Delft University of Technology

Robustness evaluation of a physical internet-based intermodal logistic network

Gallo, Federico; Shahedi, Alireza; Di Febbraro, Angela; Saeednia, Mahnam; Sacco, Nicola

DOI
10.1016/j.treng.2025.100333

Publication date
2025

Document Version
Final published version

Published in
Transportation Engineering

Transportation Engineering 20 (2025) 100333

Contents lists available at ScienceDirect

Transportation Engineering

journal homepage: www.sciencedirect.com/journal/transportation-engineering

Robustness evaluation of a physical internet-based intermodal logistic network

Federico Gallo [a], Alireza Shahedi [a], Angela Di Febbraro [a], Mahnam Saeednia [b], Nicola Sacco [a,*]

[a] Dept. of Mechanical, Energy, Management, and Transport Engineering, University of Genoa, Via Montallegro 1, Genoa, 16145, Italy
[b] Dept. of Transport and Planning, Delft University of Technology, Postbus 5, Delft, 2600 AA, The Netherlands

ARTICLE INFO

Keywords:
Physical internet
Freight transportation
Logistics
Robustness analysis
Global sensitivity analysis (GSA)

ABSTRACT

The Physical Internet (PI) paradigm, which has gained attention in research and academia in recent years, leverages advanced logistics and interconnected networks to revolutionise the way goods are transported and delivered, thereby enhancing efficiency, reducing costs and delays, and minimising environmental impact. Within this system, *PI-hubs* function similarly to cross-docks, enabling the splitting of PI-containers into smaller *modules* for delivery through a network of interconnected hubs. This allows dynamic routing optimisation and efficient consolidation of PI-containers. However, the impact of system parameters and relevant uncertainties on the performance of this innovative logistics framework is still unclear. For this reason, this work proposes a robustness analysis to understand how the PI logistics framework is affected by the handling, consolidation, and processing of PI-containers at PI-hubs. To this end, the considered PI logistics system is represented via a mathematical programming model that determines the best allocation of PI-containers in an intermodal setting with different transportation modes. In doing so, four Key Performance Indicators (KPIs) are separately considered to investigate different aspects of the PI system's performance, and the relevant robustness is assessed with respect to the PI-hub processing times and the number of modules per PI-container. In particular, a Global Sensitivity Analysis (GSA) is performed to evaluate, through a case study, the individual relevance of each input parameter on the resulting performance.

1. Introduction

Intermodal transportation integrates various modes, including rail, inland waterways, deep-sea shipping, and road to provide seamless freight movement across regions. Each mode plays a crucial role in facilitating efficient and sustainable logistics networks [1]. In the last decades, intermodal rail-road transportation has emerged as one of the crucial solutions to enhance the efficiency and sustainability of modern logistics networks [2]; inland waterways are essential for transporting bulk goods, and deep-sea shipping is critical for intercontinental logistics [3]. Additionally, road and rail offer significant flexibility and connectivity in regional and national freight systems [4]. Despite the broader spectrum of intermodal options, this study focuses on rail-road intermodal systems, which are critical components of sustainable logistics frameworks.Over the past decades, rail-road intermodal transportation has attracted researchers' attention to address key economic, social, and environmental issues. In this context, on one hand, the interdependency between road freight and socioeconomic systems has been demonstrated [5]. On the other hand, the need to reduce traffic congestion and shift freight from road transportation to environmentally friendly alternatives (e.g., rail transportation) to minimise negative environmental impacts has clearly emerged [6]. These motivations have driven carriers and terminals to optimise road transportation and integrate it with other modes to achieve an optimised and more sustainable freight delivery [7]. Road freight transportation contributes significantly to greenhouse gas emissions and is the largest emitter among the different transportation options [8]. Therefore, one of the main strategies to improve sustainability is the optimisation of freight transportation, with a particular focus on shifting the transportation process from road to rail.

The Physical Internet (PI), proposed in [9], is an innovative logistics concept that aims to enhance efficiency and sustainability in global supply chains. By adopting open, modular, and standardised systems, PI promotes seamless collaboration, better resource utilisation, and reduced environmental impacts, driven by intelligent integration and optimised decision-making across interconnected networks [9,10].

