer the following question: *How do the privacy-protecting PI routing protocols illustrate the characteristics of PI?*

We developed two routing protocols following the principle of PI and minimal data sharing. Innovatively, the protocols in this paper make unique contributions by:

(1) Integrating reservation considerations and conducting sensitivity tests on the response time of reservation (automation level) and route quality;
(2) Ensuring that only the essential data is shared for the purpose of making routing decisions in two different strategies;
(3) Using realistic monetary cost and external costs as the optimising objective to address both business and sustainability concerns;
(4) Including empty containers pick-up/drop-off and round trips of empty trucks into optimisation.

In the remainder of this paper, Section 2 will provide an overview of PI and routing problems in PI, along with a review of the relevant literature; Section 3 will introduce the problem, two routing protocols as potential solutions, and outline the simulation methodology.; Section 4 will carry out two experiments to test the performance and sensitivity of the two routing protocols; Section 5 will summarise the findings and conclude the paper.

2. Literature Review

2.1. *PI foundation*

In the initial proposed design of PI, Montreuil, Meller, and Ballot (2010) present three types of physical elements of PI - PI containers, PI nodes and PI movers, which still remains the standard framework of PI. The vision is that goods are encapsulated in standardised smart PI containers of different sizes and transported by PI movers among PI nodes. During the transit, the smaller PI containers can be shuffled and reconsolidated into larger PI containers. This assumption creates a novel logistic scenario that incurs changes in the entire logistics system for researchers to verify the theory and optimise.

Initial PI logistics research focuses on the concept design and proof of concept.

Sarraj *et al.* (2014b) compare the concept of PI and digital Internet (DI), and the improvement of PI is proved in a stylised model. There are also studies investigating the PI container specifications from the engineering point of view (Landschützer, Ehrentraut, and Jodin, 2015) and size for consolidation Lin *et al.* (2014). Maslarić, Nikoličić, and Mirčetić (2016) consider PI as the answer to Industry 4.0 from the logistics sector.

Later on, more comprehensive and detailed research is carried out to validate the benefits of PI in various contexts. Sarraj *et al.* (2014a) build a first full simulation using Agent-based Modelling (ABM) for PI and prove its potential of reducing flow travel and transport distance. Walha *et al.* (2016) propose a few approaches for an optimising problem in a multimodal PI hub. Habibi, Allaoui, and Goncalves (2018) highlight the importance of collaborating in PI, demonstrated with numerical experiments. Zheng, Beem, and Bae (2019) also incorporate the concept of PI and the share of physical assets into business-as-usual to improve the performance. Briand, Franklin, and Lafkihi (2022) present an auction-based routing protocol for PI that integrates payment function. Ji, Zhao, and Ji (2023) enable PI in a conventional supply chain and concluded that PI significantly enhances the resilience and sustainability level.

Another pillar of PI is the information system that ensures interconnectivity, since PI relies on data availability more heavily than other previous logistics concepts. In a recent review of PI information system (Sun, Cassan, and Macharis, 2023), it is found that the information system design is practical on a smaller scale while remaining conceptual on a larger scale with a clear tendency of decentralisation. It is also notable that trust has become a recent concern to tackle (Ballot, Montreuil, and Zacharia, 2021).

2.2. *Activeness and concerns about trust*

Activeness is one of the particularly emphasised characteristics of PI. It is interchangeable with intelligence or smartness but is more expressive because activeness stresses the active role it functions when interacting with other external systems (Sallez *et al.*, 2016). In Sallez *et al.* (2010), activeness refers to the extent to which a product/system can interact with other products or supportive systems and proactively provide pertinent information for better decision-making. Sallez *et al.* (2016) also investigate a higher activeness level example in smart PI containers where containers can perform grouping strategy for consolidation. Other cases of distributed intelligence cases are the employment of smart sensors and Internet of Things (IoT) devices (Tran-Dang, Krommenacker, and Charpentier, 2017; Pal and Kant, 2020).

Such individual-level intelligence supports smarter and more autonomous systems (Gumzej, 2023). Pan, Zhong, and Qu (2019) prospects a smart product-service system in PI that allows greater interoperability. Luo, Tian, and Kong (2021) demonstrate the benefits of integrating smart PI containers and vehicles into a cloud-based system. However, on the other hand, this activeness also raises concerns about trust (Klumpp and Zijm, 2019) since more and more decisions are made automatically on behalf of humans.

As trust is gaining increasing attention, other issues that can affect trust are identified, such as the amount of data shared (Cassan *et al.*, 2023) and system reliability and security (Fahim *et al.*, 2021). Taking advantage of the decentralised nature of PI, researchers have devised many architectures to address the trust issue. Betti *et al.* (2019) apply blockchain and smart contract to PI and prove the feasibility. Hasan *et al.* (2021) analyse the position of blockchain for PI network and propose two architectures.

While the industry is during the transition from manual to automated operations, it is a crucial juncture to elucidate the contribution of PI and its impacts on business operations and overall performance. Thus, it is important to investigate the trust concerns and the automation impacts. However, to the best of our knowledge, there is yet a study that inspects this issue from the angle of routing algorithms in practical operations rather than the information system.

2.3. *Multimodal container transportation*

Route planning for containers in multimodal logistic networks is a challenging task. The objective is to find efficient and sustainable routes by utilising the resources across the network. A few concepts such as multimodal, intermodal, co-modal and synchromodal transport have evolved in the research (SteadieSeifi *et al.*, 2014), with collaboration, optimality and flexibility being the focuses.

The route planning can be considered as the shortest-path problem, which aims to find a path between two given vertices in a graph (Madkour *et al.*, 2017). There are classic shortest-path algorithms such as Dijkstra's algorithm (Dijkstra, 1959) and A* (Hart, Nilsson, and Raphael, 1968). However, planning routes can be more complicated for a multimodal network. This is due to the fact that the edges represented by scheduled transport modes are associated with time factors, making the graph dynamic. Moreover, in realistic cases, the decision is often made based on considering multiple objectives. An effective treatment proposed by Vanhove and Fack (2012) is to use a k-shortest paths algorithm to generate a list of paths and select the desired one(s) afterwards. Therefore, numerous studies have been developing exact and heuristic methods to tackle this problem.

Chang (2008) present the 'multiobjective multimodal multicommodity flow problem (MMMFP)'. They solve this NP-hard problem by using relaxation and decomposition techniques to break it down into subproblems. Tao *et al.* (2017) explore the route planning problem by developing a column generation heuristic with overall route costs as the optimising objective. Xiong and Wang (2014) propose a genetic algorithm to find k-shortest paths on a multimodal network. Mes and Iacob (2016) introduce a multi-objective routing algorithm for synchromodality and a control tower as the architecture.

Although it has been nearly 15 years since PI was extensively researched, the routing problem in PI has only gained popularity in recent years. Sarraj *et al.* (2014a) build an initial PI simulation model, where A* algorithm is employed for routing containers. Fazili *et al.* (2017) compare PI and conventional logistics on a unimodal network considering the consolidation problem with routing being part of the optimisation. Briand, Franklin, and Lafkihi (2022) propose an auction-based routing protocol incorporating payments, demonstrated through a simulation of truck routing. Li *et al.* (2022) address the issue of idle runs of container trucks and develop a heuristic to solve the PI-based selective vehicle routing problem that aims to transport containers in a relay manner. Achamrah, Lafkihi, and Ballot (2023) introduce a dynamic PI routing protocol that is also responsive to disruptions.

