Hub-based Routing Algorithm Description

1. Introduction

Physical Internet (PI) is a novel concept of future logistics and supply chain management that uses the metaphor of the "data routing" in the Digital Internet into the physical world. For transportation, PI breaks a complete route of the traditional view into segments between hubs, corresponding to the routers in the Digital Internet, for which PI has a decentralised tendency compared with the traditional centralised way of management. Moreover, PI seeks to utilise advanced technologies to improve the inefficiency in the current operations. In business operation management, PI promotes technologies such as RFID and information system to achieve paperless workflow and lower waste.

In accordance with the logic, the project Physical Internet Living Lab (PILL) explores the improvement possibilities in the logistic sector by building a prototype of the PI information system and connecting the silo of different types of logistic practitioners, including carriers, forwarders, port operators, etc. While to support the validation of interconnection in a virtual and costless environment, a digital twin is to be built to mirror the reality and to be used to test what-if scenarios, in which a logistic model with a proper routing algorithm that can present PI features is to be developed. This piece of writing proposes an intercity PI routing algorithm in agent-based modelling (ABM) in which the routing decisions are completely made by PI hubs.

2. Literature Review

2.1. Physical Internet

The concept of PI was formally published and promoted in a journal article for the first time in 2011 (Montreuil, 2011). It is designed to heavily rely on Internet of Things (IoT) devices and information and communication technologies (ICT) to enable real-time computing and control of goods. Corresponding supportive infrastructures are also being designed, such as PI hub, PI container, PI composer, etc. (Montreuil, 2011). In that 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).

The research of PI has been flourished since 2015 (Ambra *et al.*, 2019), and researchers are now focusing on more specific problems of every logistic aspect (Treiblmaier *et al.*, 2020). In the early stage, research topics are mostly regarding the development of the PI concept. Montreuil *et al.* (2012) devised a 7-layered Open Logistics Interconnection (OLI) model as the information structure model for PI. Sarraj *et al.* (2014) conduct an in-depth comparison of PI and Digital Internet and prove the benefits of PI using a stylised model. Later on, more quantitative studies are published. The utilisation of PI hub and other PI related facilities into transportation networks are examined (e.g., Ben Mohamed *et al.*, 2017; Sarraj *et al.*, 2014b; Kin *et al.*, 2018), which generally returns positive reflection. Some look at the different operations in PI entities (Walha *et al.*, 2014; Chargui *et al.*, 2018; Vo *et al.*, 2018). There are also papers focusing on the efficiency of PI containers (Zhang *et al.*, 2016; Sallez *et al.*, 2016; Tran-Dang *et al.*, 2017). In addition, information system design is also a major stream. It was first considered from the industry background, such as mass-customised workshop (Zhong *et al.*, 2016), solar cell industry (Lin and Cheng, 2018), prefabricated construction (Chen *et al.*, 2018), etc. Tran-Dang *et al.* (2020) propose the prototype of PI system layers, and some researchers attempt to involve blockchain in PI (Meyer *et al.*, 2019; Betti *et al.*, 2019). However, it is also found that when a problem is brought more complicated by multimodality, the research scope is often confined to a single hub, and PI research that considers maritime ports is scarce. This unimodal tendency of research is also pointed out in Ambra *et al.* (2019).

2.2. Agent-based modelling

Agent-based modelling (ABM) is a computer simulation method that is also used in other research domains like cognitive science and economics. The commonality of those research is they need ABM to function as a tool to "conceptually bridge between the micro-level of assumptions regarding individual agent behaviours, interagent interactions, and so forth and the macro level of the overall patterns that result in the agent population" (Smith and Conrey, 2007). The appearance of the "overall pattern" is named *emergence*. According to the object to be modelled, ABM defines the agent types and the logic between the agents to construct a digital twin and interact with the physical counterpart (Ambra and Macharis, 2020).

Comparisons of conventional routing schemes and the PI-hub-based routing scheme have been studied, and ABM is often used to model the operations within PI hubs. Sarraj *et al.* (2014) propose PI transportation protocols using PI containers and a case study of real data to compare the real-life and PI routing scheme. The routing is based on PI hub and agents of different functions are set in each hub. In Walha *et al.* (2016), the multi-agent method is used to model a road-rail PI hub to study the allocation problem. ABM is also used to model facilities of higher level, such as in Kin *et al.* (2018) and Sun *et al.* (2018), agents are set to model on a higher scale of the transportation network. The advantage of ABM is that it greatly helps explain the relations and mechanisms formed among the defined agents because each agent keeps generating data on themselves. Therefore, basically, each study has its own design of agents in order to cater for their optimising needs and explain the reality in different ways.