* Corresponding author.
E-mail address: nicola.sacco@unige.it (N. Sacco).

https://doi.org/10.1016/j.treng.2025.100333
Received 20 December 2024; Received in revised form 22 March 2025; Accepted 15 April 2025
Available online 3 May 2025

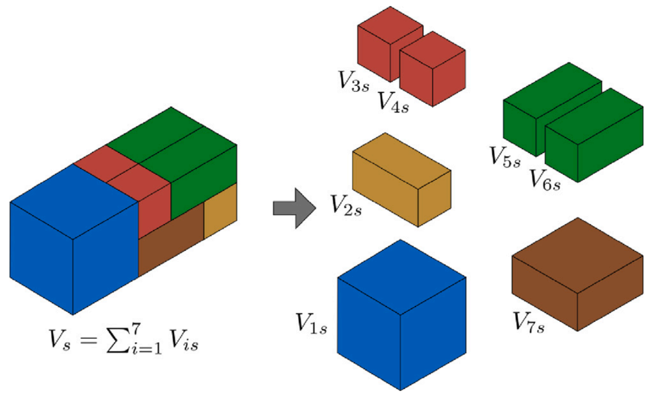

Fig. 1. Example of a PI-container split into different modules with different volumes.

The PI represents a solid example of digital transformation in supply chain operations, integrating advanced technologies such as real-time tracking, automation, and data analytics to optimise logistics, streamline transportation, and improve overall operational efficiency. Addressing inefficiencies through digital tools, the PI reduces the environmental impact of logistics operations, including pollution caused by heavy traffic. The main innovation in the logistics sector provided by PI is related to the freight transportation perspective, as it can optimise shipping operations, particularly in terms of capacity exploitation and reduction of the number of circulating trucks, thereby reducing CO_2 emissions and traffic congestion [11], since freight operations play a crucial role in addressing sustainability goals and environmental challenges in logistics networks. The growth of integrated intermodal transportation in logistics and supply chains, including urban environments, is evident in the development of urban distribution systems and passenger transportation. Today, intermodal rail-road terminals are optimising traffic flow to facilitate accessibility in rail transit systems for regional mobility.

Intermodal transportation can also enhance shipping quality across modes on a global scale. Predictions indicate that the throughput of intermodal transportation is increasing [5], creating favourable conditions for the adoption and growth of modular concepts in shipping and delivery logistics. Furthermore, the PI logistics framework is designed to integrate advanced automation technologies and intelligent systems, enabling dynamic decision-making and fostering real-time adaptability across interconnected logistics networks. One of the fundamental concepts of the PI is the modularisation of a single PI-container, as depicted in Fig. 1. These modular PI-containers can be transported using various transportation modes and along different paths. This feature allows for better exploitation of existing capacities in pre-planned services (e.g., trains or trucks) that lack the capacity to transfer an entire PI-container. The main advantage of this approach is the optimisation of transportation mode capacities and the reduction of the number of half-filled commuting vehicles. Nevertheless, a PI-container is considered delivered only if all its modules have reached the destination.

As the Physical Internet is a complex, distributed logistics network whose performance depends on the effectiveness of routing operations performed at intermodal nodes across a large set of modular units, identifying the factors that significantly affect its reliability and efficiency is fundamental. To address this, and based on the optimised PI scheme introduced in [12], this study proposes a robustness analysis to evaluate the system's capability to maintain performance under uncertainties.

Specifically, the objective of this analysis is to assess the extent to which the system's performance is influenced by key PI-related parameters, such as the number of modules making up PI-containers and the travel times between nodes or processing times within PI-hubs. The results will provide insights into the behaviour of the PI logistics framework and help identify the most influential parameters affecting system performance. These findings will guide further analyses or even support their direct integration into the optimisation models governing PI dynamics.

The remainder of this paper is structured as follows: Section 2 reviews the literature on the Physical Internet (PI) and robustness evaluation. Section 3 describes the considered optimisation-based PI network, including its structure and routing methodology. Section 4 summarises the theoretical aspects of the robustness analysis, focusing on the impact of uncertain parameters using global sensitivity analysis. The proposed methodology is applied to a case study in Section 5, with results analysed under both deterministic and uncertain conditions. Finally, Section 6 summarises the findings and provides recommendations for future research.