In summary, the shortest path problem has been well studied, while there is still great potential for research in PI, especially in its complex operational scenarios. Therefore, we believe that the following research gaps exist in PI: 1) most of the research only focuses on a single transport mode,, 2) the overall performance improvements are often the primary concern. Even though PI often implies the need for deeper collaboration, the consequent trust issue is often neglected, and 3) potentially disruptions in practical implementations such as reservation process and delays are mostly not considered.

3. Methodology

3.1. *Problem description and modelling*

Hinterland container transport plays a pivotal role in facilitating the movement of loaded and empty containers between maritime terminals and inland locations. In the context of *imports*, loaded containers are typically picked up at a terminal after being offloaded from ships, transported to hinterland locations, and then stripped of their cargo contents. Subsequently, the emptied containers are returned to depots for repositioning. Conversely, for *exports*, empty containers are collected from depots, transported to hinterland locations where they are loaded with cargo, and then delivered to terminals for shipment.

For both scenarios, containers may undergo storage or transhipment at hubs, facilitating seamless transitions between different transport modes. This intricate process involves coordination among various stakeholders, including shippers, carriers, expediters, and terminal operators.

We consider the shortest-path problem in the above context. A shortest path needs to be planned for a shipment on a network consisting of a set of physical locations N and a set of links K among the locations. The problem formulation relies on the following sets:

- N is the set of physical locations and $N = \{1, 2, ..., |N|\}$. Specially, $N_0 = \{Loc_P, Loc_D\}$.
- K is the set of movers and $K = \{1, 2, ..., |K|\}$. Each mover k has to depart from an initial departure location n_o^k before the transportation and return to a final arrival location n_d^k after. For trains and barges, n_o^k and n_d^k correspond to the same departure and arrival location as scheduled (thus does not take effect). For trucks, n_o^k and n_d^k are the base of the truck company, and $n_o^k = n_d^k$.

The sets of parameters are:

- t_i^k denotes the arrival time of mover k at location i
- f_{ij}^k represents the capacity that the mover k can carry from i to j
- d_{ij}^k is the distance that for mover k to travel from i to j. It is associated with k since movers of different modes can use different physical networks (i.e. road, railway and inland waterway)
- q is the number of containers in this shipment to be transported
- h is the handling time that includes time spent on container loading, unloading, stuffing and stripping

The decision variables are:

- X_{ij}^k is a binary variable. $X_{ij}^k = 1$ the shipment is transported by mover k from location i to j.
- Y_{ij}^k is a binary variable. $Y_{ij}^k = 1$ when mover k is planned to travel from location i to j.

For both import and export flows, we can define a shipment with the following concepts:

- Planning time (T_0) defines when the shipment planning takes place (e.g. for an import, when the container is released at the maritime terminal).
- Pick-up location ($Loc_P, Loc_P \in N$) is the physical location where the container should be picked.
- Load/Discharge location ($Loc_C, Loc_C \in N$) for exports, is the physical location where the container will be stuffed/loaded with cargo; for imports, it is where the container will be stripped/discharged.
- Drop-off location ($Loc_D, Loc_D \in N$) is the physical location where the container should be dropped off.
- Latest delivery time T_d specifies the latest delivery time of shipment. It is a soft constraint, and the violation of it can incur punishment. In the case of import shipments, the return of empty containers should also be considered.

A route can be represented by a set of transport legs $S = \{X_{ij}^k, Y_{ij}^k | i, j \in N, k \in K\}$. $\{X_{ij}^k\}$ specifies how the shipment is transported from the pick-up location Loc_P to the load/discharge location Loc_C, and subsequently to the drop-off location Loc_D. On the other hand, $\{Y_{ij}^k\}$ describes the movements of mover k. For trucks, X_{ij}^k and Y_{ij}^k can make a difference, because, in addition to transporting the shipment, the movements of empty trucks between their bases and pick-up/drop-off locations are also considered by Y_{ij}^k.

The problem can be formulated by the following model:

Objective:

$$\begin{aligned} \min \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} C^{INT}(X_{ij}^k, d_{ij}^k) + \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} C^{EXT}(Y_{ij}^k, d_{ij}^k) \\ + \sum_{k \in K} C^{TW}(t_{Loc_D}^k) \end{aligned} \tag{3.1}$$

Subject to:

$$\sum_{k \in K} \sum_{j \in N} X_{Loc_P j}^k = \sum_{k \in K} \sum_{j \in N} X_{Loc_C j}^k = \sum_{k \in K} \sum_{j \in N} X_{j Loc_D}^k = q \tag{3.2}$$

$$\sum_{k \in K} \sum_{i \in N} X_{ij}^k Y_{ij}^k = \sum_{k \in K} \sum_{i \in N} X_{ji}^k Y_{ji}^k, \forall j \in N \setminus N_0 \tag{3.3}$$

$$\sum_{i \in N} Y_{n_o^k i}^k = \sum_{i \in N} Y_{i n_d^k}^k, \forall k \in K \tag{3.4}$$

$$f_{ij}^k X_{ij}^k - q X_{ij}^k \geq 0, \forall i, j \in N, \forall k \in K \tag{3.5}$$

$$\sum_{k\in K}\sum_{j\in N} X_{ij}^k Y_{ij}^k t_i^k - \sum_{k\in K}\sum_{j\in N} X_{ji}^k Y_{ji}^k t_i^k \geq 2h, \forall i \in N \setminus \{Loc_P, Loc_C, Loc_D\} \tag{3.6}$$

$$\sum_{k\in K}\sum_{j\in N} X_{Loc_C j}^k Y_{Loc_C j}^k t_{Loc_C}^k - \sum_{k\in K}\sum_{j\in N} X_{jLoc_C}^k Y_{jLoc_C}^k t_{Loc_C}^k \geq 3h \tag{3.7}$$

$$\sum_{k\in K}\sum_{j\in N} X_{Loc_P j}^k Y_{Loc_P j}^k t_{Loc_P}^k - T_0 \geq h \tag{3.8}$$

$$X_{ij}^k, Y_{ij}^k \in \{0,1\}, \forall i,j \in N, \forall k \in K \tag{3.9}$$

The objective function (3.1) is composed of three parts, internal costs (C^{INT}), external costs (C^{EXT}) and time window violation punishment (C^{TW}). Internal costs cover empty truck runs, cargo transport costs and storage costs at hubs. It is thus relevant to X_{ij}^k and d_{ij}^k. External costs can be calculated by the mover's travels, for which it is related to Y_{ij}^k and d_{ij}^k. Lastly, the model tries to respect the soft time window. If the time window is violated, a punishment will be incurred depending on the deviation of the delivery time.

