Reinforcement Learning-Based Optimization of Logistical Hubs and Routing in the Context of the Physical Internet - A Case Study from Japan

Hisatoshi Naganawa[1] and Enna Hirata[2]
1. Faculty of Ocean Science and Technology, Kobe university, Kobe, Japan.
2. Graduate School of Maritime Sciences, Kobe University, Kobe 658-0022, Japan.
Corresponding author: enna.hirata@platinum.kobe-u.ac.jp

Abstract: The global logistics industry is currently facing a number of challenges, including labor shortages and inefficiencies due to a lack of logistics facilities and resources, as well as increasing disruptions. Under these circumstances, Physical Internet (PI) is attracting attention as an innovative logistics system that can realize a sustainable society by sharing warehouses, trucks, and other means of transportation, improving utilization rates, and reducing fuel consumption. One of the important research themes in PI implementation is how to determine the location of logistics hubs and associated transport routes. In this research, we propose a reinforcement learning-based hybrid algorithm that combines NeuroEvolution of Augmenting Topologies (NEAT) and Lin-Kernighan Heuristic (LKH-3) to solve the location and route optimization problem. To evaluate the proposed hybrid algorithm, we applied real data from Japan to simulations and evaluated the performance of NEAT. The simulation results suggest that the proposed model could quantify the reduction of CO_2 emissions in different scenarios, thus identifying the optimal scenario.

Keywords: Physical Internet, Transport Route Optimization, Logistics Hub, Lin-Kernighan Heuristic, NeuroEvolution of Augmenting Topologies, Reinforcement Learning

Physical Internet (PI) Roadmap Fitness: Select the most relevant area(s) for your paper according to the PI roadmaps adopted in Europe and Japan: ☐ PI Nodes (Customer Interfaces, Logistic Hubs, Deployment Centers, Factories), ☐ Transportation Equipment, ☒ PI Networks, ☒ System of Logistics Networks, ☐ Vertical Supply Consolidation, ☐ Horizontal Supply Chain Alignment, ☐ Logistics/Commercial Data Platform, ☐ Access and Adoption, ☐ Governance.

Targeted Delivery Mode-s: ☒ Paper, ☐ Poster, ☐ Flash Video, ☒ In-Person presentation

1 Introduction

With the rapid increase in Internet usage, online shopping has consistently grown as a percentage of total retail sales and absolute sales volume. In recent years, especially with the pandemic of the new coronavirus, online retailing has grown explosively, especially in grocery, apparel, food, and many more industries (Mohammad et al., 2023). For example, the BtoC e-commerce (EC) market size and EC conversion rate in Japan's goods sales sector increased from 599.3 billion yen and 3.85% in 2013 to 1399.7 billion yen and 9.13% (METI). As the volume of online shopping increases, demand for freight forwarding services is growing, and freight forwarding services face two challenges: reducing profit margins due to the high frequency of smaller shipments and reducing greenhouse gas emissions. For logistics providers, keeping cost efficiency and service levels high in the distribution system is key to staying competitive in the online shopping business (Anderson et al., 2007). Meanwhile, freight transport is seen as one of the most difficult sectors of the economy to decarbonize, as it is the

only industry with ever-increasing emissions (McKinnon, 2016). Under these circumstances, the Physical Internet (PI) is currently attracting attention as the ultimate logistics efficiency measure (Montreuil et al., 2010). The central concept of the PI logistics system is to use advanced modular containers through transit centers (known as PI hubs) to create a highly efficient transport network that optimizes the opportunities for consolidation (Venkatadri et al., 2016). This study aims to solve these problems by optimizing the placement of PI nodes and truck routes between nodes. The goal is to reduce the number of trucks, reduce fuel consumption, and minimize greenhouse gas emissions. To solve this problem, we propose a new hybrid algorithm that combines NeuroEvolution of Augmenting Topologies (NEAT) and Lin-Kernighan Heuristic (LKH) -3. The proposed model is applied to Geographic Information System (GIS) data for empirical validation. The contributions of this work can be summarized in three areas: 1) introduction of the PI concept to logistics networks, 2) improvement of existing optimization methods, and 3) incorporation of realistic route calculations using real data for validation. The remainder of this paper is organized to provide a comprehensive overview, including a review of previous studies on the PI concept, a detailed methodology for addressing the logistics problem, a description of the data used, experimental results, and conclusions. The literature review reveals a growing body of research on PI, with various models demonstrating the potential benefits of PI in terms of efficiency, sustainability, and cost savings. However, this study fills a gap in the existing literature by presenting a novel model that integrates the concept of PI with optimal logistics hub placement and route optimization.