2. Literature review

This section reviews the current knowledge on the Physical Internet concept (Section 2.1) and robustness evaluation methodologies (Section 2.2). It concludes with a summary of the paper's main contributions (Section 2.3).

2.1. Physical internet

The Physical Internet is an innovative concept aimed at improving the efficiency of logistics systems through automation perspective [9]. In this context, PI is commonly defined as "a global logistics system that connects networks using standardised rules, modular containers, and smart interfaces for improved efficiency and sustainability" [13], highlighting its foundation on principles borrowed from the Digital Internet, from which it also derives its name. Just as the Digital Internet consists of a vast network of servers and computers that exchange data using standardised protocols and efficient pathways, PI operates through PI-containers, which function like "data packets" and PI-hubs, which serve as "routers" directing goods through interconnected logistics networks [14–16]. In this context, an essential characteristic of the PI system is the possibility of splitting PI-containers into smaller, modular units during transportation, which are, for PI, analogous to data packets in Digital Internet [9,17]. This feature allows for significant flexibility in utilising available transportation capacities and optimising delivery routes, thereby enhancing the adaptability and efficiency of the PI system, particularly in cases of disruptions or capacity constraints.

Numerous studies have examined various aspects of PI, including infrastructure design [18], technological advancements [19], and business models [20], paving the way for its practical implementation. The significance of PI is further emphasised by the Alliance for Logistics Innovation through Collaboration in Europe (ALICE), which has developed road-maps for PI's global adoption from 2020 to 2050 [21].

Concerning PI-containers' transportation and delivery, many studies have tackled the problem of optimising routing. These challenges include determining the most efficient routes for PI-containers across the networks, minimising transportation costs, balancing load distribution, and mitigating delays caused by bottlenecks at PI-hubs. In this context, optimisation models for routing PI-containers between cross-docks were proposed in [22,23], whereas a freight routing problems incorporating virtual transfer points to enhance platoon reconfiguration in PI systems was explored in [24].

Scheduling and resource allocation in PI-hubs are crucial for overall system efficiency. Inefficient scheduling or improper resource allocation can cause delays in PI-container processing, leading to suboptimal routing decisions. For example, if a PI-hub fails to process containers on time, re-routing or waiting strategies must be applied, affecting the overall network performance. Numerous studies have addressed these challenges using queuing models, optimisation techniques, and inventory control models [25–32]. However, since this study does not focus on these aspects, random performance values are assumed for PI-hubs and PI-containers.

2.2. Global sensitivity analysis for robustness evaluation

Robustness is a widely studied concept in statistics, with different definitions tailored to specific applications. In this context, GSA analysis was first introduced in [33], where an approach based on generating input–output Monte Carlo samples was proposed. These samples were analysed using statistical techniques to estimate variance-based sensitivity indexes, providing a systematic approach to evaluate the relative importance of input parameters. Since Wagner's foundational work, GSA methods have significantly diversified. Among them, it is worth mentioning non-parametric regression methods [34] and moment-independent techniques [35]. Other advancements include value-of-information techniques [36,37] and the application of Shapley values to sensitivity analysis [38].

Furthermore, GSA has been widely applied across engineering and applied sciences, including the transportation and logistics sector. Examples are the performance robustness of different traffic light optimisation approaches with respect to parameter uncertainty and variability [39], the identification of the most relevant origin–destination pairs for planning demand-responsive railway services [40], and uncertainty assessment in transport emission models [41]. Regarding the aim of this work, GSA is considered to address the uncertainty that arising from the variability of the system inputs or parameters [42]. In particular, when the system under analysis operates according to the solutions of optimisation problems, the unpredicted variability in inputs and parameters can significantly degrade the expected performance if not adequately considered. To address this issue, GSA assesses how inputs and parameters affect the output. By identifying a "sensitivity pattern", GSA ranks parameters based on their contribution to overall uncertainty, highlighting those that must be carefully calibrated or, where possible, explicitly incorporated into the optimisation process, potentially through stochastic programming [43].