For the constraints, (3.2) and (3.3) ensure that all the shipment is transported and the shipment flow is balanced in every location except for Loc_P and Loc_D. (3.4) and (3.3) ensure the movers depart from the initial departure location and return to the final return location, with a balanced mover flow in every intermediary location. (3.5) imposes that the mover must have enough capacity to transport the shipment. (3.6) ensures enough handling time for loading and unloading operations at transit hubs. For Loc_C, (3.7) specifies that an additional time of h for stuffing or stripping operations. While for Loc_P where the shipment is initially picked up, (3.8) makes sure that there is enough time for loading operation. The time constraint at Loc_D, however, is conditioned in C^{TW} in (3.1) depending on the need to model the time window. (3.9) defines binary decision variables.

Uniquely, in our research, the process of reservation is also considered in the optimisation. The accessibility of up-to-date data is not assumed. Thus, reserving the optimal routes causes delays because transporters' responses can determine the feasibility of routes.

We highlight the important roles of the transport service provider and the expeditor in the freight container transportation process within the PI framework. The efficiency and effectiveness of these roles heavily depend on the level of software integration and automation within the system. The reactiveness of both players, particularly in terms of requesting and managing transport services, is directly influenced by the degree of software integration and automation implemented within their respective operations. A higher level of integration and automation enables smoother communication, faster decision-making, and streamlined processes between the transport service provider and the expeditor. Conversely, lower levels of integration and automation may lead to delays, inefficiencies, and potential bottlenecks in the transportation process. In our assessment, we aim to investigate how different levels of software integration and automation impact the overall performance of the system, particularly in terms of route quality (see section 3.6).

Hence, two routing protocols have been proposed: Communication-based Physical Internet Routing (CPIR) and Federared Physical Internet Routing (FPIR). These protocols aim to enable efficient planning and booking of transport routes, optimising the movement of containers between ports and hinterland locations, while keeping sensitive information private.

In Cassan *et al.* (2023), the information to be shared for routing is divided into two aspects: capability and capacity. Capability refers to the logistics services that an entity can offer, while capacity is the real amount of resources that the entity has, which is considered sensitive information. FPIR relies on federation services that only require capability information, without sharing the actual capacity. For CPIR, only basic location information is needed, with route planning conducted via peer-to-peer communication (Sun, Cassan, and Macharis, n.d.).

3.2. *Graph formation*

In this study, we base our foundational concepts on the definitions provided in Montreuil, Meller, and Ballot (2010), particularly focusing on the PI Node and its associated capabilities, such as PI Hub, PI Store, and PI Composer. Expanding upon these established definitions, we introduce two novel elements aimed at enriching the understanding and functionality of the network architecture. Firstly, we introduce the concept of a Scheduled Mover, which denotes a scheduled connection facilitated by a mover between two PI Nodes within the network, typically a train or an inland waterway vessel. This Scheduled Mover enhances predictability and reliability in freight transportation operations. Secondly, we introduce the notion of a Flexible Mover, characterised by its ability to access any PI Node within the network, albeit constrained by predefined working hours. This flexibility offers adaptability in routing decisions, particularly in dynamic logistical environments.

Therefore, the graph representation of the network is composed of nodes, representing physical locations with the aforementioned capabilities, and the two mover types act as edges, facilitating connections between these nodes to optimise freight transportation within the Physical Internet framework.

3.3. *Communication-based PI Routing (CPIR) Protocol*

CPIR is a peer-to-peer routing protocol for PI that is based on communication. It considers the messaging itself to be the computing process. The purpose of CPIR is to plan routes with as little data shared as possible.

3.3.1. Assumption

CPIR was initially designed for a trustless network. This is particularly relevant for PI because the pilot experiments of PI entail a community as the critical mass to demonstrate its benefits. However, the participants may be unfamiliar with, competitors or even hostile to each other. Therefore, in order to plan a route utilising the resources of the community, the following assumptions are made:

- There is no data space where participants share data
- The participants are connected to the network where only CPIR messages can be transmitted

- The knowledge of other participants is their existence and the means to contact them through the network
- No raw data is willing to, nor will be shared. Rather, they only share processed data in messages, i.e. the list of candidate routes they planned locally. This makes it almost impossible for outsiders to deduce their private information
- When a complete route is planned, each participant is only aware of the part that is directly relevant to them

3.3.2. Route planning

In CPIR, each physical node contains three types of agent: *Order Management Agent*, *Communication Agent* and *Computation Agent*. Their functions are as follows:

- *Order Management Agent*: managing the route planning status and initiating communication between the last nodes and the destination node if the route is not complete. When a route is planned, select the best route and provoke the reservation. Every shipment only activates one Order Management Agent, which is usually the shipper's. This node is named the *planning node*.
- *Communication Agent*: sending and receiving CPIR messages. It is the only agent that can perform inter-node communications.
- *Computation Agent*: undertaking all computing-related work, such as calculating costs and branch-cutting (mentioned in 3.3.3).

The route planning is conducted based on breadth-first search (BFS). When a shipment triggers the route planning, the Order Management Agent tracks the status and performs the following steps for every candidate route of the current depth:

(1) The last node on this candidate route (the incumbent node) contacts all its neighbours to request routes. If it is the first round of communication, and no candidate route exists, Loc_P (see 3.1) is selected as the incumbent node.
(2) Each receiver contacts all known transporters for available movers and provides the time for earliest pick-up and latest drop-off
(3) Each transporter checks available movers and replies with the information of the chosen movers
(4) The receivers in Step (2) plan the route locally with the received mover information and generate the route segments between the incumbent node and themselves. These route segments are encapsulated in message(s) and sent to the incumbent node
(5) The incumbent node concludes the round of communication, summarises the messages and sends them to the planning node

By the end of Step (5), the Order Management Agent combines the messages with the current routes and generates a set of routes of 1 more depth level. Next, if enough routes are found, the condition elaborated in Section 3.3.3.4 will be checked to determine whether the search can be terminated. If the conditions are met, the Order Management Agent initiates the reservation. If not, the steps above will be repeated over the new set of routes until the conditions are met or failure to plan is concluded.

3.3.3. Branch-cutting methods

CPIR also implements a few branch-cutting methods in the steps of 3.3.2 to cut the search space and make route planning more efficient. These methods distinguish the searching logic of CPIR from BFS. This section also introduces the parameters that CPIR can adjust to optimise the performance.

3.3.3.1. Broadcast list. The broadcast list mimics the Internet and aims to filter out a subset of the most promising neighbours for Step (1) to reduce communication overhead. It is done by 1) building a complete graph using the coordinates of all the nodes, 2) running a k-shortest path algorithm for maximum I^{MAX} iterations and ranking the routes, and 3) iterating the list and adding the containing nodes until L_B nodes are added.

3.3.3.2. Truck company list. This has a similar purpose and realisation to the broadcast list. The difference is that when building the graph, not all the nodes are used, but only the origin, destination and truck bases. The method will return L_T truck base nodes that will be used in Step (2).

3.3.3.3. Truck searching time limit. When a transporter checks its owned movers, all the scheduled movers before the final delivery time will be selected. While for flexible movers, only trucks within V hours from the current time will be considered as in the vision. If this results in no trucks, search again with $V = VE$ where E is an expansion coefficient.

3.3.3.4. Final acceptance coefficient. The final acceptance coefficient A is relevant to the conditions to stop the route planning. Besides enough number (P) of routes is found, another important condition is whether the discovered complete routes are superior to incomplete routes considering their potential. Therefore, this coefficient ensures routing continues until the worst complete route is at least A times better than the best incomplete routes.

