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Communication is computation: A privacy-protecting routing protocol for Physical Internet

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ABSTRACT

Logistics research has been emphasising the importance of interconnectivity for better resource utilisation and real-time response against disruptions. However, lack of trust has become a significant obstacle in the business world, blocking the way to building an open information system and, thus, more effective route-finding protocols. This paper proposes a decentralised routing protocol for multimodal transportation in a new logistic paradigm named Physical Internet (PI), performing under a privacy-protecting information-sharing policy. We seek the possibility of building a system to connect entities in a trustless environment that strictly limits data usage to the embedded services at a structural level. In the proposed protocol, the only service is to find the shortest path while minimising unnecessary data-sharing, with the potential to plug in more services. If no party initiates the routing, the entities remain in the equivalent state of disconnected. This routing protocol avoids sharing over 90% of the information in a simple scenario. In addition, a numerical experiment is performed to justify the quality of routes planned by the protocol.

1. Introduction

Collaboration is a well-researched supply chain management strategy, which can help gain a competitive advantage. On the other hand, it also challenges each participant to maintain unique internal resources. As a result of globalisation and technical evolution, trust, as a critical enabler of collaboration (Fawcett et al., 2012), is becoming a bottleneck of improvement. The reason is that technology makes it technically possible for supply chains to benefit from collaboration, however, without a matching level of trust (Plasch et al., 2021).

For logistics, collaboration is increasingly required for multimodal transport, especially on a more extensive network. In terms of the cargo routing problem therein, many studies have justified the benefits of new logistics concepts such as intermodality and synchromodality. For example, based on the idea of multimodal transport, intermodal transport requires a higher level of integration to provide door-to-door delivery (SteadieSeifi et al., 2014). Synchromodal transport then makes transport resources on a network reachable in an integrated and optimised way (Pfoser et al., 2022)

However, while these transport resources can belong to different business entities, most studies naturally assume the availability of shared data and unified protocol, which hardly exist in the real world. This fact and its resulting emphasis on trust have been called by many researchers (Barratt, 2004). SteadieSeifi et al. (2014) note that the individual role of participants of a service network is ignored, and they only share limited data in practice. In an overview of synchromodality by van Riessen et al. (2015a), it is pointed out that a lack of trust hampers integration, which they, in response, stress the importance of flexibility, and this aspect is not further

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addressed. Ballot et al. (2021) proposes pilot demonstrations of Physical Internet are needed to help build trust and consensus about the design of PI. In a more recent review by Pfoser et al. (2022), an evident lack of studies on trust building is highlighted, while the assumed neutral orchestrator in the synchromodality architecture did not ease the problem.

On the other hand, existing trustworthy logistics solutions are more conceptual. For example, Meyer et al. (2019) propose a blockchain framework as a decentralised approach to facilitate trustful collaboration and data sharing. Klumpp and Zijm (2019) identify the trust issue in human–computer interaction in automated systems and outline a theoretical framework for analysis. Hence, for routing algorithms, more attentions are still needed for trust issues in interconnectivity settings in order to be applied to real-life scenarios more easily.

This paper focuses on container route planning in a trustless multimodal transport network that arises from reality. The limited level of trust causes each participant to be reluctant to share the essential data for routing. Nonetheless, they are still willing to use the information to gain benefits by routing in a multimodal network. The scope of the paper is thus confined to the shortest path problem. In particular, the accessibility of data for route planning is not assumed but, rather, becomes the concern of the paper by minimising the amount of data shared among its owners.

As a solution, we see the potential in a novel logistics paradigm named Physical Internet (PI). PI has a unique vision for describing multimodal logistics networks. It takes the metaphor of "data routing" in the Digital Internet (DI) into the physical world (Montreuil, 2011). PI makes use of various types of standardised containers as its operating units. The PI transportation network is composed of PI hubs (nodes), which can be intermodal terminals, seaports, or warehouses, like routers in DI.

Similar to other logistics concepts like synchromodality, interconnectivity is also a focus of PI as an essential enabler of resource-sharing and collaborative planning for multimodal transport. Intuitively, centralised data sharing has been viewed as a popular realisation for interconnectivity (e.g., control tower in synchromodality). Whereas, the potential vulnerability of a supply chain with a centralised system is also identified in terms of such as data integrity, privacy, and other weaknesses (Rejeb et al., 2019). On the contrary, PI shows a decentralisation tendency (Ambra et al., 2019; Betti et al., 2019; Meyer et al., 2019; Hasan et al., 2021), in which collaboration has also been widely stressed (Pan et al., 2019a; Simmer et al., 2017).

Therefore, we are exploring a privacy-protecting solution to route containers in PI, taking advantage of its decentralisation nature. The aim of this paper is to present a novel prototype of a Communication-based PI-routing protocol for a multimodal logistic network that protects logistics practitioners' privacy. This protocol finds routes of similar optimality as a centralised benchmark algorithm but without collecting as much information. To the best of our knowledge, a decentralised private-protecting routing algorithm has yet to be applied to PI. The main contribution of this paper is to propose this routing protocol with the justification of how privacy is protected.

The remainder of this paper is structured as follows. Section 2 is the literature review. Section 3 defines the problem with a mathematical model and outlines the methodology. Section 4 describes the algorithm and justifies the privacy protection policy through decentralised communication. Section 5 compares the protocol with the existing algorithms representing the centralised method. Section 6 concludes this paper with discussions of findings and future developments.

2. Literature review

2.1. Introducing PI and synchromodality

PI was first promoted by Montreuil et al. (2010), in which it was introduced as a revolutionary paradigm in which cargoes are transported in standardised, modular and intelligent containers. In this paradigm, new logistic networks, information systems, and business models are designed accordingly, and the containers are thus transported on a distributed, interconnected, and well-organised network similar to DI. To mimic DI in the physical world, PI heavily relies on Internet of Things (IoT) devices and interconnectivity to enable real-time computing and control of goods. Sarraj et al. (2014b) discuss the analogy between PI and DI in terms of interconnection, architecture and routing and prove the benefits of PI using a stylised routing scheme. Cassan et al. (2022) also give insights into how DI governance and business models can be transferred into PI. In this sense, PI is formally defined as "an open global logistics system founded on physical, digital and operational interconnectivity through encapsulation, interfaces and protocols" (Pan et al., 2017).