2.3. Paper contributions

From the literature discussed in Section 2.1, it is evident that intermodal freight transportation in the PI sector has been extensively studied. However, the impact of key PI characteristics, such as the processing of PI-containers at PI-hubs and the splitting of PI-containers into modules, on freight transportation performance remains unclear, particularly regarding delivery times and transportation costs. This issue becomes even more critical under uncertainty. For instance, the exact processing time for a PI-container at a PI-hub may be unknown at the time of routing decisions. Ignoring such uncertainties can degrade system performance and reduce the effectiveness of optimised PI-container routing.

To address this gap, this paper performs a robustness analysis based on the PI logistics framework proposed by the authors in [12], and recalled in Section 3 of this paper. Specifically, it evaluates how system performance is affected by the division of PI-containers into modules and their processing times at PI-hubs.

The analysis follows a two-step approach. First, system performance variability is assessed using four Key Performance Indicators (KPIs), each reflecting a different aspect of the PI framework: (1) utilisation of trucks from origin to destination (KPI_1), (2) total delivery time (KPI_2), (3) transportation costs (KPI_3), and (4) delivery time gap between PI-container modules (KPI_4). These KPIs capture crucial dimensions of operational efficiency, cost-effectiveness, and reliability in intermodal logistics. Second, a Global Sensitivity Analysis (GSA) is conducted to quantify the impact of each PI parameter on system performance, providing a robustness assessment. The results offer valuable insights into which parameters require more precise estimation or should be directly incorporated into the optimisation model.

3. The considered optimisation-based physical internet network

This section describes the Physical Internet network and the corresponding optimisation problem considered in this paper.

3.1. The considered PI network scheme

Let consider the PI network scheme depicted in Fig. 2. This schematic represents the structure of the PI network analysed in this paper, consisting of a graph where nodes represent distribution centres, terminals, and PI-hubs, while links represent connections between these nodes. In this logistic network, PI-containers are initially transferred from the origin distribution centres to an origin terminal. At the terminal, PI-containers are disaggregated into smaller modules, which are then transported to destination terminals based on available transportation services. These modules can be transferred via trains or trucks through the PI-hub network, or by "direct" truck connections between terminals. Upon arrival at the destination terminal, the modules are aggregated into a single PI-container and delivered to the destination distribution centre.

In further detail, **distribution centres** are the starting and ending points of the PI-containers and are directly connected to suppliers and customers. **Terminals** are linked to both distribution centres and PI-hubs and play a central role within the network. At these nodes, PI-containers are either disassembled into modules or reassembled into a single PI-container for delivery. Terminals can hence function as both origin and destination points, depending on the specific PI-container. **PI-hubs** are the nodes where modules are transferred between different transportation modes (i.e., from train to truck, from truck to train, from one truck to another, or from a train to another). These hubs are exclusively dedicated to PI operations and enable routing optimisation within the PI logistics framework. PI hubs are assumed to employ rapid switching systems between incoming and outgoing vehicles (trains and trucks), with fully automated operations and minimal storage capacity.

In Fig. 2, the rail and road links are operated by scheduled and capacitated trains and trucks, each with a specified departure time.

Regarding operations, the PI network operates according to the solution of a centralised optimisation problem that determines the optimal routing for each module, also indicating the specific train or truck for transportation.

The following assumptions hold throughout the paper:

- The travel times of each transportation mode on each link are fixed and known;
- Holding modules at destination terminals due to arrival time gaps between the first and last modules incurs inventory costs. These costs are assumed to be proportional to the module size and the arrival gaps. For simplicity, the model minimises the gap between the arrival times of the first and last modules.

These assumptions are intended to simplify the computational effort of robustness analysis, enabling a focus on the key aspect of the Physical Internet (PI): the modularity of PI-containers and operations within PI-hubs. In fact, while it is well known that variability in travel times and inventory costs affect the effectiveness of all logistics schemes, these specific characteristics are unique to the PI framework.

3.2. PI centralised optimisation model

In this section, the centralised optimisation problem that determines the routing and assignment of the modules is presented. It is worth noting that the presented model was previously proposed by the authors in [12], with slight differences that will be highlighted below. For clarity, it is summarised here. The detailed notation is provided in Tables 1, 2, and 3.