3.3.3.5. Maximum effective movement. This parameter M limits the maximum allowed number of legs for making an effective movement. The effective movement refers to the process when the shipment is transported from Loc_P to Loc_C, and from Loc_C to Loc_D. M allows control of the elasticity of the routes between key locations and excludes the possibilities of unwanted circuitous or deviating routes.

3.4. *Federated PI Routing (FPIR) Protocol*

The FPIR protocol leverages recent data space frameworks to plan and book freight container transports. Data spaces promise a playing field for data sharing and exchange, allowing for secure and controlled data sharing and collaboration between different parties, where data producers retain control and sovereignty (Nagel *et al.*, 2021). Based on this principle, we propose a three-phased system, where: (1) operators will publish non-confidential transport services data (e.g. schedules and capabilities) into a federated service; (2) expeditors will use this federated service's aggregated data to plan transports; and (3) consignment booking is done peer-to-peer between expeditor and operators.

3.4.1. Publishing

The Federated Network Service (FNS) acts as a shared database that is available for operators to contribute information regarding their operations. A federation might be set up to achieve a variety of goals, depending on the logistics or regional context, e.g. city logistics, hinterland transport and so forth. Its role is to store and offer an aggregated view of the available logistics services, by collecting published data from operators, which amounts to the network state graph (NS) detailed in Section 3.2. Operators are expected to publish, as soon as possible, any update regarding the services they offer. In order to protect operational data, operators are not expected to share sensitive information, like real capacity, to others, just openly available and standardised data.

In hindsight, the aggregated view's quality depends on how proactive operators are. Highly automated transport management system allow for instant publishing, on the other hand, a human interaction with the system might result in publish delay. In the numerical experiments section, we will model this delay as a random variable, and explore its impact on the overall system performance.

3.4.2. Planning

Route planning is done based on the known information by querying the FNS for the latest logistic network state NS. This is then used in conjunction with an implementation of A*, which is a popular option to solve shortest-path problems (Fu, Sun, and Rilett, 2006). This heuristic is a breadth-first search algorithm, which is interesting because it allows to only evaluate neighbouring nodes, making the path exploration with flexible movers more efficient, as edges composed of flexible movers are not pre-defined.

This phase utilises a combined heuristic function to guide the A* search for the shortest path. The first component considers the minimum transportation cost per kilometre within the considered NS. This ensures the algorithm prioritises paths that utilise the most economical transport options. Secondly, the heuristic factors in the minimum external cost per tonne-kilometre are proposed in 3.6. By combining these aspects, this admissible heuristic aims to efficiently navigate the trade-off between minimising both transportation costs and external costs, achieving optimal solutions.

3.4.3. Booking

After a route is generated, it's divided into individual consignments, each representing a leg of the journey. Booking requests are then sent to the corresponding operators responsible for handling those specific legs. Operators can either accept (positive response) indicating available capacity, or reject (negative response) the request due to capacity limitations (previously existing capacity has been reserved for another expeditor, or the operator failed to publish in time an update to the FNS due to PD). If all operators respond positively, signifying successful booking for all legs, then the entire route is confirmed. However, if even one operator rejects a request, the entire booking process needs to be restarted. This is because a single missing leg renders the entire route unusable. It's important to consider the automation level of each operator, as some may take longer to respond to booking requests compared to others, resulting in an answer delay (AD).

3.5. ***Agent-based modelling***

In order to test and measure the performance of the two protocols, we developed an agent-based model with a geographic information system (GIS) component. Simulations allow the study of dynamic systems, where interactions between agents are based on stochastic processes. It simulates a group of logistic service providers and expeditors, importing and exporting freight container thought the Port of Antwerp-Bruges to the hinterland, over a period of time.

3.5.1. Agents

In this modelling paradigm, agents play the most important role, acting independently and reacting to environment changes. We propose the following agents: the operator that handles transport services, by managing the available capacity; the expeditor that requests and/or plans transports, by effectively communicating with operators to book consignments; and the mover, with a more passive role of transporting containers between locations;

3.5.2. Environment

Operators and expeditors rely on a fully connected graph in order to exchange information. To model different automation levels, we propose that messages sent across this network will incur a delay D, sampled from a probability density function (PDF). The frequency and information communicated via this mechanism' will depend on the protocol being used.

The mover agent follows a GIS representation of the real physical infrastructure, represented on a separate graph for road, rail and inland waterways. The routing is planned using the fastest route A* algorithm.

3.5.3. Process and scheduling

This section details the process and scheduling procedures followed within each simulation iteration of the agent-based logistics network model. The flow is divided into three stages:

3.5.3.1. Transport management. Operator agents are responsible for sharing information about their transport offerings, as well as managing requests for bookings. Depending on the protocol, the data publish procedure is modelled as follows:

- using FPIR, at simulation start, the operators will share their schedules and slots into the FNS, which stores and offers this data for expeditors to plan transports. As mentioned above in 3.4, real capacities are not published into this federated service.
- whilst with CPIR, this information is kept locally and consumed upon request by expeditors when planning transports.

For scheduled movers (rail and barges), the operator is responsible for providing, for each planned transport, origin and destination locations with departure and arrival timestamps. The remaining free-capacity (in TEU) is sampled from a probability density function, hence all transports, even for the same corridor, have different capacity that can be used by expeditors. In the case of flexible movers (road transport), the operator shares its operating slots, i.e. when a truck is available to drive for a given amount of hours in a day, and the departing location (base). This type of mover has a fixed capacity of 2 TEU.

3.5.3.2. ***Demand generation.*** A pre-determined number of shipments are scheduled to occur on a specific date. For each shipment, the date is sampled from a predefined discrete probability density function. The shipment duration is fixed at a given number of days, reflecting the typical time window where demurrage and detention are not charged for a freight container in Belgium. At the shipment's start date, the expeditor initiates the planning process. This process is depending on the protocol in use, CPIR or FPIR.

3.5.3.3. ***Consignment execution.*** Movers fulfil the transportation of consignments based on the confirmed reservations made during the planning stage. This involves picking up the shipment from the origin and delivering it to the destination as per the agreed-upon schedule. If the leg involves the composing or decomposing of a container at the expeditor's location, the flexible mover will wait for this procedure to complete and then move to the next location. This process flow ensures a dynamic and adaptable system where demand triggers planning, transport options are published and selected, and finally, shipments are executed by available movers. The specific protocols and parameters employed within each stage influence the overall efficiency and performance of the simulated logistics network.

3.6. *Cost function*

As explained in Section 3.1, the cost function (3.1) is composed of internal costs, external costs and time window deviation punishment. The costs are summarised in table 3.1.

Internal costs are evaluated based on the samples from real business history. It includes per-km transport costs, storage costs and handling costs. Note that the handling costs are associated with modes and per single operation. For instance, unloading a container and loading it again on a train are considered two operations for two modes.

External costs can be calculated from various aspects. The structure and factors provided by Van Essen *et al.* (2019) are adopted. In our model, the following aspects are considered for external costs: climate change, air pollution, accident, noise, congestion and well-to-tank emissions.