To enable the operations in PI, researchers have designed dedicated components. They are initially categorised into PI container, PI mover, and PI node (Montreuil et al., 2010). PI container is a type of standardised smart box varying in size that is used to transport cargo; a PI node is a physical site or facility that supports the operations in PI, and a PI mover is anything that moves PI containers, such as trucks, trains, barges or conveyors. The initial design of the three standard sizes of PI containers was proposed by Montreuil et al. (2014). The specifications have been further studied and justified (for example, Lin et al. (2014) and Landschützer et al. (2015)). The movements of PI containers can happen intra- or inter-PI nodes, composing a route that fulfils cargo transportation. Utilising all the available components under the framework of PI, the cargo can be transported to the destination. Therefore, the flexible management and usage of all the facilities and equipment under the framework of PI is crucial. In that sense, PI is very similar to the concept of synchromodality.

Another innovative concept is synchromodality. As the latest logistics concept besides PI, understanding this idea can help illustrate the distinctive features of PI. Synchromodality has evolved from multimodal transport. Different from the previous multimodal transport concepts such as intermodal and co-modal transport, synchromodality allows flexible operations among transport modes, last-minute change of transport plan despite the ownership of the facilities and equipment involved, and a central

Table 2.1
Relevant PI route planning research.

Article	Network size	Modality	Problem	Main focus	Data availability
Sarraj et al. (2014a)	418 nodes	Road and rail	Routing, consolidation, bin packing	Compare with conventional system	Complete access assumed
Fazili et al. (2017)	18 nodes	Road	Routing, consolidation, truck scheduling	Compare with conventional system	Complete access assumed
Briand et al. (2022)	11 nodes	Road (unlimited)	Routing	Pricing and bidding	Share price and bids when needed
Achamrah et al. (2023)	418 nodes	Road and rail	Routing, consolidation, user preference	Disruption, preference	Shared with a centralised orchestrator
Naganawa et al. (2024)	Not specified	Road	Routing	Optimising routes	Complete access assumed
This paper	23/49 nodes	Road and rail	Routing	Privacy	Only by passive reply

orchestrator providing the integrated transport as a single service (van Riessen et al., 2015b). It stresses horizontal collaboration in addition to vertical collaboration (Tavasszy et al., 2015) by centralising data sharing and information management.

However, PI has the nature of decentralisation on the contrary (Ambra et al., 2019). The decentralisation of the activeness of the PI components like PI containers has been well-researched (Zhang et al., 2016; Sallez et al., 2016; Tran-Dang et al., 2020), while there are only a few studies on the network-level, i.e., decentralisation of practitioners of the PI network as the decision-making parties on a logistic network (Sun et al., 2023). In addition, although synchromodality naturally assumes data availability, PI has a particular focus on the interconnectivity issue (Sun et al., 2023), exploring how to make the assumed data availability feasible. This can greatly increase the possibilities of applying PI in reality, while it also creates more problems that need to be solved.

2.2. Routing models in PI

Studies on the optimisation of the routes in a PI network have not been one of the main subjects until recently. Table 2.1 summarises relevant work that focuses on route planning in PI.

Sarraj et al. (2014a) conduct comprehensive research on the multimodal PI network considering cargo consolidation, routing, and container bundling algorithms using agent-based modelling (ABM). It defines every node on the network as a hub, which contains the agents to perform the cargo consolidation, routing and bundling functions in an organised way. The optimality is justified by an empirical study in France in terms of costs, time and environmental effects. Fazili et al. (2017) compare the PI with the conventional logistic system regarding container packing, truck routing and truck scheduling problems on an unimodal corridor network with 5 PI hubs. Both Sarraj et al. (2014a) and Fazili et al. (2017) identify the trade-off brought by PI between time caused by container transfer and other conventional objectives like reducing distance and CO_2 emissions. However, Sarraj et al. (2014a) does not clearly specify how the A* algorithm optimises the usage of trains. And Fazili et al. (2017) solves the routing problem using a mixed integer programming (MIP) method on an unimodal network. To give insights into how PI reduces CO_2 emissions, Naganawa et al. (2024) develop a hybrid routing algorithm to optimise the route planning in PI.

A recent communication-based PI routing protocol was proposed by Briand et al. (2022). Shippers and carriers can build ad hoc connections to exchange price information and bid in a dynamic manner. With privacy and efficiency not being the focus, they suggested the easiness of implementation and flexibility as the advantages of such a protocol.

Another relevant research of Achamrah et al. (2023) proposes a dynamic, reactive and flexible routing protocol for PI using ABM. Their solution covers order consolidation and container routing while considering the preferences of network participants under the orchestration of a central party. Besides, they pay special attention to the disruption scenarios.

In summary, to the best of our knowledge, there is yet a PI routing protocol that takes privacy as the primary focus. Moreover, although decentralisation has been identified as a tendency of PI, full decentralisation is still a unique characteristic of PI routing protocols.

2.3. Routing models in synchromodality

Besides PI, many other models have been developed to utilise the additional capacity in multimodal network. Pérez Rivera and Mes (2016) develop an Approximate Dynamic Programming (ADP) model with a one-step look-ahead method as the solution to the synchromodal freight transport problem. Agbo and Zhang (2017) use MIP to consider the modal split and waiting penalty for a transportation problem on a synchromodal network of three modes. Giusti et al. (2018) present a decision support toolset for finding synchromodal solutions and evaluating the benefits. Meanwhile, some studies have also considered methods to enable cooperation among stakeholders. Mes and Iacob (2016) present an algorithm for the k-shortest path problem that seeks the k-shortest paths on a multimodal network, as well as an architecture with Synchromodal Control Tower (SCT). Li et al. (2017) study the freight transport planning problem of synchromodality as a Distributed Model Predictive Flow Control (DMPFC) problem, including a cooperation process.

However, there are potential gaps that make the non-PI algorithms no longer applicable to PI. First, the multimodal transport problem is mainly studied using exact methods, resulting in a limited network size. In comparison, PI stresses the scalability and interconnectivity on a much larger scale. Besides, the availability of the data used for optimisation is conventionally assumed,

Table 3.1
Indices.

Item	Description
i, j	Node, $i, j \in N$
u	A trip leg of truck, $u \in U$
v	A transport line of train, $v \in V$
o, d	Origin and destination of the order
b	Amount of containers in the order
T	The delivery time limit of the order
$\alpha_1, \alpha_2, \alpha_3$	Weight for distance, time and emission

Table 3.2
Decision variables.