In this paper, the mathematical programming model determining the optimal assignment and routing of modules is formulated as the minimisation of a single KPI

$$\min J_i, \quad i = 1, \dots, 4 \tag{1}$$

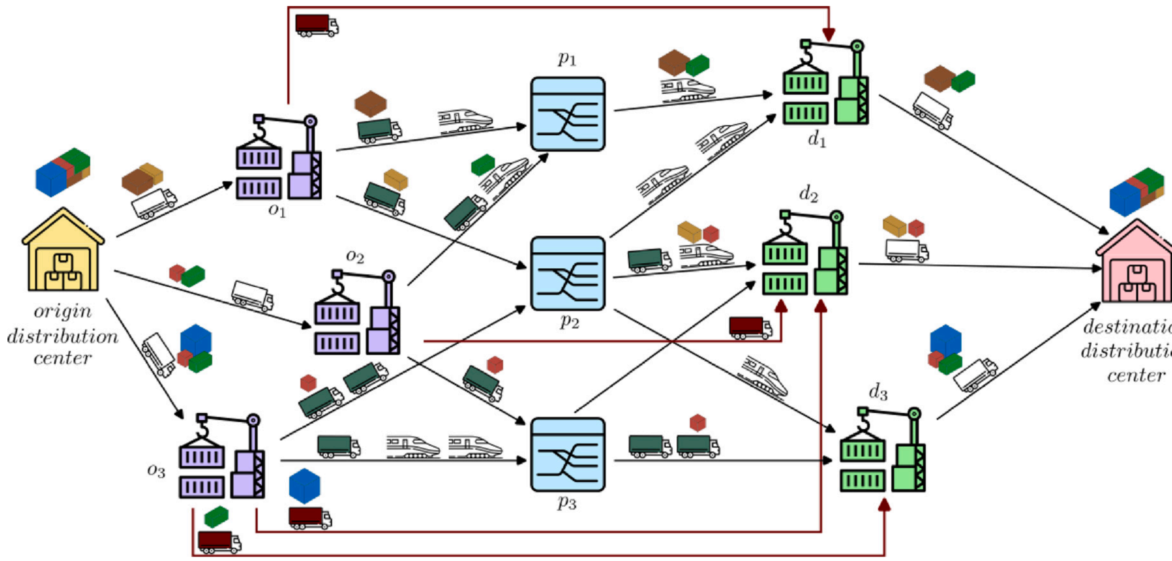

Fig. 2. Schematic of a generic PI network, illustrating the breakdown and routing of a PI-container using trucks (green), trains, and direct truck connections between origin and destination terminals (red).

Table 1
Sets.

Symbol	Meaning
$\mathcal{S}$	Set of PI-containers
$\mathcal{O}_s$	Set of origin terminals of the PI-container $s \in \mathcal{S}$
$\mathcal{D}_s$	Set of destination terminals of the PI-container $s \in \mathcal{S}$
$\mathcal{P}$	Set of the PI-hubs
$\mathcal{N}$	Set of all nodes, i.e., $\mathcal{N} = \mathcal{O}_s \cup \mathcal{D}_s \cup \mathcal{P}$
$\mathcal{L}$	Set of all links (j,k), $\forall j,k \in \mathcal{N}$
$\mathcal{J}_s$	Set of the modules corresponding to the generic PI-container $s \in \mathcal{S}$
$\mathcal{B}^j$	Set gathering all the nodes $k \in \mathcal{N}$ such that a link (k,j) exists
$\mathcal{F}^j$	Set gathering all the nodes $k \in \mathcal{N}$ such that the link (j,k) exists
$\mathcal{R}^{jk}$	Set of trains operating on the link $(j,k) \in \mathcal{L}$
$\mathcal{C}^{jk}$	Set of trucks operating on the link $(j,k) \in \mathcal{L}$
$\mathcal{T}^{jk}$	Set of direct trucks connecting two generic nodes $j \in \mathcal{O}_s$ and $k \in \mathcal{D}_s$
$\mathcal{G}^{jk}$	Set of all the vehicles operating on the link $(j,k) \in \mathcal{L}$, i.e., $\mathcal{G}^{jk} = \mathcal{R}^{jk} \cup \mathcal{C}^{jk} \cup \mathcal{T}^{jk}$

Table 2
Parameters.