2.3. Routing algorithms

Conventionally, the most popular routing problem have been researched is the vehicle routing problem (VRP), which can be defined as "the problem to find delivery routes from a depot to a set of locations which can minimise the cost subject to the constraints" (Kumar and Panneerselvam, 2012). For smaller scale VRP, the exact method as mixed-integer programming can provide the optimal solution. Whilst with the problem scale increases, additional constraints are also considered, such as time window, limited fleet size, the capacity of vehicles, various types of vehicle etc., which often makes exact methods intractable (Soonpracha *et al.*, 2014). Thus, heuristics and other searching algorithms are developed to find a suboptimal solution in a large search space at an acceptable cost of computation power. Usually, the popular algorithms include tabu search, genetic algorithm, simulated annealing, ant colony optimisation, etc. Related studies are too many to be referred to here, but they all carefully design the algorithm to cater for the problem settings in each research. While more recently they are often to be applied in a combinational way (for example, Barma *et al.*, 2019; Chargui *et al.*, 2020).

However, enough about VRP, because in PILL, the problem is not completely a VRP variant, because there are not only trucks but also capacitated trains and barges which run mostly according to their schedules, involving cooperation at the business level. In that case, the containers to be shipped need to find their own way to their destination and fit the availability of the transportation modes and the transition nodes. It is a multi-objective multimodal multi-commodity flow problem with schedule (Archetti *et al.*, 2021). A very closely related problem studied is the Intermodal Multicommodity Routing Problem with Scheduled Services (Ayar and Yaman, 2012), in which a set of commodities is to be picked up and delivered before a specified time for each commodity using scheduled maritime services and trucks. The objective is to minimise the incurred cost while respecting the time and capacity constraints. With a scale of 100 nodes in two service networks, the problem is solved by mixed integer programming models with Lagrangian relaxation. They also point out their willingness to devise heuristics for this problem. Nevertheless, their model does not consider railway transportation and the complexity brought by scalability. This problem is then more studied due to the prevalence of the idea of synchromodality.

Synchromodal planning "is a form of multimodal planning in which the best possible combination of transport modes is selected for every transport order" (Mes, M.R. and Iacob, 2016). It envisions allowing the en-route changes to transportation plans. In Zhang and Pel (2016), a path-level freight transport model is built with considerations on the time limit, schedule, capacity and multimodality at the same time for the first time. Their aim is to compare the cost of intermodal and synchromodal by designing a route selection model in a route assigning algorithm for a real-life case. Qu *et al.* (2019) study a similar question by designing a mixed-integer programming model for synchromodal transportation with a schedule and time window on a network consisting of 6 nodes.

It is considered that the optimising problem of more than two modalities on a large network is still unexplored (Archetti *et al.*, 2021), and most of the relevant research focuses on small scale networks and improved exact methods. However, the growth of problem complexity and scale is thought to be faster than the methodological revolution of operational research. Therefore, it makes sense to look for heuristic algorithms as what VRP research has been going through. To our best knowledge, there is no available heuristic solution is known to solve the multi-objective multimodal multi-commodity flow problem with schedule for a large network.

3. Hub-based routing algorithm

3.1. problem definition

As the first step in PILL, a transportation network $G(N, A)$ of the hinterland area of Port of Antwerp and Port of Zeebrugge in the Flanders area is to be studied during all simulation time $\mathcal{T}$. $A = \{a^t,\ a^r, a^b\}$, representing the arcs of roadway, railways and in inland water ways (IWWs). Logistic practitioners are composed of shipper, carrier, port operator, port authority, terminal operator, which involves the planning of trucks V^T, trains V^R, and barges V^B. The shipper has a set of orders K to be shipped, measured by a set of containers C_k and time window t_k for each order $k \in K$. Each container $c \in C_k$ is characterised by the origin, destination, cargo type, and delivery time (o_c, d_c, τ_c, t_c). The time window for early and late delivery $t_k = \{t_k^E, t_k^L\}$ of order k should be respected, in which $t_k^e = \min\{\tau_1, \tau_2, \dots, \tau_c\}$, $t_k^l = \max\{\tau_1, \tau_2, \dots, \tau_c\}$, $for\ each\ c \in C_k$. Trucks are flexible while trains and IWW barges are operated according to their respective schedule. The available capacity of all trucks D^T, train D^R, barges D^B and PI nodes D^N should be considered. For the capacity of each truck element at time t, there are $D^T = \{d_t^{T_u} | u = 1, 2, \dots, u_t, t \in \mathcal{T}\}$, the same for d_t^R, $d_t^B$and d_t^N, and $D^V = D^T \cup D^R \cup D^B$. And for IWWs, the class and capacity are also to be considered. It is also necessary to take scalability into consideration because PILL builds a prototype, which means it should have the potential to accommodate more parties in the future. The network should have the ability to replan the route when unexpected manifestations of changes occur to the current route (e.g., traffic jam, order cancellation). The good thing is, PI enables the connection between parties which are not possible in the past. The aim of this algorithm is to support the comparison between PI and conventional transportation patterns in a quantitative way.