Item	Description
X_{ij}^{a}	Decision variable, whether to use a to transport order k from i to j, $a \in A$

Table 3.3
Parameters.

Item	Description
f_{ij}^{a}	The available capacity on mover a between node i and j
t_i^{a}	The arrival time of mover a at node i
H_i	Handling time at node i
c_{ij}^{a}	The cost incurred to use mover a to transport from i to j
d_{ij}	Distance between node i and j
e_{ij}^{a}	Emission for mover a to travel between node i and j

while we noticed that this is the very reason that hampers the realisation of these concepts in the business world. Although PI shares many features with synchromodality, a distinguishing feature of decentralisation to protect privacy is yet to be studied in the multimodal routing process. Last, building upon the decentralisation feature, a communication protocol is needed to support the implementation. Therefore, this paper proposes a prototype of a decentralised Communication-based PI Routing (CPIR hereafter) protocol that respects the privacy in a transportation network.

2.4. Measuring the amount of information

Since CPIR aims to protect sensitive information, it is crucial to employ a method that can effectively evaluate the amount of information.

Shannon (1948) firstly use the thermodynamics concept of *entropy* to quantitatively measure information by the amount of freedom of choice in communication. A higher entropy can represent a high randomness and, thus, uncertainty of a state, while a lower entropy indicates a low degree of choice. Therefore, as time passes and more information on the outcome of an event is gained, the information entropy tends to decrease, although the total amount of information remains unchanged.

Other alternatives to Shannon entropy are proposed. For example, Renyi entropy (Rényi, 1961) introduces a parameter α to give more weight to events of higher probabilities so that it can capture different characteristics of data. Now, such an information-measuring method has seen a wide range of applications in different disciplines (Verdú, 2019).

3. Problem description

This section provides a mathematical model to describe the problem more explicitly for better understanding.

3.1. Mathematical formulation

Consider a transport network composed of independent nodes owned by different business entities that are reluctant to share information due to their competitive relationship. Every node owns a fleet of trucks to serve the nodes within the network. Scheduled trains with fixed capacities are run by a third-party company that discloses different capacities to the node owners. This hostile atmosphere and attitude possibly exist among the node operators because they have never cooperated before, their insecurity about participating in PI being a new concept, or some are intense business rivals. In such a network, orders are placed to be routed among the nodes.

On a transportation network $G(N, A)$, where N is the set of nodes, and the set of arcs A is represented by a group of movers running to transport containers, including a set of flexible movers (trucks) U and a set of scheduled movers (trains) V, i.e. $A = U \cup V$. Each train leg covers the transport from a series of nodes, between which the train has limited capacity f^{v}_{ij}. As for trucks, it is assumed they have a maximum driving distance limit d_{max} but without a fleet number limit (thus without capacity limit). In the discrete-time simulation model, correspondingly, it is assumed that, for each time unit, there is a truck moving with an infinite capacity between nodes with a distance less than d_{max}. Therefore, for trucks, $f^{u}_{ij} \in \{0, \inf\}$ depending on d_{ij} and d_{max}. A set of orders is to be placed on the network, representing a request to send b containers from o to d, where $o, d \in N$. When full data visibility can be gained (in a trusted network with all the data equally shared), the problem can be constructed from the general transhipment problem (GTP) (Agadaga and Akpan, 2017). Notations of sets, parameters and variables are specified in Tables 3.1–3.3.

Objective:

$$\min \sum_{a\in A}\sum_{i\in N}\sum_{j\in N} c^{a}_{ij} X^{a}_{ij} \tag{3.1}$$

Subject to:

$$\sum_{a\in A}\sum_{i\in N} X^{a}_{iD} = \sum_{a\in A}\sum_{i\in N} X^{a}_{Oi} = 1 \tag{3.2}$$

$$\sum_{a\in A}\sum_{i\in N} X^{a}_{ij} = \sum_{a\in A}\sum_{i\in N} X^{a}_{ji}, \quad \forall j \in N \setminus \{O, D\} \tag{3.3}$$

$$X^{a}_{ij} \in \{0, 1\}, \quad \forall i, j \in N, \forall a \in A \tag{3.4}$$

The objective (3.1) is to minimise the total cost of transportation. (3.2) ensures containers are sent and received for the origin and destination nodes, and (3.3) ensures the flow and its balance for the intermediate nodes. Different from the original format of GTP, a constraint (3.4) sets the decision variable to be binary so as to make the shipment unsplittable for simplicity.

Considering the capacitated arcs A (especially for the trains V), constraint (3.5) is added to prevent overloading of each arc $a \in A$.

$$\sum_{i\in N}\sum_{j\in N} bX^{a}_{ij} - \sum_{i\in N}\sum_{j\in N} f^{a}_{ij} \le 0, \quad \forall a \in A \tag{3.5}$$

Furthermore, the time dimension is also considered in the problem. The order has to be shipped before a specified time T. A handling time H_i will also be incurred to load/unload the cargo at nodes o and d, while in other nodes, H_i corresponds to the transhipment handling time. Therefore, the following three constraints are added to meet the time window requirement, assuming the order is placed at time t_0.

$$\sum_{a\in A}\sum_{j\in N} X^{a}_{ij} t^{a}_{i} - \sum_{a\in A}\sum_{j\in N} X^{a}_{ji} t^{a}_{i} \ge H_i, \quad \forall i \in N \tag{3.6}$$

$$\sum_{a\in A}\sum_{i\in N} X^{a}_{oi} t^{a}_{o} - t_0 \ge H_o \tag{3.7}$$

$$\sum_{a\in A}\sum_{i\in N} X^{a}_{id} t^{a}_{i} + H_d \le T \tag{3.8}$$

where (3.6) and (3.7) ensure enough time for handling among transportation legs and also for loading and unloading at the origin and the destination nodes. (3.8) is a hard constraint of closing time.

While to make the optimisation objective consider distance, transportation time and emissions, (3.9) can be added as an additional constraint or integrated into (3.1).

$$c^{a}_{ij} = \alpha_1 d_{ij} + \alpha_2 (t^{a}_{j} - t^{a}_{i} + H_j) + \alpha_3 e^{a}_{ij} \tag{3.9}$$

The above model is based on full data visibility. However, the problem to be addressed in this paper is the reluctance to share data, which affects many parameters. For instance, there is no longer a common view on the value of H_i; knowledge of available trucks and trains (A) also varies depending on nodes, thus f^{a}_{ij}. With the data varying in value and the availability strictly limited to the data owners' view, mathematical modelling is eventually inapplicable because the routing function itself is impossible. Therefore, a particular design is needed to treat the reluctance to share the data so that compromises can be made to find quality routes with minimal data leakage.