Symbol	Meaning
n_s	Number of modules in which a PI-container $s \in \mathcal{S}$ is divided
V_{is}	Volume of module $i \in \mathcal{J}_s$ in PI-container $s \in \mathcal{S}$
$c^{jk\ell}$	Unitary cost per distance and module for the link (j,k) and transportation mode $\ell \in \mathcal{G}^{jk}$
$\Gamma^{jk\ell}$	Capacity of a generic vehicle $\ell \in \mathcal{G}^{jk}$ operating on the link (j,k)
$t^{jk\ell}$	Travel time of the vehicle $\ell \in \mathcal{G}^{jk}$ operating on the link (j,k)
t^k	Travel time from the terminal $k \in \mathcal{D}$ to the destination distribution terminal
τ_p	Average operation time of the PI-hub (unloading, sorting, and reloading time for each module) $p \in \mathcal{P}$
$dp^{jk\ell}$	Departure time of the vehicle $\ell \in \mathcal{G}^{jk}$ connecting the nodes $j \in \mathcal{N}$ and $k \in \mathcal{N}$
θ_s	Priority associated with PI-container $s \in \mathcal{S}$
a_{is}^k	Arrival time of module $i \in \mathcal{J}_s$ of PI-container s at node $k \in \mathcal{O}_s$
$d^{jk\ell}$	Length of the link $(j,k) \in \mathcal{L}$ when the freight is transferred by vehicle $\ell \in \mathcal{G}^{jk}$

where

$$J_1 = \sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{J}_S} \sum_{j\in\mathcal{O}_s} \sum_{k\in\mathcal{D}_s} \sum_{\ell\in\mathcal{T}^{jk}} z_{is}^{jk\ell} \tag{2}$$

represents the total usage of the direct trucks for the shipping operations between terminals;

$$J_2 = \sum_{k\in\mathcal{D}_S} \sum_{s\in\mathcal{S}} \theta_s \cdot DT_s^k \tag{3}$$

represents the total delivery time for each PI-container;

$$\begin{aligned} J_3 = \sum_{i\in\mathcal{J}_s} \sum_{s\in\mathcal{S}} \Bigg(\sum_{j,k\in\mathcal{N}} \Bigg(\sum_{\ell\in\mathcal{R}^{jk}} c^{jk\ell} \cdot V_{is} \cdot d^{jk\ell} \cdot y_{is}^{jk\ell} + \\ + \sum_{\ell\in\mathcal{C}^{jk}} c^{jk\ell} \cdot V_{is} \cdot d^{jk\ell} \cdot x_{is}^{jk\ell} \Bigg) + \\ + \sum_{j\in\mathcal{O}_s} \sum_{k\in\mathcal{D}_s} \sum_{\ell\in\mathcal{T}^{jk}} c^{jk\ell} \cdot V_{is} \cdot d^{jk\ell} \cdot z_{is}^{jk\ell} \Bigg) \end{aligned} \tag{4}$$

represents the total cost of the transportation of the PI-container in the network;

$$J_4 = \sum_{s\in\mathcal{S}} \omega_s - \alpha_s \tag{5}$$

represents the total temporal difference between the delivery times of the last arrived module of PI-containers (ω_s) and the delivery times of the first one (α_s).

Note that the cost function in Eq. (1) represents a significant difference compared to [12], where all the KPIs J_i were considered in a weighted sum. The aim of this choice, which will be further clarified in the robustness analysis, is to separate the effects of the different parameters on each KPI. Furthermore, unlike [12], parametric transportation costs (i.e., costs per travelled distance and volume of the PI-container) and an additional KPI (J_4) are considered here.

As regards the constraints, they are formulated as:

$$DT_s^k \geq \varphi_{is}^k, \quad \forall i \in \mathcal{J}_s, s \in \mathcal{S}, k \in \mathcal{D}_s \tag{6}$$

$$DT_s^k \geq \rho_{is}^k, \quad \forall i \in \mathcal{J}_s, s \in \mathcal{S}, k \in \mathcal{D}_s \tag{7}$$

which define the delivery time of each PI-container at the destination terminal as the delivery time of the latest of its modules;

$$DT_s \geq DT_s^k + t^k, \quad \forall s \in \mathcal{S}, \forall k \in \mathcal{D}_s \tag{8}$$

Table 3
Variables.