3.2. *Algorithm design*

The algorithm starts with the ABM method, which breaks the problem into different agent types and defines their behaving logic. In this algorithm, there are two types of agents, active and passive agents. Active agents are the PI nodes $n \in N$ in the transportation network, performing as an intermodal centre, transition depot, etc., which has the computing power to communicate and make decisions in route planning. Passive agents are the PI movers $V = V^T \cup V^R \cup V^B$, referring to all the traffic modes in the network. The outcome of this algorithm is a solution S_c for each container $c \in k$, and the solution of an order $\mathcal{S}_k = \{S_1, S_2, \dots, S_c\}$. P denotes the set of all the candidate plans p. Each p is defined by $(\mathcal{A}, F, \omega)$, in which $\mathcal{A} = \{x_{i,j,v,t} \cdot a_{i,j,v,t} | i, j \in N, i \neq j, v \in V\} \setminus \{0\}$, $a_{i,j,v} \in A$, representing that the container is brought from i to j by vehicle v at time t; $x_{i,j,v,t}$ is decision variable; F is the total cost; and ω is a flag to show whether the plan is in the end state. Thus, $S_c = p^{opt}$ where $F_{p^{opt}} = min\ \{F_p | p \in P\}$, break the tie arbitrarily if there is any. By end state, it means either this plan has reached the destination of the order, or the plan violates hard constraints.

By default, F is the objective function to be minimised, which is calculated as follows:

$$To\ minimise\colon F = \sum_i f_i + \beta \cdot T_k^{dev}, \qquad i \in N \tag{1}$$

$$f_i = \alpha_{i1} \cdot travelling\ time + \alpha_{i2} \cdot vehicle\ cost + \alpha_{i3} \cdot CO_2\ emission + \cdots, \qquad i \in N \tag{2}$$

where $\boldsymbol{\alpha} = [\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{in}]^{-1}$ is a vector containing the user-defined weight parameters, and T_k^{dev} is the time window deviation:

$$T_k^{dev} = \begin{cases} inf, & d_{t_k^l}^N < |C_k|, and\ t_k^l < t_k^E\ or\ t_k^l > t_k^L \\ p_1, & d_{t_k^l}^N \geq |C_k|, and\ t_k^l < t_k^E \\ r \cdot (t_k^L - t_k^l)^{-1}, & t_k^E \leq t_k^l \leq t_k^L \\ p_2, & d_{t_k^l}^N \geq |C_k|, and\ t_k^l > t_k^L \end{cases}$$

where $p_1, p_2 > 0, r < 0$. By this, it is encouraged to deliver on time rather than too early, and the maximum throughput of the network is expected to be increased, i.e., the network can deliver more goods on time.

The communication logic is defined for the active agents as their behaving logic, and a route is concluded through communication (demonstration shown in Figure 1). When an order k is input to the system, data will be updated to relevant nodes in the network. According to the o_c and t_k, n_o sends message to n_δ, where $n_o = o_c$, $n_\delta \in N$ and $n_\delta \neq n_o$. Then for n_δ, it checks its available capacity $d_t^{n_\delta}$ before the late delivery time limit t_k^L. For order k, if n_δ finds any feasible slot $[t_1, t_2]$ that meets the following hard constraints, it will respond to n_o according to the slots:

$$\sum_v \sum_t d_t^v \cdot a_{n_o, n_\delta, v, t} \geq |C_k|, \qquad n_o, n_\delta \in N, n_o \neq n_\delta, v \in V, t_0 \leq t \leq t_1 \leq t_k^L \tag{3}$$

$$\sum_v \sum_t a_{n_o, n_\delta, v, t} \leq 1, \qquad n_o, n_\delta \in N, n_o \neq n_\delta, v \in V, t_0 \leq t \leq t_1 \leq t_k^L \tag{4}$$