3.2. Research methodology

In this section, the problem has been defined by mathematical formulation. Next, we will introduce a PI-routing protocol to fulfil the decentralised characteristics of routing in the PI network and the need for privacy protection in such an interconnected PI information system.

The research methodology and experiments are going to be explained in the following sections. Fig. 3.1 presents the methodology taken in this research for the following sections.

In Section 4, we will first describe how the CPIR protocol works and discuss the relevant component designs. For example, the Routing Table and Broadcast List algorithm are specifically designed for larger networks to limit the search space. The agents

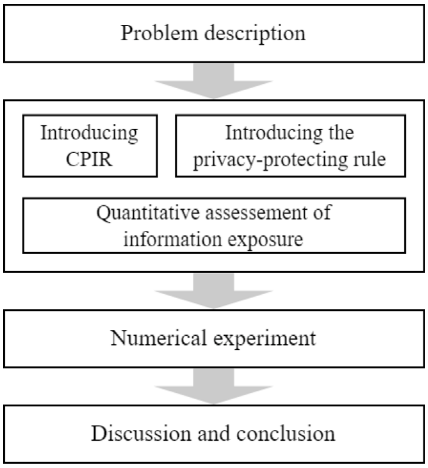


Fig. 3.1. Flow chart of the research methodology.

that comprise the protocol will also be elaborated upon. We will then introduce the core logic behind the CPIR protocol to answer this question: how can this different data-sharing policy avoid unnecessary information exposure? Finally, we will quantitatively evaluate the amount of data exposed in a Semi-Markov process.

In Section 5, numerical experiments are conducted to compare CPIR and other shortest path algorithms to evaluate the optimality and computing time in four varying scenarios. The analyses of the results lead to discussion and conclusion in the end.

4. Design of CPIR and the approach

This section describes how the CPIR protocol works and justifies how much information is protected under its privacy-protecting policy.

4.1. Description of the approach

CPIR is based on communication among nodes. In other words, no central unit performs a routing algorithm or manages all the data of the participant nodes, and every node keeps its data within itself. This is similar to Achamrah et al. (2023), in which every entity has its own knowledge. However, there is no central party to orchestrate the resource planning. To model the activeness of the nodes, an ABM approach is applied to allow communication among the agents.

ABM is applied as a simulation method, which explains the emergence of the overall patterns and seeks the causes of each individual. In agent-based models, varying behaviour rules and functions can be defined in each agent. Then during the simulation, agents can behave differently according to their surrounding environment. In the existing papers, agents can be defined by function to perform (Sarraj et al., 2014a; Walha et al., 2016), physical object (Sallez et al., 2016) or both Kin et al. (2018).

In CPIR, agents are defined both by function and physical object. Every node agent accommodates three classes of agents: *Order Management Agent*, *Communication Agent* and *Computing Agent* (see Fig. 4.1). The Order Management Agent in the origin node of an input order is directly responsible for tackling the order by finding the other agents to contact and managing the search process. The Communication Agent is the interface among nodes that enables the inter-node communication to find routes. The Computing Agent checks the available means of transportation between the asking node and its affiliated node.

A *Routing Table* is also designed in CPIR mimicking the DI. In Achamrah et al. (2023), Routing Tables are created to keep track of the states of containers, movers and hubs. Whereas in CPIR, it is only used to indicate the possible next nodes towards the destination. The Routing Table is structured as a dictionary, where the Keys are the destination node and each Key is mapped to a Broadcast List. A Broadcast List contains a list of nodes that are most likely to form the shortest path from its belonging node to the destination node (the key it maps to in the Routing Table). The Routing Table remains mostly cached statically and is only updated when the current subset of nodes cannot return a feasible route.

The routing is initiated as follows (also as indicated in Fig. 4.1):

- Order is placed and managed by the Order Management Agent in the origin node;
- The initial one-node (the origin node) route is picked as the initial route;
- Route searching for one step:
  - The last node on the current route is identified as the incumbent node;