Decision variables	
Symbol	Meaning
$z_{is}^{jk\ell}$	Binary variable equal to 1 if module i of the PI-container s is assigned to direct truck $\ell \in \mathcal{T}^{jk}$ from origin terminal $j \in \mathcal{O}_s$ to destination terminal $k \in \mathcal{D}_s$, and 0 otherwise, $\forall i \in \mathcal{I}_s, s \in \mathcal{S}$
$y_{is}^{jk\ell}$	Binary variable equal to 1 if module i of the PI-container s is assigned to train $\ell \in \mathcal{R}^{jk}$ connecting the nodes $j \in \mathcal{N}$ and $k \in \mathcal{N}$, and 0 otherwise, $\forall i \in \mathcal{I}_s, s \in \mathcal{S}$
$x_{is}^{jk\ell}$	Binary variable equal to 1 if module i of the PI-container s is assigned to truck $\ell \in \mathcal{C}^{jk}$ connecting the nodes $j \in \mathcal{N}$ and $k \in \mathcal{N}$, and 0 otherwise, $\forall i \in \mathcal{I}_s, s \in \mathcal{S}$
Other variables	
Symbol	Meaning
DT_s	Delivery time of PI-container $s \in \mathcal{S}$
DT_s^k	Delivery time of PI-container $s \in \mathcal{S}$ to destination terminal $k \in \mathcal{D}_s$
ρ_{is}^k	Delivery time of module $i \in \mathcal{I}_s$ of PI-container $s \in \mathcal{S}$ at the node $k \in \mathcal{P} \cup \mathcal{D}_s$
φ_{is}^k	Delivery time of module $i \in \mathcal{I}_s$ of PI-container $s \in \mathcal{S}$ sent entirely by truck to destination terminal $k \in \mathcal{D}_s$
α_s	Delivery time of the first module of PI-container $s \in \mathcal{S}$ delivered to the destination terminal
ω_s	Delivery time of the last module of PI-container $s \in \mathcal{S}$ delivered to the destination terminal

which define the delivery time of each PI-container at the destination distribution centre as the maximum delivery time at the destination terminal, where the modules are reassembled, plus the travel time required to reach the destination distribution centre;

$$a_{is}^{j} \le dp^{jk\ell} x_{is}^{jk\ell} + M\left(1 - x_{is}^{jk\ell}\right), \quad \forall \ell \in \mathcal{C}^{jk}, j \in \mathcal{O}_s, k \in \mathcal{P}, i \in \mathcal{J}_s, s \in \mathcal{S} \tag{9}$$

$$a_{is}^{j} \le dp^{jk\ell} y_{is}^{jk\ell} + M\left(1 - y_{is}^{jk\ell}\right), \quad \forall \ell \in \mathcal{R}^{jk}, j \in \mathcal{O}_s, k \in \mathcal{P}, i \in \mathcal{J}_s, s \in \mathcal{S} \tag{10}$$

$$a_{is}^{j} \le dp^{jk\ell} z_{is}^{jk\ell} + M\left(1 - z_{is}^{jk\ell}\right), \quad \forall \ell \in \mathcal{T}^{jk}, j \in \mathcal{O}_s, k \in \mathcal{D}_s, i \in \mathcal{J}_s, s \in \mathcal{S} \tag{11}$$

which state that the departure time of each module from an origin terminal must be greater than or equal to its arrival time at that terminal;

$$\rho_{is}^{k} \ge dp^{jk\ell} + t^{jk\ell} - M\left(1 - x_{is}^{jk\ell}\right), \quad \forall \ell \in \mathcal{C}^{jk}, k \in \mathcal{P} \cup \mathcal{D}_s, j \in \mathcal{B}_k, \; i \in \mathcal{J}_s, s \in \mathcal{S} \tag{12}$$

$$\rho_{is}^{k} \ge dp^{jk\ell} + t^{jk\ell} - M\left(1 - y_{is}^{jk\ell}\right), \quad \forall \ell \in \mathcal{R}^{jk}, k \in \mathcal{P} \cup \mathcal{D}_s, j \in \mathcal{B}_k, \; i \in \mathcal{J}_s, s \in \mathcal{S} \tag{13}$$