2 Literature review

The PI concept was introduced by Montreuil in 2010, who defined PI as an open, global logistics network built on the efficient and sustainable interconnection of all aspects of the logistics process (Montreuil et al., 2010). The PI concept has attracted numerous stakeholders who support the development of PI logistics networks in the last few years. ALICE[1] and JPIC[2] were formed to promote the practical application of the PI concept by aligning the interests of experts with those of companies and other stakeholders. Demonstration studies for practical application of PI concepts such as MODULUSHCA and ICONET are underway, mainly in Western countries. The literature on PI has increased dramatically over the past decade. The literature on PI has increased dramatically over the past decade. Previous studies and future issues related to PI have been summarized by Neila et al. (2022) and Münch et al.(2022). The challenges of PI distribution and transportation network optimization, optimized routing, loading patterns, and truck scheduling are being addressed by many researchers. Table 1 is a consolidated and redacted version of the table prepared by Neila et al. (2022) for PI distribution and transportation network optimization and optimized routing. In the table, the decision-making levels are classified as L1: strategic, L2: tactical, and L3: operational. The table also classifies sustainability dimensions as D1: economic, D2: social, and D3: environmental.

After 2020, more and more studies are using hybrid heuristic algorithms. Pan et al. proposed a hybrid algorithm integrating genetic algorithms (GA) and LKH for a collaborative delivery network using parcel lockers (Pan et al., 2019). Feng et al. proposed crowdsourced integrated production and transportation for smart city logistics for the scheduling problem using a genetic algorithm and showed that GA outperformed the commercial mixed integer programming problem (MIP) solver CPLEX (Feng et al., 2021). However, multi-agent system (MAS) is often used to optimize PI transport networks, and none of the studies have incorporated artificial neural networks or other techniques into their research methodology. It is clear from this

---

[1] ALICE: Alliance for Logistics Innovation through Collaboration in Europe

[2] JPIC: Japan Physical Internet Center

literature review that research leading to the realization of PI has developed significantly over the past decade. Recent studies have proposed various models that confirm the usefulness of logistics networks in the framework of PI. This study proposes a method to incorporate a new artificial neural network into a model that addresses the optimal placement of logistics hubs and optimization of delivery routes in the framework of PI. Furthermore, it makes a significant contribution to the literature by presenting it together with empirical validation using real data.

Table.1 Classification of literature on PI distribution and transportation network optimization and optimized routing

Authors	Year	Methods	Levels	Dimensions
Chargui et al.	2019	MAS (multi-agent system)	L2+L3	D1+D3
Gontara et al.	2018	BGP (border gateway protocol)	L3	D1
Fazili et al.	2017	MC (Monte-Carlo simulation)	L2+L3	D1+D3
Venkatadri et al.	2016	MIP (mixed integer programming)	L2+L3	D1
Walha et al.	2016	SA (simulated annealing)	L2+L3	D1
Montreuil et al.	2012	KPIs (key performance indicators)	L1	D1+D2+D3
Zheng et al.	2019	MAS	L3	D1+D2+D3
Ben Mohamed et al.	2017	MIP	L3	D1+D2+D3
Chen et al.	2016	DES (destination-orientated spreading)	L3	D1+D2+D3
Pan et al.	2021	GA	L3	D1+D2+D3
Feng et al.	2020	GA	L1+L3	D1+D2
Zhang et al.	2023	MIP	L1+L2	D1+D3
Li et al.	2023	HA (heuristic algorithms)	L1+L3	D1+D2
Essghaier et al.	2023	MIP	L3	D1
Ji et al.	2023	MIP	L2+L3	D1+D2
Kantasa-ard et al.	2023	MIP	L3	D1+D2+D3
H. Liu et al.	2024	MIP	L1+L3	D1+D3
Liu X. et al.	2024	SOP (stochastic optimization programming)	L2+L3	D1+D2