Table 3.1. Cost factors

Category	Cost	Unit	For trucks	For trains	For barges
Internal	Transport cost	€ per vkm	1.65	See Appendix A	See Appendix A
	Handling cost	€ per operation	20	53	25
	Storage cost	€ per day	0 under 2 days; 5 for 20ft containers; 12 for 40ft containers		
External	Climate change	€-cent per tkm	0.68	0	0.21
	Air pollution	€-cent per tkm	0.26	0.004	1.02
	Accident	€-cent per tkm	0.07	0	0
	Noise	€-cent per tkm	0.01	0.01	no data
	Congestion	€-cent per tkm	4.9	0	0
	Well-to-tank emissions	€-cent per tkm	0.16	0.11	0.09

4. Numerical Experiments

Agent-based models (ABMs) excel at simulating complex systems with interacting elements. However, due to their inherent stochasticity and non-linear dynamics, analytical solutions are often intractable. Here's where Monte Carlo (MC) experiments come in. By running the ABM multiple times with random variations within defined ranges for key parameters, MC simulations allow us to explore the statistical properties of the entire system. This probabilistic approach helps us to approximate the stochastic probability distributions of the mean cost function value. The aim of these Monte Carlo experiments is to ensure that any differences in results can be meaningfully interpreted, without being attributed to statistical error.

One challenge in running MC simulations for ABMs lies in determining how many iterations are sufficient. Ideally, we want to achieve a statistically significant estimate of the desired outcome metric, such as mean cost. A common stopping criterion leverages the concept of confidence intervals. Here, we can set a desired confidence level (e.g., 95%) and a tolerable margin of error δ around the estimated mean cost. Where at the end of each iteration, we compute the margin of error for the realised simulations:

$$MOE = 1.96 \frac{S_n}{\sqrt{n}} \tag{4.1}$$

Where:

$$S_n^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{4.2}$$

$$\bar{x}_n = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{4.3}$$

$$= \frac{n-1}{n} \bar{x}_{n-1} + \frac{1}{n} x_n \tag{4.4}$$

Algorithm 1: Pseudo code for Monte Carlo simulation stopping rule

Input: M^{min}, M^{max}, δ

for $i \leftarrow 0$ **to** M^{max} **by** 1 **do**
    if $m > M^{min}$ **then**
        $x_m, S_m \leftarrow Simulation(m)$
        Update MOE, $\bar{x}_m$
        if $MOE/\bar{x}_m \leq \delta$ **then**
            Stop Monte Carlo
        end
    end
end

The stopping rule is specified in Algorithm 1. We stop if the current minimum number of iterations have been performed (M^{min}=30) and the relation between MOE and $\bar{x}$ is smaller than 0.1% ($\delta \leq 0.1\%$), or M^{max} (M^{max}=2000) iterations are reached.

Fig.4.1 shows the area for simulation to be used in the experiments that contain 49 nodes, of which 8 are hubs. Nodes are physical locations that could potentially have some of the capabilities including Transit (change of carriers), Store (container storage) and Depot (empty container pick-up and return site). And hubs are nodes with all three capabilities above that can also conduct intermodal transitions. For the sake of simplicity, all hubs act as a base for flexible movers, with enough capacity to serve all demands. In addition, full containers enter or exit the network through the nodes of the Port of Antwerp (BEANR) and Port of Zeebrugge (BEZEE), acting as Gateways. See Cassan *et al.* (2023) for more descriptions of PI capabilities.

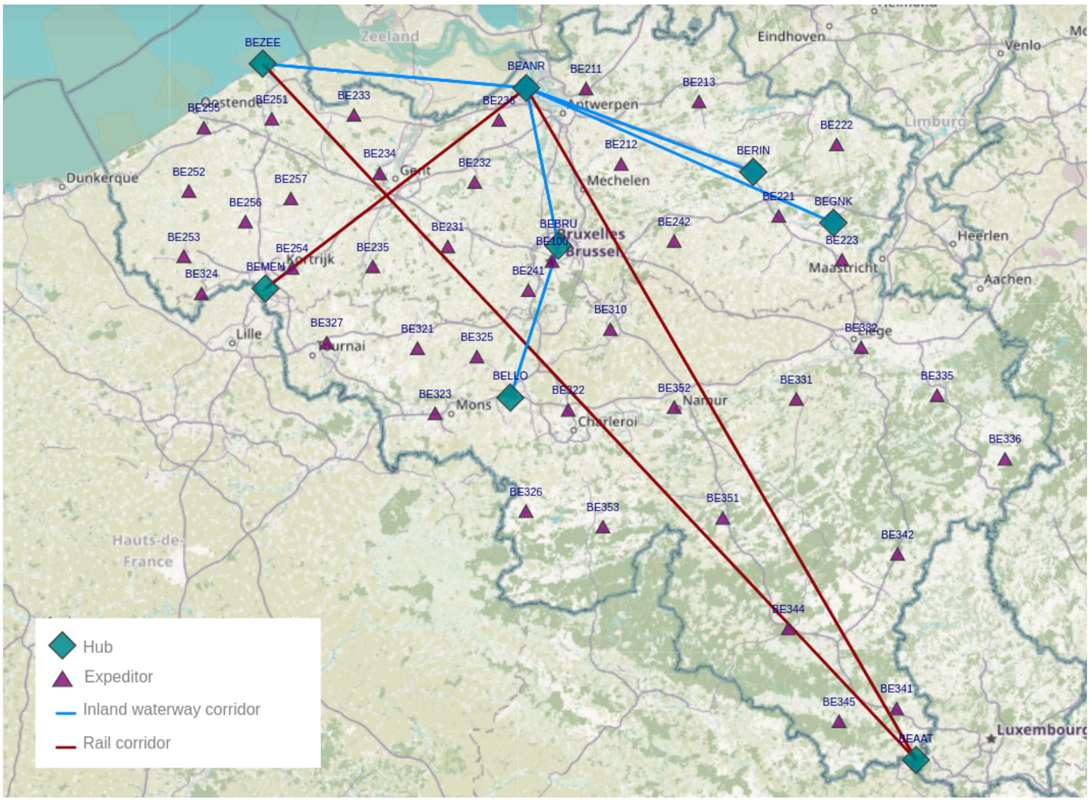

Figure 4.1. The simulation area

The model simulates a multimodal network, with trucks being the flexible movers and trains and barges the scheduled movers. Flexible movers depart and return to their base node after a transport task. Scheduled movers are capacitated and operate on a weekly basis. Trains and barges are both considered scheduled movers, and they are modelled in the same way. The main differences are that trains are cheaper and operate over larger distances than barges (see Appendix A).

During each simulation span of 33 days, 1300 shipments are generated. Each shipment is between a random pair of nodes, with one of them as the Gateway node depending on whether the shipment is import or export (see Section 3.1 about import and export shipment). The shipment consists of cargo with varying weights sampled from real business data to be loaded into standard 20 or 40 ft containers. All the shipments need to be delivered within 5 days. Deliveries violating the time window will not be executed, and the shipment will be marked as 'not completed'.

Lastly, before the experiments, CPIR is calibrated to the network for the best achievable performance. The parameters used are detailed in Table 4.1. Regarding the denotation of the parameters, please refer to Section 3.3.3.