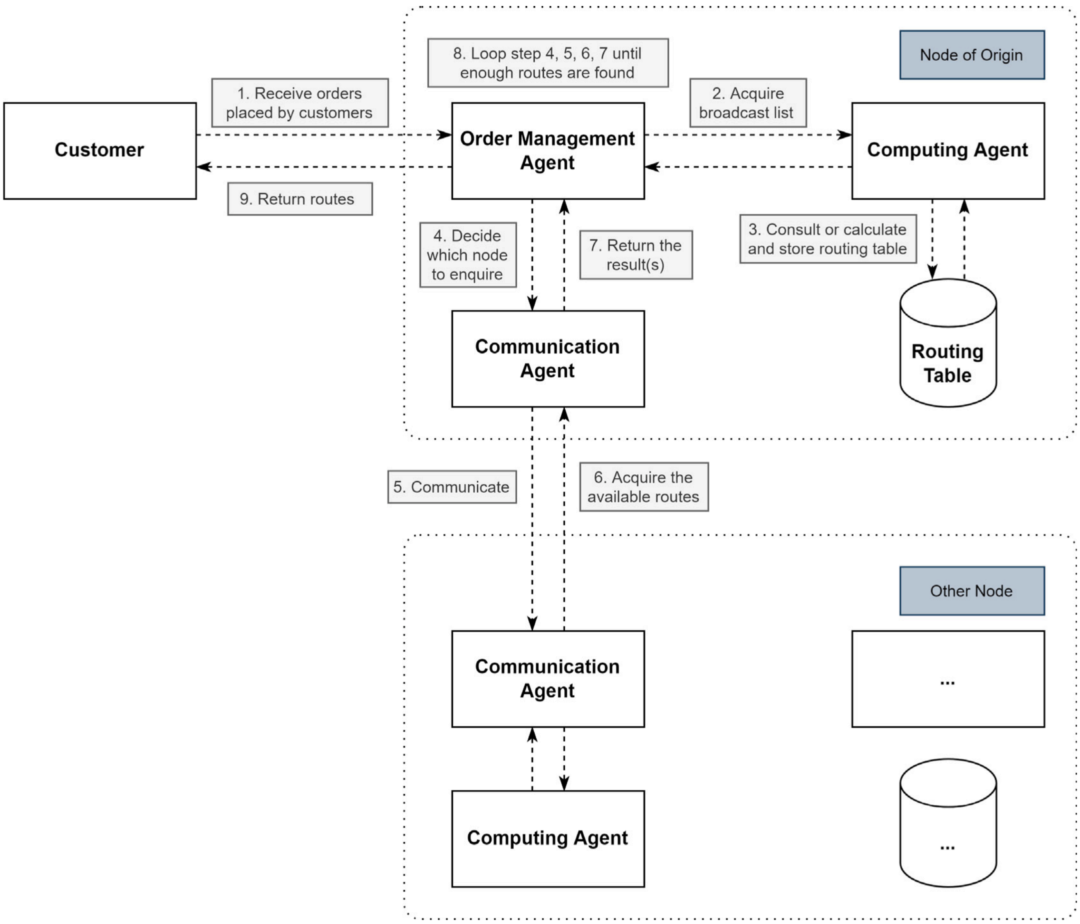


Fig. 4.1. Agents and communication process among nodes.

- The communication agent of the incumbent node consults the Routing Table using the destination of the order as the key to get a list of neighbour nodes;
  - If the key is absent in the Routing Table, the computing agent will compute a Broadcast List using a k-shortest path algorithm and cache it in the Routing Table for further use;
- The communication agent of the incumbent node sends CPIR messages to every neighbour node to request routes between the incumbent node and the receiver node;
- Each receiver node checks constraints (available known mover services, capacities, time window, etc.) and reply route(s) thorough CPIR messages;
- The communication agent of the incumbent node gathers the information and sends it to the Order Management Agent;

• The Order Management Agent find the next candidate route and conduct the above one-step route search again;
• If enough routes are found, rank them by user-defined weight and end the search.

The foremost and only aim of the CPIR protocol is to exchange CPIR messages, by which routes are spontaneously formulated as the conclusion of the communication, but not sharing data. It ensures that data is encapsulated and transmitted in CPIR messages and, therefore can only be utilised by the embedded services. Besides, due to the decentralised design of the system, every participant entity only receives and answers messages that directly pertain to the segment of tasks relevant to them without knowing the whole picture.

4.2. Protecting the privacy

One of the distinct features of this protocol is the privacy-protecting policy. As a decentralised system, the participants are not required to share information proactively but only reply ‘Yes’ or ‘No’ to the questions regarding the capacity. If the answer is “Yes”,

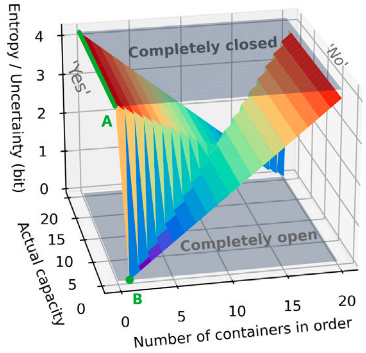


Fig. 4.2. An example of explaining information leakage by entropy.

the following message containing the connecting routes between the asker and answerer will be sent. The routes are calculated internally by the answerer according to its own knowledge of availability.

In information theory, entropy measures the uncertainty of information or the amount of information a message carries. Therefore, when a message has higher entropy, it remains more unclear to others because the degree of uncertainty is higher. Here, we adopt the Shannon entropy (Shannon, 1948) to measure the information entropy for event X (in bits):

$$H(X) = -\sum_{x \in X} P(x) \log_2 P(x)$$

where $P(x)$ denotes the probability when x is the outcome of event X, and $H(X)$ is the entropy representing the uncertainty of event X.

Fig. 4.2 illustrates the example of a carrier exposing its information by replying 'yes' or 'no'. The information that the carrier holds is its real capacity for containers ranging from 0 to 20. There are two alternative policies plotted in the figure compared with the policy represented by the colourful surface:

- *Completely open*: the carrier's information is known all the time to any outsiders. This is equivalent to the case when the carrier shares its data to a centralised database that everyone can access;
- *Completely closed*: the carrier protects its information perfectly when no one can access it. This policy, however, disables the routing possibilities, as mentioned at the end of Section 3.1.

Assuming the carrier is an honest party, who answers 'yes' when there is enough capacity and 'no' when not. For the possible order enquiring with from 0 to 20 containers, if the carrier only answers "yes" or "no", the expected information leakage will be at the level of the drawn colourful surface in Fig. 4.2. For example, if the carrier is enquired with an order with 0 containers (as shown by line A in Fig. 4.2), no information can be revealed no matter how much capacity he has, because this enquiry does not rule out any possibility. If an order enquiring with one container receives a "no" answer (as shown by point B in Fig. 4.2), then the information absolutely has a complete leakage because the only possible fact is that the carrier does not have any capacity left. In short, the space between the drawn surface and the 'completely open' surface corresponds to the information avoided from being published, thus the privacy protected by CPIR compared with a centralised method. Furthermore, in a discrete-time simulation, if a carrier's capacity is not enquired in the next time unit, the data turns closed again because the carrier is subject to receiving orders from other sources at any time.

4.3. Assessment of information leakage

For a quantitative assessment, it is assumed that the order amount (x) should satisfy $0 \le x \le m$, where m is the maximum possible capacity an entity can have, and $m \ge 1$. And y denotes the value of the actual capacity of a carrier as the information to be protected, which satisfies $0 \le y \le m$. Both x and y obey discrete uniform distribution.

In real-life cases, m is usually a very large number because it corresponds to all the information the owner wants to protect. Therefore, despite the discreteness of x, y and m, $h(m)$ can be calculated by integral. The expected amount of leakage as described in Fig. 4.2 (the space between the drawn surface and the 'completely closed' surface') can be calculated as follows:

$$h(m) \approx \frac{\left(\int_0^m \int_0^y \frac{x}{m} dx dy + \int_0^m \int_y^m \frac{m-x}{m} dx dy\right)}{m^2} H(m) = \frac{1}{3} H(m)$$

Next, we consider how to compare the information exposure in CPIR and open policy (i.e., the data is accessible to anyone all the time). The states of the node can be defined by two factors: whether the node is asked to send messages according to its capacity, and whether the node has its capacity changed due to individual reasons, which are irrelevant to the PI network (e.g. orders from

Table 4.1
Transition matrix.