3 Formulation of the mathematical model

This section describes the challenge of identifying optimal locations for logistics hubs and devising efficient vehicle routing strategies for delivery companies operating within the PI. We also present a model designed to address this particular problem. The model incorporates a clustering approach, and a detailed description of this approach is provided, as well as a hybrid algorithm that combines NEAT and LKH-3.

3.1 Assumptions

To construct the model of the joint delivery network, let S be the set of suppliers and C be the set of customers. $p\alpha = (s, c)$ denote the delivery task, where $p\alpha = [10, 30, 60]$, where goods are transferred from supplier s to collection point Sc between logistics node l in set L and collection point C_c, and from there to customer c delivery. In the context of our modeling, we assume that each customer (called a distributor) generates a single delivery request addressed to a single customer (distributor). Given this basic assumption, the set of requests $A_s(A_c)$ originating from supplier s (for customer c) contains exactly one delivery task. Furthermore, to keep the model simple, we do not specify pickup or delivery times.

3.2 Logistics nodes

The logistics nodes set, denoted as L, includes all logistics nodes identified by their geographical positions. Within L, there exists a delivery task represented as $p\alpha = (s, c)$. Each logistics hub is equipped with a capacity of $q_l = 2000$. We assume the existence of a transport service for the exchange of goods between logistics nodes, if necessary. The costs of setting up logistics hubs are not considered and their capacities are known a priori. Accordingly, the

collection points S_c, C_c are connected to the nearest logistics hub. It is assumed that S_c, C_c can replace the logistics hub l that is supposed to be newly generated.

3.3 Transport by trucks

For the transport of goods, a set of trucks V can be operated and these vehicles are associated with a collection point or a distribution centre. The set of vehicles includes three types of trucks with different carrying capacities $q_v = [10, 30, 60]$. Operational costs, consisting of financial and environmental costs due to truck ownership, are not considered.

3.4 Constraints

The proposed model has a structure consisting of three levels. First, any given number of suppliers and customers are clustered using the fuzzy c-means method to obtain supplier agglomeration S_c and customer agglomeration C_c. Next, we consider the least-cost trucking network flow problem associated with generating an appropriate number of distribution points between agglomerations by NEAT, and finally, we address the multi-depot capacity vehicle routing problem between agglomerations and distribution points by LKH-3. Given a set of vehicles V tasked with picking up goods at pickup point S_c, let $x_{ijv} = 1$ if vehicle $v \in V$ moves from node i to node j (either supplier or pickup point) $(i, j \in S \cup \{d\})$ and $x_{ijv} = 0$ if it does not move. The variable x_{ijv} is used to indicate the transportation route of trucks from the supplier's depot S_c to the logistics depot l, and the variable z_{ijv} is used to indicate the transportation route of trucks from the logistics depot l to the customer depot C_c. The multi-depot capacity vehicle routing problem does not explicitly consider demand, vehicle, and DC capacity constraints. Instead, they are considered in the least-cost trucking network flow problem. In the formulation of the least-cost trucking network flow problem, we classify collection points, logistics nodes, and trucks as intermediate nodes, while suppliers and customers are designated as "origin" and "destination" nodes, respectively. The objective is to efficiently distribute goods throughout the network while adjusting for capacity constraints at each node. The optimization aims to meet the demand requirements at the origin and destination nodes while minimizing the total truck mileage. The binary variable y_{ij}^{α} represents a flow variable, specifying whether the goods in delivery task α pass through node i and node j, and adapts all capacity constraints through y_{ij}^{α}. Next, we consider the least-cost track network flow problem together with the multi-depot capacity vehicle routing problem. When node i is a supplier, the binary variable y_{ij}^{α} is defined by the vehicle flow variable x_{ijv}. The right side of (1) represents the number of loads sent by the supplier. The maximum value of the right side is 1.