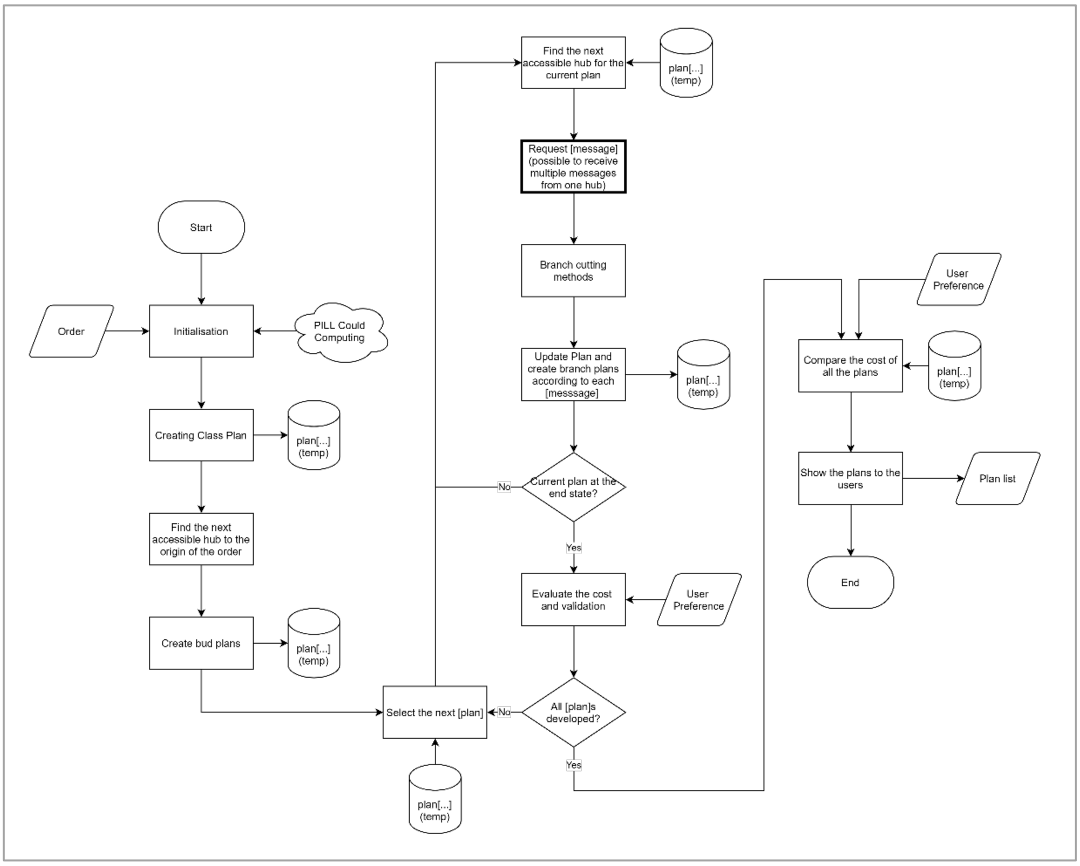

Figure 1. Demonstration of the route planning process

$$d_{t_1}^{n_\delta}, d_{t_w}^{n_\delta}, d_{t_2}^{n_\delta} \geq |C_k|, \qquad n_\delta \in N, k \in K, t_0 \leq t_w \leq t_2 \leq t_k^L \tag{5}$$

(3) ensures there is a transportation mode can deliver goods to n_δ to meet the given feasible slot $[t_1, t_2]$; (4) ensures the dedicated transportation mode has enough capacity to transport the $|C_k|$ containers of order k so that the order is not delivered in batches; (5) ensures enough handling capacity during a given feasible slot $[t_1, t_2]$. By this, some bud plans are created, and more plans will grow and branch from the bud plans later.

Next, for each plan p in P, the last node of p is responsible to send message to all the other accessible nodes n_{δ^+}. The asked nodes calculate $f_{n_{\delta^+}}$ and reply messages according to the hard constraints (3), (4) and (5) of themselves, and check the end status. p is grown and branched by updating $\mathcal{A}_p$, F_p and ω_p. However, the selection of p should always be the one with the least depth $|\mathcal{A}|$. In that way, the algorithm becomes the equivalent of a breadth-first search (BFS). When all the p in P are in the end state, S_{opt} is concluded by comparing $\{F_p | p \in P\}$.