Table 4.1. Parameter settings for CPIR

Algorithm	Parameter	Description	Value
CPIR	I^{MAX}	Maximum broadcast list search steps	50
	L_B	Broadcast list size	3 per 100 km
	L_T	Truck list size	0.02 per 100 km
	V	Hours in advance for truck service search	24
	E	Expansion coefficient for V	2
	M	Maximum allowable step for each effective movement	2
	A	Final route acceptance coefficient	3.2
	P	Number of routes required to terminate search	10

4.1. *Experiment 1: performance*

In Experiment 1, we aim to demonstrate and make a preliminary comparison of the performance of the two algorithms. Table 4.2 shows the 6 scenarios being tested in Experiment 1. Scenario 1 serves as a benchmark for comparing the route quality. Note that with the capacity constraint relaxed, S1 yields the lower bound of the problem, because FPIR is A* equivalent, and the estimator heuristic is admissible (i.e., it never overestimates the cost). When the estimator heuristic is admissible, A* is cost-optimal (Russell and Norvig, 2020, pp.86-88). S2 and S3 use different route planners when capacity is limited. The actual capacity for each corridor is randomly generated using the maximum corridor capacity and a uniform distribution as shown in (4.5).

$$f_{ij}^k \sim U(0,\, 50\% \cdot f_{MAX}^k), \forall k \in K, \forall i, j \in N \tag{4.5}$$

S4, S5 and S6 have the same design as S1, S2 and S3. The purpose is to demonstrate how results differ from the first 3 scenarios when only monetary costs are considered in route planning decisions, mimicking the present business situation.

Table 4.2. Scenarios for Experiment 1

Scenario	Algorithm	Capacity Limit	Cost Function
S1	FPIR	No limit	Internal + external
S2	FPIR	50%	Internal + external
S3	CPIR	50%	Internal + external
S4	FPIR	No limit	Internal
S5	FPIR	50%	Internal
S6	CPIR	50%	Internal

In Table 4.3, the outcomes of Experiment 1 are presented. Analysing the scenarios S1, S2, and S3 indicates that capacity limitations may introduce an approximate 10% deviation from the theoretical lower bound. While the performance of the CPIR and FPIR methodologies is similar. FPIR returns marginally lower costs, approximately 1% less than CPIR. Besides, CPIR prefers a greater utilisation of barges, which, in turn, contributes to a slightly lower external cost.

Upon examination of scenarios S4, S5, and S6, a trend emerges that trucks are prioritised when only internal costs are considered. This observation highlights that within the specified problem size illustrated in Fig. 4.1, trucks maintain a cost advantage in the simulated scenario under realistically modelled business settings. The deviation in costs between the two route planners is also greater in this case.

Table 4.3. Results of experiment 1

Scenario	Iterations to converge	Costs				Modal split			
		Internal cost (€)	External cost (€)	Total cost (€)	Internal cost ratio	Road ton·km	Rail ton·km	Barge ton·km	Road ratio
S1	329	415.19	131.89	547.07	75.89%	1955.49	1705.55	824.02	43.60%
S2	928	440.58	154.40	594.98	74.05%	2294.21	1074.37	1028.74	52.17%
S3	1031	449.83	151.51	601.35	74.80%	2228.10	938.46	1127.17	51.89%
S4	328	412.87	136.45	549.32	75.16%	2065.51	1687.20	664.58	46.76%
S5	965	435.35	163.81	599.16	72.66%	2526.17	1063.88	674.35	59.24%
S6	892	446.11	168.26	614.37	72.61%	2596.85	839.05	706.84	62.68%

However, it is also important to note that despite significant variances in ton·km data, the overall cost implications remain minimal in the lower bound scenarios (S1 and S4). The ton·km data also indicates that trucks are taking mostly the shipments that should have been transported with barges. This effect is more noticeable when capacity is limited and planning using CPIR rather than FPIR.

4.2. *Experiment 2: sensitivity to delays*

The goal of Experiment 2 is to test the model's sensitivity to response time delays using the two route planners. Here, by 'response time delays', we are referring to the time a service provider is expected to take from receiving a reservation request to replying with confirmation of the price and booked capacity. Ideally, in a developed PI network, this reservation process should be done automatically. However, most ongoing operations still require manual intervention in the current stage.

The delays are modelled by a uniform distribution where the lower bound (LB) and upper bound (UB) are set. The intervals of LB and UB are exponential in order to effectively cover a larger range with a limited number of experiments. The scenarios are summarised in Table 4.4.

Table 4.4. Experiment 2 scenarios

LB (h) \ UB (h)	0	1	2	4	8	16
0	S2/S3	FPIR/CPIR	FPIR/CPIR	FPIR/CPIR	FPIR/CPIR	FPIR/CPIR
1	-	-	FPIR/CPIR	FPIR/CPIR	FPIR/CPIR	FPIR/CPIR
2	-	-	-	FPIR/CPIR	FPIR/CPIR	FPIR/CPIR
4	-	-	-	-	FPIR/CPIR	FPIR/CPIR
8	-	-	-	-	-	FPIR/CPIR

To better measure the impact of response delays, we have collected several indicators: internal, external and total cost (in €) per shipment, ton·km per modality per shipment, time consumed for reservation per shipment (in hours), number of consignments per shipment, and shipment completion rate. Each consignment is defined as a reservation of a transport leg.

The experiment results are displayed in Fig 4.2 and Fig 4.3. Delayed responses show negative effects on almost all of the indicators. In general, higher delay increases costs, especially monetary costs. This is because a higher delay leads to less time available for transport within a fixed time window. As a result, the planners are compelled to choose faster mover services instead of the optimal ones. This effect can also be confirmed from the ton·km data per modality. Moreover, it is also quite evident that higher delays cause a significant reduction in the completion rate since the transport time is too short for even the fastest shippers to fulfill the shipment on time. Lastly, as expected, a higher delay significantly increases the time needed for route planning