s	AC	AU	NC	NU
AC	$p_a p_c$	$p_a(1-p_c)$	$(1-p_a)p_c$	$(1-p_a)(1-p_c)$
AU	$p_a p_c$	$p_a(1-p_c)$	$(1-p_a)p_c$	$(1-p_a)(1-p_c)$
NC	$p_a p_c$	$p_a(1-p_c)$	$(1-p_a)p_c$	$(1-p_a)(1-p_c)$
NU	$p_a p_c$	$p_a(1-p_c)$	$(1-p_a)p_c$	$(1-p_a)(1-p_c)$

Table 4.2
Costs for leaving a state.

s	$L_s(t)$
AC	$h(m)$
AU	$h(m)$
NC	0
$NU(t)$	$l(t,m)$

Table 4.3
Stationary distribution.

s	π_s
AC	$p_a p_c$
AU	$p_a(1-p_c)$
NC	$(1-p_a)p_c$
NU	$(1-p_a)(1-p_c)$

outside the PI network), denoted respectively by asked and changed (AC), asked and unchanged (AU), not asked and changed (NC) and not asked and unchanged (NU), i.e., the set of states $I = \{AC, AU, NC, NU\}$. It is assumed that the number of orders placed to the PI network obeys a Poisson distribution with an arriving rate of λ_1, and individual capacity changes λ_2. Due to the memoryless property of the Poisson distribution, the information leakage of a single node in the network can be modelled as a Markov process.

Fortunately, the world is big enough to let us assume that λ_1 and λ_2 are independent. Therefore, for a discrete-time simulation with a span of M (a large enough integer), it is safe to define the following transition matrix $\boldsymbol{P}$ as shown in Table 4.1, where $p_a = \frac{\lambda_1 p_b}{M}$, $p_c = \frac{\lambda_2}{M}$, and p_b denotes the probability when the modelled node is included into the Broadcast List due to an order being placed to the PI network.

According to the state that the node is in, a corresponding amount of information leakage (i.e., cost, denoted by $L_s(t), s \in I, t \in \mathbb{N}^+$) is incurred (see Table 4.2) when a node leaves a state. There are two sources of the cost, from replying "yes" or "no" to an enquiry, and from the lasting effect after a reply because, after the exposure of capacity, it can still remain deducible to outsiders for a while.

The lasting effect is modelled by:

$$l(t,m) = (1-p_c)^t \cdot l(t-1,m)$$

$$l(0,m) = \frac{p_a p_c h(m) + p_a(1-p_c)h(m)}{1-(1-p_a)(1-p_c)}$$

As it can be seen, unlike the cost for other states, the cost of leaving the state NU is associated with the sojourn time (t). Therefore, we model this problem as a semi-Markov process so as to model the sojourn time. Define a $(J-X)$ process over the modelling span M:

$$(J-X) = (J_n - X_n), n \geq 0, J_n \in I$$

where X_n stands for the sojourn time for the node in state J_{n-1}, and $M = \sum_{r=1}^{n} X_r$. Supposing $J_0 = NU(0)$, $X_0 = 0$, and for $r \in [1,n]$:

$$X \sim G(1-(1-p_a)(1-p_c)), J_r = NU(t)$$

$$X_r \equiv 1, J_r \in \{AC, AU, NC\}$$

Therefore, this semi-Markov process is homogeneous and ergodic, i.e., it has a stationary distribution $\boldsymbol{\pi} = \{\pi_s; s \in I\}$. Due to the special transition matrix $\boldsymbol{P}$ in this case, it is evident that the Markov chain converges in one step, where $\boldsymbol{\pi}$ is shown in Table 4.3.

With the above variables defined, the expected incurred cost of a node for one time step can be estimated as such:

$$E(C^{\text{CPIR}}) = p_b \sum_{s \in I} \frac{\pi_s L_s(t) dt}{E(X_n)}$$

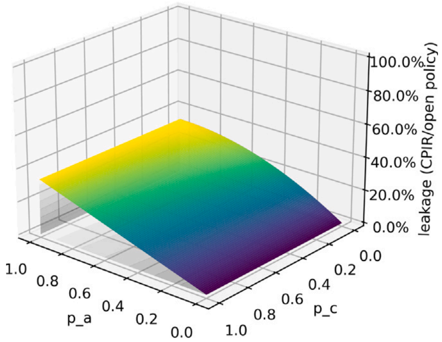


Fig. 4.3. Leakage comparison between CPIR and open policy.

Table 4.4
Parameter settings.

Item	Value
MAX_LOOP	150
MAX_RECUR	5
n_routes	10
k'	10,000
m	3
α, β, γ	1.5, 99, 1.5
Order delivery time limit (h)	24
Handling time in node (h)[a]	1
Train velocity (km/h)[b]	45
Train emission (kg CO_2/km)[c]	0.02749
Truck velocity (km/h)[d]	63.44
Truck emission (kg CO_2/km)[c]	0.90019
Truck max driving time for a single trip (h)	3

[a] Sarraj et al. (2014a).
[b] Janic (2008).
[c] Data from Gov.uk (2021).
[d] Briand et al. (2022).

Consider an open sharing policy, where the node operator has to share the data in a real-time manner, thus incurring $H(m)$ information leakage every time step, we can make the following comparison:

$$\frac{E(C^{\text{CPIR}})}{E(C^{\text{Open}})} \times 100\% = \frac{E(C^{\text{CPIR}})}{H(m)} \times 100\%$$

When $p_b = 1$ (i.e., the node is always selected into the Broadcast List, which is a worst-case and very unlikely in reality) the result can be plotted in a 3D manner as shown in Fig. 4.3. It is in line with the intuition that almost no information is exposed when $p_a \to 0$ because the capacity can never be known if it is never asked. Whereas it is the worst case when $p_a \to 1$ or $p_c \to 0$ (with the ratio approaching 33.33%) because the capacity is never changed. So once a node is asked, its capacity information is equivalent to remaining completely open since then. A positive but insignificant effect of a higher p_c when p_a is the same can also be observed from the figure.

For a lucid and logical demonstration considering the effects of p_b, in the case that $p_a \sim U(0, p_b)$ (because $p_a = \frac{\lambda_1 p_b}{M}$), and $p_b, p_c \sim U(0, 1)$, we have:

$$\begin{aligned} E &= E\left(\frac{E(C^{\text{CPIR}})}{E(C^{\text{Open}})}\right) \times 100\% \\ &= \int_0^1 \int_0^1 \int_0^{p_b} \frac{E(C^{\text{CPIR}})}{H(m)} dp_a dp_b dp_c \times 100\% \\ &\approx 6.5730\% \end{aligned}$$

which shows that most of the information can be protected. The CPIR policy can avoid over 90% of unnecessary information exposure. In addition, it is very rare to have a large p_b in real-life cases. Therefore E can be further reduced when p_b is brought down.