3.3. Searching Space Limiting Methods

For a larger network, BFS is less efficient due to the exponentially increasing searching space. Some cutting methods are needed. First of all, the branch and bound method can be used in BFS. In this context, when a feasible route is found with the cost f_b, any other branch from which the plans that are to be grown cost at least f_b will be cut and marked to end state.

Moreover, user-preference settings can also help to cut the searching space. Users can not only define α, but also add hard constraints. For example: do not accept solutions with travelling distance more than a certain number. Or it is even possible to confine some parameters not included in the objective function F, like do not accept solutions of more than a certain time of transition in hubs.

For a larger transportation network, it is unrealistic to ask all the nodes on a graph for each step in each plan. Therefore, other auxiliary routing heuristics which are used for VRPs can be added while omitting the complex realistic settings (capacity, transportation mode availability, etc.). This way the problem is simplified, and more advanced algorithms become available with delicate designs such as A* and genetic algorithm. These extra heuristics can help the nodes to point out a specific group of nodes to ask for messages rather than ask all the nodes for replies.

4. Discussion

In this piece of writing, a routing algorithm is introduced which can be used in a complex but realistic background using the ABM method. The advantages of using this algorithm are:

- Good compatibility with other algorithms or methods. Due to the flexible ABM method, if the problem to be treated grows more complicated (and it will because PILL is a prototype towards universal application), auxiliary algorithms can be plugged and used easily.

- Decentralised computing power. PI and ABM have a decentralisation tendency, which becomes more advantageous especially in a large network. Considering the real-life application in the future, it could be energy-consuming and unsafe to route in a centralised way, while it is not too decentralised to grant every truck, train and barge the computational power. The power is bounded in the nodes, which is beneficial for scalability.

- Supporting to test more functions. As so far, not much has come true in PI, and we thus need an algorithm that is able to accommodate the current and future operations so that comparisons and conclusions can be carried out. For example, if disruptions occurred while the order is en route, PILL allows the route to be replanned and information is changed timely between the companies; if (4) is relaxed and (2) is changed accordingly, the PI feature of batched delivery can be tested; by varying the vector α, the variation of individual perspectives and its resulting effects of the overall perspective can then be studied; as the trains and barges are operated according to a schedule, and ABM allows to define individual logic, it could be useful to involve learning mechanism for the nodes.

However, BFS is a simple searching method. Without a quantitative study of the algorithm performance, it could happen that this algorithm works inefficiently, and auxiliary algorithms are needed to be introduced earlier than expected to solve the problem.

References

Ambra, T. et al. (2019) Towards freight transport system unification: reviewing and combining the advancements in the physical internet and synchromodal transport research. *International Journal of Production Research*, 57(6), 1606–1623. Taylor & Francis.

Ambra, T. & Macharis, C. (2020) Agent-Based Digital Twins (ABM-Dt) in Synchromodal Transport and Logistics: The Fusion of Virtual and Pysical Spaces. *Proceedings - Winter Simulation Conference*, 2020-Decem, 159–169. [Accessed: 21 May 2021].

Archetti, C. et al. (2021) Optimization in Multimodal Freight Transportation Problems: A Survey. *European Journal of Operational Research*. Elsevier B.V.

Ayar, B. & Yaman, H. (2012) An intermodal multicommodity routing problem with scheduled services. *Computational Optimization and Applications*, 53(1), 131–153.

Barma, P.S. et al. (2019) A 2-opt guided discrete antlion optimizationalgorithm for multi-depotvehicle routing problem. *Decision Making: Applications in Management and Engineering*, 2(2), 112–125.

Betti, Q. et al. (2019) Improving Hyperconnected Logistics with Blockchains and Smart Contracts. *IT Professional*, 21(4), 25–32.

Chargui, T. et al. (2018) *Simulation for PI-Hub Cross-Docking Robustness*.

Chargui, T. et al. (2020) Proposal of a multi-agent model for the sustainable truck scheduling and containers grouping problem in a Road-Rail physical internet hub. *International Journal of Production Research*, 58(18), 5477–5501. Taylor & Francis.

Chen, K. et al. (2018) A Physical Internet-enabled Building Information Modelling System for prefabricated construction. *International Journal of Computer Integrated Manufacturing*, 31(4–5), 349–361. Taylor & Francis.

Kin, B. et al. (2018) Tackling fragmented last mile deliveries to nanostores by utilizing spare transportation capacity-A simulation study. *Sustainability (Switzerland)*, 10(3).