$$\sum_{j \in S \cup \{l\}} x_{sjv} = \sum_{\alpha \in A_s} y_{sv}^{\alpha} \quad \forall l \in L, \forall v \in V, \forall s \in S \tag{1}$$

Once the connection between the parcel flow and vehicle flow variables is set, the vehicle and depot capacity constraints are imposed using the variable y_{ij}^{α}.

$$\sum_{s \in S} \sum_{\alpha \in A_s} p \alpha y_{sv}^{\alpha} \leq q_v \quad \forall v \in V, \forall l \in L \tag{2}$$

$$\sum_{v \in V} \sum_{s \in S} p \alpha y_{sl}^{\alpha} \leq q_l \quad \forall l \in L \tag{3}$$

The left sides of (2) and (3) determine the total quantity of goods carried to track v and distribution point l, respectively. The same capacity constraints as in (2) can be applied to the trucks used.

$$\varepsilon = \sum_{i=1}^{n} y_{il}^{\alpha} \tag{4}$$

$$T_d = min \sum_{l_i, l_{i+1} \in L} \|l_i - l_{i+1}\| + min \sum_{l_i \in L} \sum_{s_{c_i} \in S_c} \|l_i - s_{c_i}\| + min \sum_{l_i \in L} \sum_{c_{c_i} \in C_c} \|l_i - c_{c_i}\| \tag{5}$$

$$p = \sum_{i=1}^{n} \sum_{v \in V} \sum_{s \in S} p \times \alpha \times y_{sl}^{\alpha} - \varepsilon q_l + \sum_{s \in S} \sum_{\alpha \in A_s} p \times \alpha \times y_{sv}^{\alpha} - q_l \tag{6}$$

$$f = T_d - p \times C_{penalty} \tag{7}$$

(4) determines the number of logistics hubs to be used (ε) and limits the number of logistics hubs to be used by a maximum value n. (5) represents the distance between the logistics hub and the supplier's collection point and the minimum distance between the logistics hub and the customer's collection point. (6) is the sum of the difference between the total cargo at the distribution depot and the capacity of the distribution depot and the total truckload capacity and the capacity of the distribution depot. Adapt the difference between (5) and (6) as the evaluation function. $C_{penalty}$ is the penalty coefficient. Figure 1 is a flow diagram of the algorithm.

3.5 Neuro Evolution of Augmenting Topologies (NEAT)

NEAT is a method proposed by Stanley et al. (2002) that uses GAs to optimize the structure and weights of neural nets for a problem. NEAT addresses the challenges associated with evolving neural networks, including the delicate balance between exploring new architectural possibilities and reusing existing solutions. In contrast to traditional neural network optimization methods which require human design and hyperparameter adjustment, NEAT uses a process modeled on genetic algorithms. Its starting point is a population of small, simple neural networks, or "genomes. Through processes such as mutation, crossover, and selection, these genomes evolve over many generations into more complex and sophisticated network structures.

3.6 LKH-3

The LKH-3 heuristic solver developed by Helsgaun (2017) demonstrates its adaptability in solving a wide range of problems involving capacity, time, pickup, and distance constraints (known as vehicle routing problems or VRP) (Helsgaun, 2017). It also excels at handling facility processing constraints and multi-traveling salesman problems (mTSP), and sensitivity analysis can be used to guide and constrain the solution search. In our study, we used a Python library known as elkai (Dimitrovski 2023) based on LKH-3. This library has been shown to provide optimal solutions for problem sizes up to N=315, outperforming the accuracy of Google's OR tool. It also simplifies the retrieval of results with a single line of code.

4 Introduction to data

Data on logistics facilities and factory sites were obtained from e-Stat, a government statistics portal site, where GIS data for each prefecture was combined into a single dataset and converted into a format suitable for the purpose of the survey (e-Stat, 2023). Average total floor area data from 2019 to 2022 was used as an indicator for the total floor area of distribution centers. Warehouse area data was the product of the allowable storage volume (1900 m^3), which is the floor area of each building divided by the number of buildings, the assumed height of the storage building (5.5 m), and the occupancy rate (40%). Truck bed dimension data was

obtained from Isuzu Motors, a Japanese automobile manufacturer that mainly produces trucks, buses, and other commercial vehicles. Table 2 shows the capacity of the warehouse and the three types of trucks used in the simulation.