Table 5.1
Scenarios of experiments.

Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Compare to	A*	A*	Mes and Iacob (2016)	Mes and Iacob (2016)
Network size	23 nodes	49 nodes	23 nodes	23 nodes
Modality	Unimodal	Unimodal	Multimodal	Multimodal
Max driving hour	No limit	No limit	3	3
Max train capacity	No limit	No limit	No limit	$U(0, 20)$ CTRs
CTR[a] per order	1	1	1	$U(0, 5)$ CTRs

[a] CTR = container.

5. Model validation

Following the justification of privacy protection, this section compares CPIR with A* and a simple heuristic. The purpose of this section is to demonstrate that even with much less information shared, CPIR can still achieve similar optimality as conventional algorithms.

5.1. Model settings

In this section, comparisons are made with the A* algorithm on a unimodal network to examine a basic performance, and Mes and Iacob (2016) on a multimodal network because their problem settings are similar and simple.

The experiment runs on the Geographic Information System (GIS) based transportation network. The comparison with A* is conducted in the Belgium area (23 nodes) and BeNeLux area (49 nodes), respectively, while the comparison with Mes and Iacob (2016) is conducted in the Belgium area (23 nodes) but with trucks and trains (see Fig. 5.1). It can be challenging to figure out the optimal parameters for CPIR and Mes and Iacob (2016), but a set of calibrated parameters is tested and set in Table 4.4 for this specific problem scale. As no financial aspect is considered here, the constraint placed by β is relaxed by setting β to a large number, and γ is set to be relevant to the desired optimising target. The algorithm calculating the Broadcast List is attached in Appendix. Other parameter settings of the experiments can also be found in Table 4.4.

A summary of the experiment scenarios can be found in Table 5.1. In Scenario 1, CPIR is compared with A* on an unimodal network to give a baseline understanding of the performance of CPIR. Then, in Scenario 2, the problem size is increased to test the sensitivity of CPIR further. Scenario 3 and Scenario 4 are done on a multimodal network, where CPIR is compared to Mes and Iacob (2016) under the conditions of unlimited or limited train capacity. This can help to reveal how the two algorithms utilised trains, and how much the performance could be affected if the capacity is greatly limited.

The optimising target for both Mes and Iacob (2016) and the CPIR algorithm in this paper is one among total distance, transport time or emission. In the end, the performance is evaluated through the average travelling time, CO_2 emission, distance and computing time, as well as the total number of trucks used.

Some additional assumptions are made upon the problem described in Section 3 in order to run the simulation:

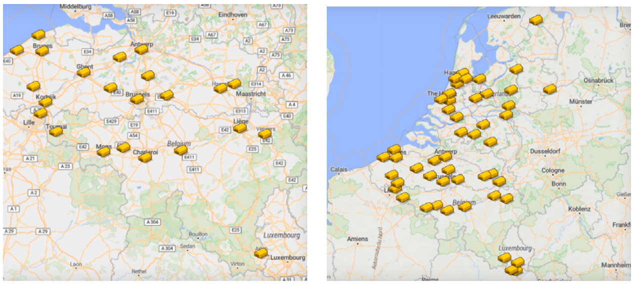
- **Limited truck driving distance.** The trucks are considered to have a maximum driving range to simulate the fact that local drivers cannot drive too far because they need to return home every day. This can make the problem more interesting since the direct route from the origin to the destination is not always available.
- **Bounded knowledge.** Each node has its knowledge of the train schedules and the respective capacity available for itself to load containers. However, the nodes only know the trains starting from themselves, not before. The CPIR setting is meant to vary the available capacity information kept in different nodes, which is to be protected as the privacy of each of the node operators.

The total simulation time is four weeks, with 6000 orders being randomly placed on the network (approximately ten orders per hour), each of which is a transport task for one container. Due to the computation of the Routing Table, the computation time for the CPIR algorithm is longer in the beginning and decreases and remains constant at a lower level after Routing Tables are computed and stored. Hence, the results shown are after the level-off of the computing time (5000 orders). The experiments are run using AnyLogic 8 Professional v8.8.0 on Intel® Core™i7-10750H CPU with 64 GB RAM. The results are shown in Table 5.2.

5.2. Performance comparison

The comparison in Scenario 1 and 2 shows that the CPIR returns slightly better results than A*, and remains insensitive to the number of nodes. This is because the GIS map is a weighted graph equivalent, in which neither A* nor CPIR is guaranteed to find the optimal route. But with an additional design of the Routing Table, CPIR could perform slightly better than A*, with the computing time remaining less sensitive to the problem size, being however much longer than A*.

In the results of Scenario 3, the optimised objective is marked in bold. Overall, the algorithm in Mes and Iacob (2016) has similar optimality to CPIR but with a better ability to trade off between emission and other objectives, causing a much higher need



(a) GIS map - Belgium area (23 nodes) (b) GIS map - BeNeLux area (49 nodes)

Fig. 5.1. GIS maps of the simulation cases.

Table 5.2
Experiment results.

Scenario	Algorithm	Delivery time (h)	Distance (km)	Emission (kg CO_2)	Computing time (ms)	Trucks
1	A*	3.99	**118.50**	106.67	0.0536	6731
1	CPIR_D	4.01	**116.73**	105.08	0.5946	6965
2	A*	5.40	**184.34**	165.94	0.0760	8975
2	CPIR_D	5.46	**181.38**	163.28	0.5588	9607
3	Sync_T	**3.99**	118.51	106.68	80.8717	6701
3	Sync_D	6.55	**116.64**	98.13	91.5561	6756
3	Sync_E	14.20	149.60	**65.78**	80.4555	7983
3	CPIR_T	**4.02**	117.01	104.97	1.3626	6635
3	CPIR_D	5.88	**115.92**	97.97	1.3133	6209
3	CPIR_E	11.50	135.70	**76.65**	1.4424	4853
4	Sync_T	**3.99**	118.51	322.93	77.9273	22 196
4	Sync_D	6.22	**116.90**	296.99	46.9297	22 624
4	Sync_E	14.49	136.20	**257.23**	5.1950	22 624
4	CPIR_T	**4.01**	117.12	314.76	1.0706	25 477
4	CPIR_D	5.66	**115.87**	299.90	1.0448	29 433
4	CPIR_E	10.84	128.74	**257.54**	0.9556	29 433

* Optimised objectives are marked in **bold**.
** Sync = the algorithm proposed by Mes and Iacob (2016).
*** T/D/E = the optimising objective (time, distance and emission).

for trucks and, consequently, delivery time due to the handling time within nodes. Another remarkable difference is that the needed computing time and the number of trucks for CPIR are significantly less than Mes and Iacob (2016).