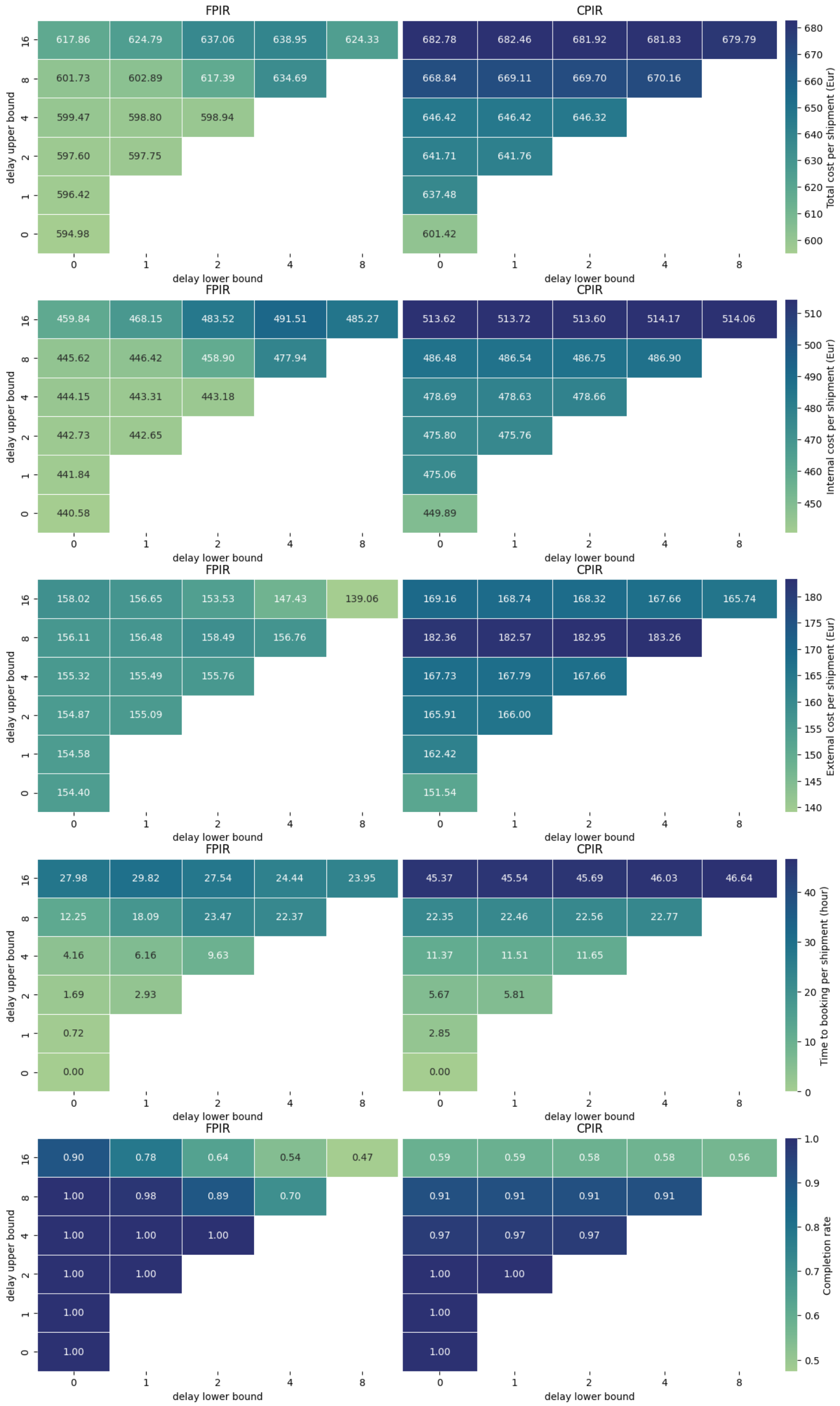

Figure 4.2. Results of experiment 2

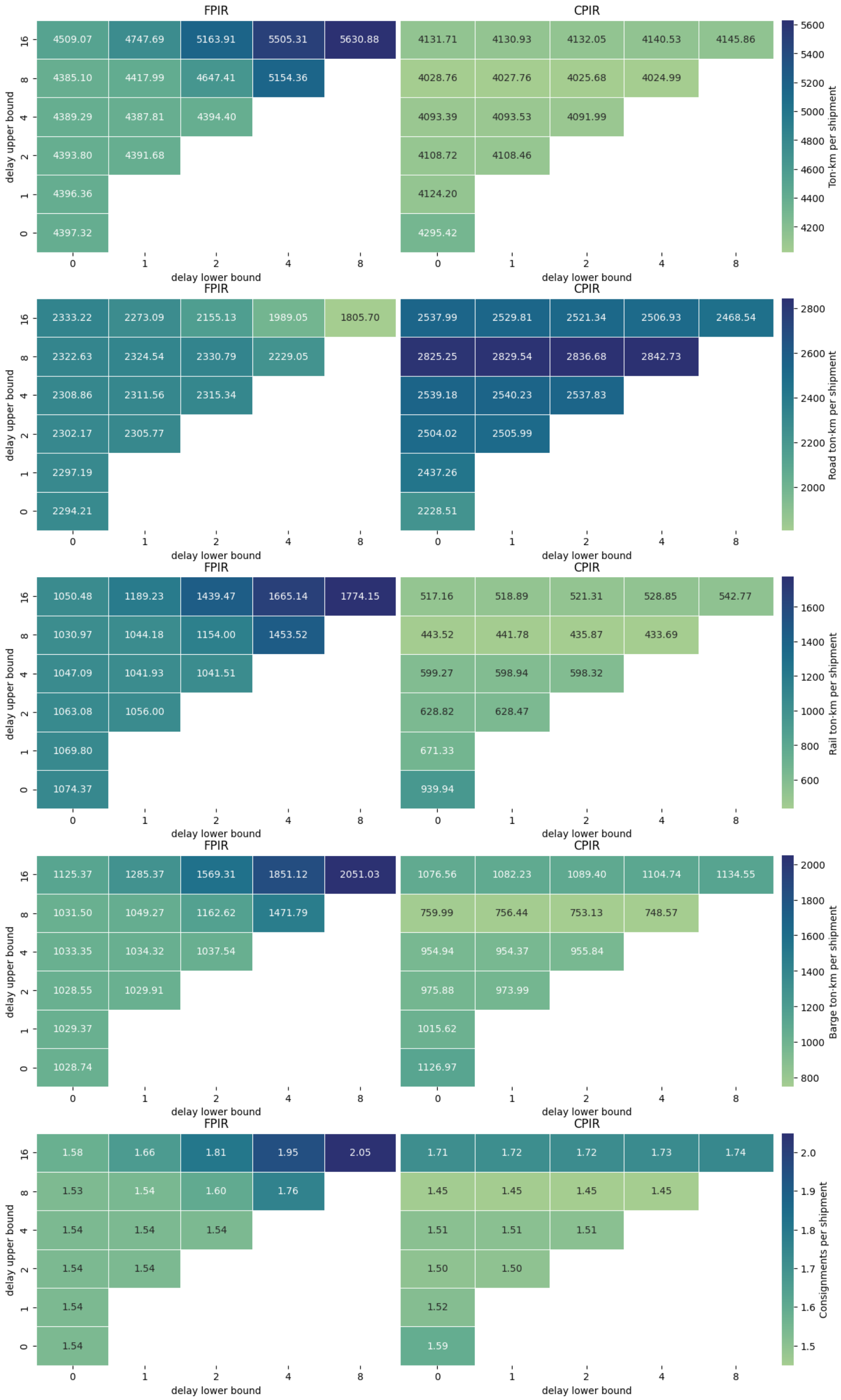

Figure 4.3. Results of experiment 2

and reservations.

Comparing the two planners, FPIR seems to be less sensitive than CPIR for most of the cases. While CPIR is less responsive to changes in LB, FPIR always outperforms CPIR. CPIR only proceeds to the next depth when all the current respondents reply, which is equivalent to the worst case of LB. The experiment discovers the elbow point for both algorithms where the completion rate plummets. Nevertheless, FPIR is likely to perform worse than CPIR when the delay is even higher than $U(8, 16)$ hours. Finally, both FPIR and CPIR show a more or less U-shaped pattern in many indicators like the cost indicators, road ton·km and time to booking. This effect will be discussed in Section 5.