<p align="center">Table 2. Warehouse and truck capacities</p>

Type	Capacity (m^3)
Warehouse	1900
Light-duty trucks (2t)	12
Medium trucks (4t)	34
Heavy trucks (10t)	59

5 Depiction of the results and evaluation of the proposed algorithm

Depiction on map

The map displays the actual simulation results for determining the optimal placement of logistics centers and the corresponding delivery routes. Optimal routes are indicated by black lines, suppliers by red dots, supplier cluster centers by red pins, customers by blue dots, customer cluster centers by blue pins, and logistics nodes by green pins. Figure 2 depicts only centers, lockers and their routes.
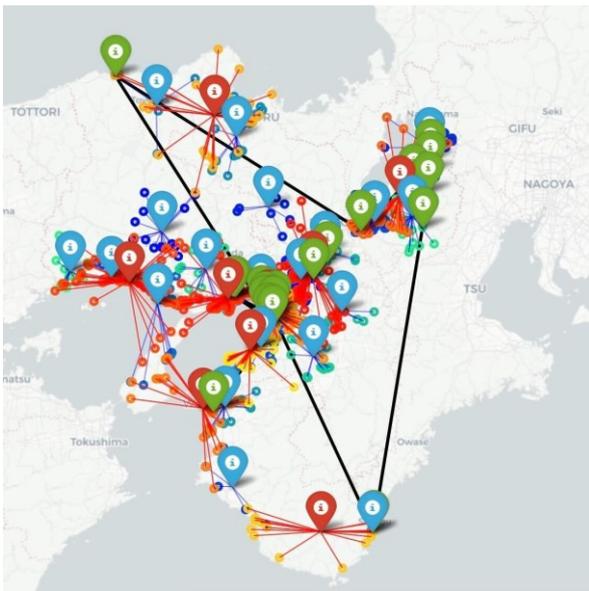

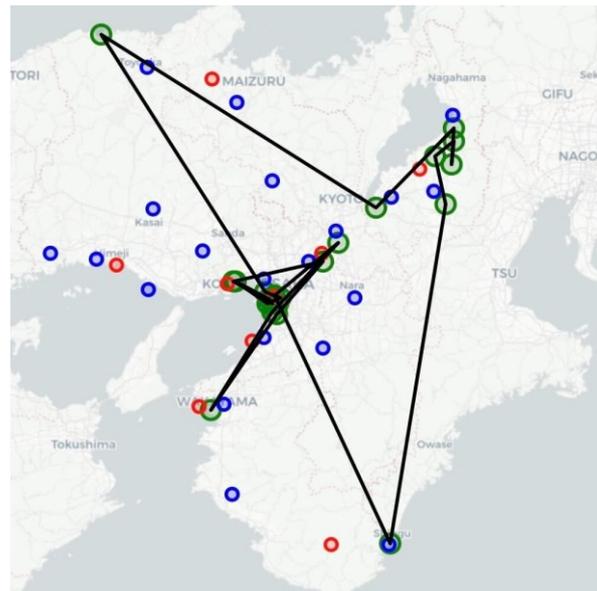<div align="center">

Figure 1. Drawing on the map (1)   *Figure 2. Drawing on the map (2)*

</div>

5.1 Evaluation of NEAT

The graphs in Figure 1 show the maximum fitness of NEAT for different population numbers (20, 30, 40, 50, and 60), the maximum fitness per generation, and the average fitness. In the early generations, the population had a low level of adaptation; once NEAT was initiated, the level of adaptation increased rapidly during the early stages of evolution. Later, after a certain number of generations, the level of adaptability reached a stable state and became less variable. The graph in Figure 2 compares the results of NEAT with different population numbers (30, 40, 50, and 60). In the case of our algorithm, the best results are shown when the population is 40.