Kumar, S.N. & Panneerselvam, R. (2012) A Survey on the Vehicle Routing Problem and Its Variants. *Intelligent Information Management*, 04(03), 66–74.

Lin, I.C. & Cheng, C.Y. (2018) Case study of physical internet for improving efficiency in solar cell industry. *Journal of Ambient Intelligence and Humanized Computing*, 9(2), 285–294. Springer Berlin Heidelberg.

Mes, M.R. and Iacob, M.E. (2016) Synchromodal transport planning at a logistics service provider.

Logistics and Supply Chain Innovation, 23–36.

Meyer, T. et al. (2019) Blockchain technology enabling the Physical Internet: A synergetic application framework. *Computers and Industrial Engineering*, 136(July), 5–17. Elsevier.

Ben Mohamed, I. et al. (2017) Modelling and solution approaches for the interconnected city logistics. *International Journal of Production Research*, 55(9), 2664–2684. Taylor & Francis.

Montreuil, B. (2011) Toward a Physical Internet: meeting the global logistics sustainability grand challenge. *Logistics Research*, 3(2–3), 71–87.

Montreuil, B. et al. (2012) An open logistics interconnection model for the physical internet. In: IFAC *IFAC Proceedings Volumes (IFAC-PapersOnline)*. [Online]. IFAC. Available at: doi:10.3182/20120523-3-RO-2023.00385

Pan, S. et al. (2017) Physical Internet and interconnected logistics services: research and applications. *International Journal of Production Research*, 55(9), 2603–2609. Taylor & Francis.

Qu, W. et al. (2019) Hinterland freight transportation replanning model under the framework of synchromodality. *Transportation Research Part E: Logistics and Transportation Review*, 131(October), 308–328. Elsevier.

Sallez, Y. et al. (2016) On the activeness of intelligent Physical Internet containers. *Computers in Industry*, 81, 96–104. Elsevier B.V.

Sarraj, R. et al. (2014a) Analogies between Internet network and logistics service networks: challenges involved in the interconnection. *Journal of Intelligent Manufacturing*, 25(6), 1207–1219.

Sarraj, R. et al. (2014b) Interconnected logistic networks and protocols: Simulation-based efficiency assessment. *International Journal of Production Research*, 52(11), 3185–3208.

Smith, E.R. & Conrey, F.R. (2007) Agent-based modeling: A new approach for theory building in social psychology. *Personality and Social Psychology Review*, 11(1), 87–104.

Soonpracha, K. et al. (2014) *Heterogeneous VRP review and conceptual frameworks*. In: 2014.

Sun, Y. et al. (2018) Multiagent Modelling and Simulation of a Physical Internet Enabled Rail-Road Intermodal Transport System. *Urban Rail Transit*, 4(3), 141–154. Springer Berlin Heidelberg.

Tran-Dang, H. et al. (2017) Containers monitoring through the Physical Internet: a spatial 3D model based on wireless sensor networks. *International Journal of Production Research*, 55(9), 2650–2663. Taylor & Francis.

Tran-Dang, H. et al. (2020) Toward the internet of things for physical internet: Perspectives and challenges. *IEEE Internet of Things Journal*, 7(6), 4711–4736. IEEE.

Treiblmaier, H. et al. (2020) The physical internet as a new supply chain paradigm: a systematic literature review and a comprehensive framework. *International Journal of Logistics Management*, 31(2), 239–287.

Vo, N.V. et al. (2018) Control of Rail-Road PI-Hub: The ORCA Hybrid Control Architecture. *Studies in Computational Intelligence*, 762, 291–302.

Walha, F. et al. (2014) A rail road PI hub allocation problems: model and heuristic. *Proceedings of 1st International Physical Internet Conference (IPIC 2014)*, 1–12.

Walha, F. et al. (2016) A rail-road PI-hub allocation problem: Active and reactive approaches. *Computers in Industry*, 81, 138–151. Elsevier B.V.

Zhang, M. & Pel, A.J. (2016) Synchromodal hinterland freight transport: Model study for the port of Rotterdam. *Journal of Transport Geography*, 52, 1–10. Elsevier Ltd.

Zhang, Y. et al. (2016) Smart box-enabled product–service system for cloud logistics. *International Journal of Production Research*, 54(22), 6693–6706. Taylor & Francis.

Zhong, R.Y. et al. (2016) Physical Internet-Enabled Manufacturing Execution System for Intelligent Workshop Production. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, 9(6), 121–132.