While Scenario 4 shows a similar result to Scenario 3. CPIR uses more trucks than Mes and Iacob (2016), but the computing time still remains very low. Moreover, Sync_E also runs very fast, because a vast majority of trains are filtered out due to their limited capacity, and the searching space thus decreases.

5.3. Discussion

The model has been tested in Belgium and the Benelux region. While since the model is based on data, the methodology can be applied to other contexts as well. The data of nodes and transport modes are stored externally and can be imported into the model, which allows the same routing protocol to be tested in different contexts.

In addition to privacy protection, CPIR also allows for the integration of other algorithms and constraints without increasing the complexity. For instance, if node B receives a request to provide a route from A to B, it can either respond directly or apply a mover scheduling or consolidation algorithm to filter out infeasible routes before sending its response.

These features are particularly useful when evaluating the effects of disruptions such as the COVID-19 pandemic. Since this model is data-based, input changes (the graph configuration, resources on the network, etc.) can be conveniently made. Furthermore, unexpected events can impose additional constraints, such as restricted driving areas and time-changing availability. The CPIR framework can include these constraints by assigning them to the Computing Agent so that the computation happens locally at the responder's agent without violating the privacy-protecting policy.

6. Conclusion

This paper proposes a routing protocol named CPIR that finds routes in a multimodal transport network with much less information needed from the logistic practitioners. It envisions building a system where services can be provided with message communication rather than sharing data. Moreover, the optimality of CPIR is justified to some extent through comparison with benchmark heuristics. The routes found by CPIR are based on decentralised communication, and each party can keep private information on its own. There is no centralised database or computing unit for routing either because communication behaviour itself is the computation. This design also supports the implementation of PI from a structural point of view. It is justified that CPIR can return a quality routing result while the open information is protected to a great extent.

Besides being a protocol, CPIR can also be viewed as a framework, as this way of routing through communication can result in structural redesign in the back end of the supporting information system of the normal routing algorithm. Under this framework, CPIR can accommodate other algorithms like hierarchical shortest path algorithm, bin-packing algorithm (for containers), warehouse scheduling algorithm, and more constraints such as capacitated nodes, limited in-house truck fleets and individual relationship concerns (like blacklists, varying access controls). This feature makes CPIR a flexible method to solve shortest-path problems on multimodal transport networks with rich constraints. Another advantage is that the need for a central supercomputing unit is eliminated in CPIR. The computation is conducted in a decentralised way, exploiting more potential for scalability. Lastly, models utilising CPIR can be highly decentralised and modular, allowing for the accommodating of other services, such as pricing models, container filling optimisers, and truck schedulers. Such a transition aligns with PI's future towards a service-oriented architecture (Pan et al., 2019b).

We identify a few limitations of this research. To begin, CPIR could be tested on a larger problem size and compared with more recent algorithms with realistic business data to further evaluate the efficiency, especially under scenarios with disruptions. Moreover, the design of CPIR could benefit from a survey regarding the extent to which this privacy policy is helpful. Also, the implementation cost of CPIR could be high because it assumes participants are connected and able to respond automatically. Lastly, it would be useful to include consolidation and other distinctive PI models in CPIR.

There are some potential improvements in the current CPIR protocol itself. First, the parameters of CPIR can be dynamic and machine learning-based, so the parameters in the algorithm for Broadcast Lists can be adjusted according to the problem size. By comparing Scenario 1 and 2, we have found that the computing time of CPIR has been reduced. This is because the local search algorithm that was used did not return additional nodes as the network size grew in Scenario 2. As a result, the shortest path was found more quickly. While on the other hand, it limits the scope for potential optimisation. Next, the message-sending logic can be improved to make communication more efficient. Furthermore, the calculation of the Routing Table is based on the GIS distance, which might not reflect the actual travel cost due to the existence of trains or other potential modes.

For future research, we suggest the development of a larger PI community network, which implies more nodes and better interconnectivity. A hierarchical architecture (Madkour et al., 2017) following the same privacy policy can be applied to solve the routing problem at different levels. More advanced information-protecting strategies also need to be researched for communication under such an interconnected network. We also refer to the research on Privacy-Preserving Computation techniques such as secure multi-party computing (Zhao et al., 2019) and differentiated privacy (Ye et al., 2020) as a possible future direction.

CRediT authorship contribution statement

Shiqi Sun: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Cathérine Cassan:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization. **Cathy Macharis:** Writing – review & editing, Supervision, Resources, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Broadcast list algorithm used in the simulation

Algorithm 1: computing broadcasting list

```
Input: origin, destination, dist_mtx (distance matrix), n_routes (number of shortest routes to conclude), MAX_RECUR (a loop
    counter to prevent infinite loop), MAX_LOOP (limit of loop times)
Output: result (a subset of nodes)
routes.put({origin, destination}, dist_mtx[origin, destination]);
while MAX_LOOP > 0 do
    randomly pick a route element temp_route from routes;
    switch randomly from one of the following cases, if applicable do
        case (1 && if (temp_route.length ≥ 3)) do
            remove a random node between origin and destination from temp_route;
        case (2 && if (temp_route.length ≥ 3)) do
            mutate a random node between origin and destination;
        case (3 && if (temp_route.length ≥ 4)) do
            randomly swap two nodes between origin and destination;
        case 4 do
            add a random node between origin and destination;
    end
    calculate the cost temp_cost for temp_route according to dist_mtx;
    if temp_route is not in routes && temp_cost != infinity then
        routes.put(temp_route, temp_cost);
        MAX_LOOP -= 1;
    else if MAX_RECUR == 0 then
        break;
    else
        MAX_RECUR -= 1;
        continue;
    end
end
rank routes according to the costs;
add all the nodes in the top n_routes routes to the set result;
return result;
```

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