5.2 Sensitive test

Sensitivity test was performed with $C_{penalty}$ as [0,250,500,750,1000] The population number of NEAT was fixed at 40.
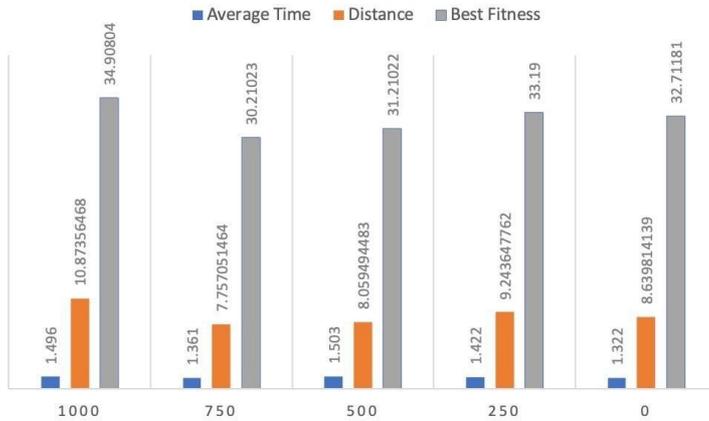

Figure 5. Sensitive test

6 Conclusion

Optimal location of distribution centers and optimization of delivery routes in the physical Internet are indispensable for the establishment of an efficient logistics system. The sharing of logistics resources can improve the efficiency of logistics processes, reduce costs, and mitigate environmental burdens. In this study, a method is proposed to identify the optimal location of logistics centers using NEAT, and to calculate the shortest and optimal delivery routes using LKH-3.

This paper contributes to research related to urban logistics, physical Internet, and logistics hubs. In addition, the proposed hybrid method using LKH-3, clustering, and genetic algorithm to derive the optimal number of clusters is applicable to other real data sets such as factory sites, logistics hubs, and important logistics roads, and can be applied to solve real problems in society.

This study is currently limited to truck transportation. There remain challenges, such as the combination of appropriate transportation modes among different modes based on the concept of physical Internet and the optimization of transportation planning. Future studies may focus on addressing these issues and developing more practical optimization models. In general, this study provides a novel method to obtain important insights for the optimal location of logistics hubs and the optimization of delivery routes.

7 Acknowledgements

References

- ALICE Alliance for Logistics Innovation through Collaboration in Europe – ALICE supporting logistics innovation through collaboration in Europe [WWW Document]. URL https://www.etp-logistics.eu/ (accessed 2.11.24).