5. Discussion

5.1. *Analysis of experiment results*

We are able to explain any result where the difference is greater than 0.1% ($\delta = 0.1\%$) thanks to the MC experiments. Experiment 1 shows that both algorithms perform well, with FPIR yielding better results than CPIR at a lower total cost. While CPIR tends to use more scheduled movers, it also showed a clear preference for using barges over trains. This is due to the reason that, in the area studied in this paper, 2 train schedules are connecting the node near the border of the network. However, these nodes are often overlooked by the search algorithm for Broadcast List in Section 3.3.3.1 because it is more likely to only include nodes in the area between the origin and destination node.

CPIR and FPIR show different sensitivity to response delays because their messaging logic is different. For CPIR, a round of messaging, and thus delays, happens each time the algorithm explores routes with one more transport leg (in other words, depth in BFS) during route planning. Whereas FPIR is only influenced by response delays in the booking stage (see Section 3.4.3 for the booking stage). Hence, the lead time for FPIR is usually much less than that for CPIR.

Shipments that use multiple transport legs and modalities, which are often long-distance shipments, are more likely to be impacted by response delays. According to our experiment results, a higher delay in response time can lead to the following direct effects:

- Significantly higher internal costs and slightly higher external costs;
- Higher utilisation rate of trucks taking over shipments from scheduled movers. It is also the reason for a lower total ton·km;
- Longer lead time for route planning and reservation;
- Lower completion rate due to prolonged planning time and compressed transport time.

As the completion rate plunges, it triggers opposite and even more substantial effects than response delay effects. These secondary effects result in long-haul shipments transported by trucks not being able to complete in time. Therefore, it is remarkable in Fig. 4.2 and Fig. 4.3 that U-shaped patterns can be observed in many indicators.

A good example of such a synthesised effect is the peculiar results of consignments per shipment. The number of consignments per shipment initially decreases with increasing delay because transport time is shorter, and direct transport by trucks is preferred for timely delivery. However, the time for trucks to depart and return to base needs to be taken into account, which is not the case for scheduled movers.

Therefore, when an even higher delay causes the completion rate to plunge, scheduled movers are more often adopted instead, although they may require more transfers. As a result, the number of consignments per shipment increases. That also explains the U-shape pattern in cost and road ton·km indicators.

For FPIR, when the delay is as high as $U(4, 16)$ and more, it has a lower completion rate than CPIR. Because scheduled movers are at capacity in this situation, the booking stage for FPIR may take too long, since the transporters' responses are often negative.

5.2. *Practical implications*

Two privacy-protecting routing protocols for PI are presented. Due to the difference in privacy strategy, the mechanisms and features are different. In general, FPIR has better results and higher robustness, while CPIR focuses on maximising data privacy. Additionally, CPIR allows for customised parameters for specific needs, but more settings and calibrations are required for optimal performance.

Our experiments also reveal that if route planning and reservation decisions are made only considering monetary cost, trucks will prevail among all the modalities in the case of the Belgian scale. This finding is related to another research on the Belgian scale by Pekin *et al.* (2013). Their study concludes that intermodal transport is relatively competitive to trucks, especially in eastern, south-central and southeastern Belgium, and in western Flanders, because of the proximity of intermodal hubs in these areas. The main reason for the difference with their study is that in this study, most of the capacity is usually carried by short-haul trains and barges with a range close to or less than the break-even distance on the Belgian scale (about 100 km) (Macharis *et al.*, 2010). Additionally, in our study, we found that while using more trucks saves internal costs, it generates more external costs.

We also believe that privacy should be one of the key focuses of PI at the current stage to facilitate more trust and cooperation, so as to attract more pilot users to form the critical mass to demonstrate the initial benefits of PI (Ballot, Montreuil, and Zacharia, 2021).

Besides emphasising privacy, automation has also been considered an essential aspect of trust, as suggested by Sun *et al.* (2024). This is because engaging in an automated system means that the operator must trust and delegate to the virtual agent a great deal of decision-making in a state of unknowing and uncertainty for the operator. The importance of a PI network to be automatic is demonstrated in Experiment 2. However, at the moment, cooperation in living labs and projects is still experimental and on a manual basis. Therefore, it is crucial to take response time among partners into account by setting a proper limit for it. When the delay is too high, it affects not only the feasibility of route planning but also route quality, leading to potential inefficiencies.

6. Conclusion

In this study, we presented two privacy-protecting routing protocols for PI and examined their performance and sensitivity to response delays. Through ABM and MC simulations using realistic business data and procedures, we demonstrated that both algorithms exhibit distinct strengths and weaknesses influenced by their differing privacy strategies and messaging logic.

Our experiments reveal that FPIR has better performance in cost optimisation and robustness, while CPIR maximises data protection with similar optimality. We found that, in our problem scale, trucks are the preferred modality of choice if only the monetary costs are considered. Meanwhile, it results in increased external costs and higher total costs.

In addition, it is highlighted that response delays can have a substantial impact on costs and modality choices. The U-shaped patterns observed in many indicators, such as costs and ton·km, further illustrate the complex inefficiencies stemming from the delays. This emphasises the importance of automation for a PI network to improve reliability and efficiency in route planning and execution. We believe that trust is a critical enabler in this regard.

There are a few limitations in this paper. First, it would be beneficial to run more simulations on a larger scale with increased numbers of movers to evaluate the scalability and to thoroughly investigate the features of the route planners. However, due to the availability of data and the high runtime cost of MC simulation, we have not been able to do it yet. Next, for a larger problem scale, delays in messaging latency could potentially cause significant impacts, as messaging in a larger network can be intense and challenge the internet infrastructure. Lastly, since CPIR has many parameters to adjust, implementing a learning mechanism could help achieve maximum performance.

Future research directions include integrating with the information system and developing the routing algorithm to include more optimising aspects, such as consolidation, while following the same privacy-protecting rules. We suggest that trust should be one of the key focuses for the current PI research, and the incorporation of privacy and automation not only fosters increased trust and collaboration among stakeholders but also serves as a pivotal step towards realising an efficient and resilient PI network capable of adapting to dynamic logistical challenges.

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Declaration of AI-based Tools

The authors declare that this paper uses artificial intelligence tools for linguistic embellishment. The relevant content has been carefully checked and the authors are responsible for the validity, originality and completeness of the text.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, Sun S., upon reasonable request.

Disclosure Statement

No potential competing interest was reported by the authors.

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Appendix A. Scheduled mover information

The table below displays the parameter settings of trains and barges in our model.

Table A1. Scheduled mover information

Terminal Pair	Modality	Times per Week	Capacity (TEU)	Cost for 20ft Container (€)	Cost for 40ft Container (€)	Distance (km)
BEANR-BEAAT	Train	5	U(0,45)	255.00	255.00	275.00
BEZEE-BEAAT	Train	1	U(0,45)	365.75	322.00	280.50
BEANR-BEMEN	Train	2	U(0,45)	103.96	123.71	113.00
BEANR-BEGNK	Barge	6	U(0,100)	154.00	198.00	107.00
BEANR-BERIN	Barge	7	U(0,100)	148.50	167.75	75.00
BEANR-BEBRU	Barge	6	U(0,100)	132.00	154.00	62.00
BEBRU-BELLO	Barge	5	U(0,100)	110.00	137.50	52.00
BEZEE-BEANR	Barge	5	U(0,100)	154.00	198.00	104.00