- Anderson W. P., Leinbach T.R. (2007). *E-Commerce, Logistics and the Future of Globalized Freight*, Chapters, in: Leinbach T.R. & Capineri C. (ed.), Globalized Freight Transport, chapter 6, Edward Elgar Publishing.
-
- Ben Mohamed, I., Klibi, W., Labarthe, O., Deschamps, J.-C., Babai, M.Z. (2017). Modelling and solution approaches for the interconnected city logistics. International Journal of Production Research 55, 2664–2684. https://doi.org/10.1080/00207543.2016.1267412
- Chargui, T., Bekrar, A., Reghioui, M., Trentesaux, D. (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, 5477–5501. https://doi.org/10.1080/00207543.2019.1660825
- Chen, C., Pan, S., Wang, Z., Zhong, R.Y. (2017). Using taxis to collect citywide E-commerce reverse flows: a crowdsourcing solution. International Journal of Production Research 55, 1833–1844. https://doi.org/10.1080/00207543.2016.1173258
- elkai: elkai is a Python library for solving travelling salesman problems (TSP) based on LKH 3, PyPI https://pypi.org/project/elkai/ (accessed 2.11.24)
- Essghaier, F., Chargui, T., Hsu, T., Bekrar, A., Allaoui, H., Trentesaux, D., Goncalves, G. (2023). Fuzzy multi-objective truck scheduling in multi-modal rail–road Physical Internet hubs. Computers & Industrial Engineering 182, 109404. https://doi.org/10.1016/j.cie.2023.109404
- e-Stat https://www.e-stat.go.jp/ (accessed 2.18.24).
- Fazili, M., Venkatadri, U., Cyrus, P., Tajbakhsh, M. (2017). Physical Internet, conventional and hybrid logistic systems: a routing optimisation-based comparison using the Eastern Canada road network case study. International Journal of Production Research 55, 2703–2730. https://doi.org/10.1080/00207543.2017.1285075
- Feng, X., Chu, F., Chu, C., Huang, Y. (2021). Crowdsource-enabled integrated production and transportation scheduling for smart city logistics. Int. J. Prod. Res. 59, 2157–2176. https://doi.org/10.1080/00207543.2020.1808258
- Final Report Summary - MODULUSHCA (Modular Logistics Units in Shared Co-modal Networks) | FP7 [WWW Document], n.d. . CORDIS | European Commission. URL https://cordis.europa.eu/project/id/314468/reporting (accessed 2.17.24).
- Gontara, S., Boufaied, A., & Korbaa, O. (2018, October). Routing the PI-Containers in the Physical Internet using the PI-BGP Protocol. In 2018 IEEE/ACS 15th International Conference on Computer Systems and Applications (AICCSA) (pp. 1-8). IEEE.
- Helsgaun, K., n.d. An Extension of the Lin-Kernighan-Helsgaun TSP Solver for Constrained Traveling Salesman and Vehicle Routing Problems.
- Ji, S., Zhao, P., Ji, T. (2023). A Hybrid Optimization Method for Sustainable and Flexible Design of Supply–Production–Distribution Network in the Physical Internet. Sustainability 15, 6327. https://doi.org/10.3390/su15076327
- JPIC. https://j-pic.or.jp/about-jpic/ (accessed 2.11.24).
- Kantasa-ard, A., Chargui, T., Bekrar, A., AitElCadi, A., Sallez, Y. (2023). Dynamic sustainable multiple-depot vehicle routing problem with simultaneous pickup and delivery in the context of the physical internet. Journal of International Logistics and Trade 21, 110–134. https://doi.org/10.1108/JILT-10-2022-0058
- Li, Siyu, Lang, M., Chen, X., Li, Shiqi, Liu, W., Tang, W. (2023). Logistics hub location for high-speed rail freight transport with road-rail intermodal transport network. PLOS ONE 18, e0288333. https://doi.org/10.1371/journal.pone.0288333

- Liu, H., Ji, S., Ji, Y. (2024). Blockchain-enabled integrated model for production-inventory-delivery problem in Physical Internet. Computers & Industrial Engineering 187, 109740. https://doi.org/10.1016/j.cie.2023.109740
- Liu X., Li J., Montreuil B. (2024). Logistics Hub Capacity Deployment in Hyperconnected Transportation Network Under Uncertainty. arXiv preprint arXiv:2402.06227.
- McKinnon, A.C. (2016). Freight Transport Deceleration: Its Possible Contribution to the Decarbonisation of Logistics. Transport Reviews 36, 418–436. https://doi.org/10.1080/01441647.2015.1137992
- Mohammad, W.A., Nazih Diab, Y., Elomri, A., Triki, C. (2023). Innovative solutions in last mile delivery: concepts, practices, challenges, and future directions. Supply Chain Forum: An International Journal 24, 151–169. https://doi.org/10.1080/16258312.2023.2173488
- Montreuil, B., Meller, R., Ballot, E. (2010). Towards a Physical Internet: the Impact on Logistics Facilities and Material Handling Systems Design and Innovation.
- Montreuil, B., Meller, R.D., Thivierge, C., Montreuil, Z. (2012). Functional Design of Physical Internet Facilities: A Road-Based Crossdocking hub. Proceedings of 12th IMHRC (Gardanne, France – 2012)
- Münch, C., Wehrle, M., Kuhn, T., Hartmann, E. (2024). The research landscape around the physical internet – a bibliometric analysis. International Journal of Production Research 62, 2015–2033. https://doi.org/10.1080/00207543.2023.2205969
- Neila, S.B., Rejeb, A., Németh, P. (2022). The Interplay between the Physical Internet and Logistics: A Literature Review and Future Research Directions. Acta Technica Jaurinensis 15, 22–35. https://doi.org/10.14513/actatechjaur.00638
- New ICT infrastructure and reference architecture to support Operations in future PI Logistics NETworks | ICONET Project | Fact Sheet | H2020 [WWW Document], n.d. . CORDIS | European Commission. URL https://cordis.europa.eu/project/id/769119 (accessed 2.17.24).
- Pan, S., Zhang, L., Thompson, R. G., & Ghaderi, H. (2021). A parcel network flow approach for joint delivery networks using parcel lockers. International Journal of Production Research, 59(7), 2090-2115. https://doi.org/10.1080/00207543.2020.1856440
- Venkatadri, U., Krishna, K.S., Ülkü, M.A. (2016). On Physical Internet Logistics: Modeling the Impact of Consolidation on Transportation and Inventory Costs. IEEE Transactions on Automation Science and Engineering 13, 1517–1527. https://doi.org/10.1109/TASE.2016.2590823
- Walha, F., Bekrar, A., Chaabane, S., Loukil, T.M. (2016). A rail-road PI-hub allocation problem: Active and reactive approaches. Computers in Industry, Emerging ICT concepts for smart, safe and sustainable industrial systems 81, 138–151. https://doi.org/10.1016/j.compind.2016.04.007
- Zheng, L., Beem, P., & Bae, K. H. G. (2019). Assessment of the physical internet enabled urban logistics using agent-based simulation. International Journal of Logistics Systems and Management, 33(4), 441-466. https://doi.org/10.1504/IJLSM.2019.101793
- Zhang, S., Le, T.V., Roorda, M. (2023). Optimizing Parcel Locker Locations in a City Crowd Logistics Network. Transportation Research Record 2677, 267–283. https://doi.org/10.1177/03611981231167425
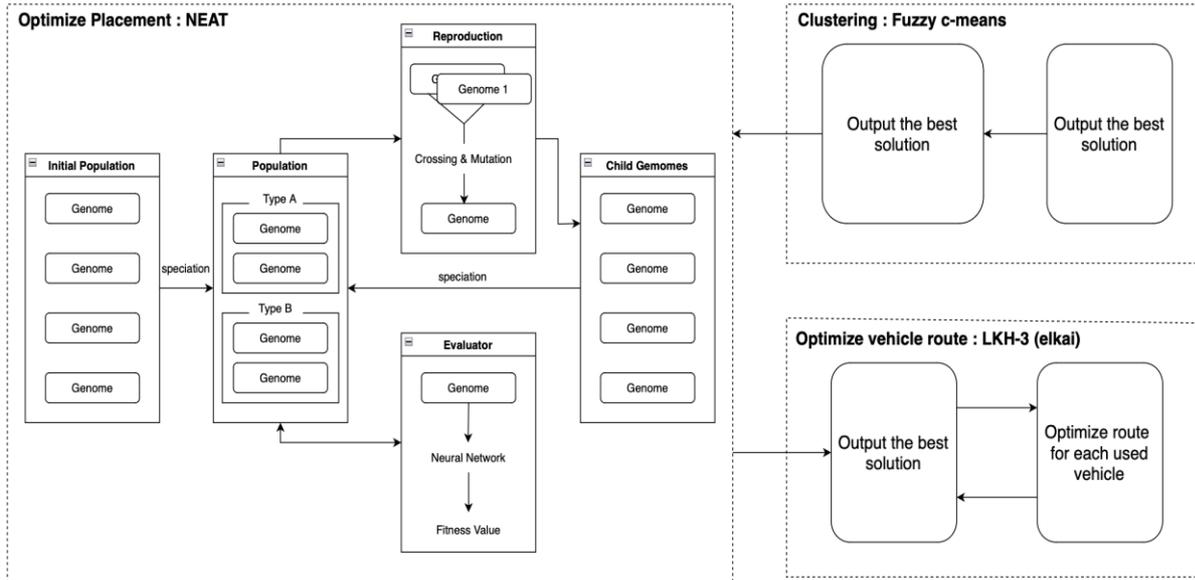
8 Appendix

Figure A1. Algorithm flow diagram