which define the arrival time at the nodes for each module transferred from the origin terminals to the PI-hubs by trucks and trains, respectively;

$$\rho_{is}^{j} \le dp^{jk\ell} x_{is}^{jk\ell} + \tau_p + M\left(1 - x_{is}^{jk\ell}\right), \quad \forall \ell \in \mathcal{C}^{jk}, j \in \mathcal{P}, k \in \mathcal{F}_k, \; i \in \mathcal{J}_s, s \in \mathcal{S} \tag{14}$$

$$\rho_{is}^{j} \le dp^{jk\ell} y_{is}^{jk\ell} + \tau_p + M\left(1 - y_{is}^{jk\ell}\right), \quad \forall \ell \in \mathcal{R}^{jk}, j \in \mathcal{P}, k \in \mathcal{F}_k, \; i \in \mathcal{J}_s, s \in \mathcal{S} \tag{15}$$

stating that modules cannot depart from PI-hubs towards the destination terminals by trucks or trains before arriving;

$$\varphi_{is}^{k} \ge dp^{jk\ell} + t^{jk\ell} - M\left(1 - z_{is}^{jk\ell}\right), \quad \forall \ell \in \mathcal{T}^{jk}, j \in \mathcal{O}_s, k \in \mathcal{D}_s, \; i \in \mathcal{J}_s, s \in \mathcal{S} \tag{16}$$

which define the delivery time of each module at the destination terminal transferred by means of direct trucks;

$$\sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{J}_S} V_{is} x_{is}^{jk\ell} \le \Gamma^{jk\ell}, \quad \forall \ell \in \mathcal{C}^{jk}, \forall j,k \in \mathcal{N}, i \in \mathcal{J}_s, s \in \mathcal{S} \tag{17}$$

$$\sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{J}_S} V_{is} y_{is}^{jk\ell} \le \Gamma^{jk\ell}, \quad \forall \ell \in \mathcal{R}^{jk}, \forall j,k \in \mathcal{N}, i \in \mathcal{J}_s, s \in \mathcal{S} \tag{18}$$

$$\sum_{s\in\mathcal{S}} \sum_{i\in\mathcal{J}_S} V_{is} z_{is}^{jk\ell} \le \Gamma^{jk\ell}, \quad \forall \ell \in \mathcal{T}^{jk}, j \in \mathcal{O}_s, k \in \mathcal{D}_s, i \in \mathcal{J}_s, s \in \mathcal{S} \tag{19}$$

which guarantee that the modules assigned to each transportation mode do not exceed their capacity;

$$\sum_{o\in\mathcal{O}_s} \sum_{k\in\mathcal{F}^o} \left(\sum_{\ell\in\mathcal{C}^{ok}} x_{is}^{ok\ell} + \sum_{\ell\in\mathcal{R}^{ok}} y_{is}^{ok\ell} + \sum_{\ell\in\mathcal{T}^{ok}} z_{is}^{ok\ell} \right) = 1, \quad \forall i \in \mathcal{J}_s, \forall s \in \mathcal{S} \tag{20}$$

$$\sum_{d\in\mathcal{D}_s} \sum_{k\in\mathcal{B}^d} \left(\sum_{\ell\in\mathcal{C}^{kd}} x_{is}^{kd\ell} + \sum_{\ell\in\mathcal{R}^{kd}} y_{is}^{kd\ell} + \sum_{\ell\in\mathcal{T}^{kd}} z_{is}^{kd\ell} \right) = 1, \quad \forall i \in \mathcal{J}_s, \forall s \in \mathcal{S} \tag{21}$$

which guarantee that each PI-container starts (resp., ends) its trip from an origin (resp., at a destination) terminal by means of a train, a truck directed to a PI-hub, or a direct truck directed to a destination terminal. For each module, the variable $x_{is}^{ok\ell}$, $y_{is}^{ok\ell}$, or $z_{is}^{ok\ell}$ set to 1 in the optimal solution indicates, for the module i of the PI-container s, the assigned origin terminal o. Analogously, the variable $x_{is}^{kd\ell}$, $y_{is}^{kd\ell}$, or $z_{is}^{kd\ell}$ set to 1 in the optimal solution indicates the assigned destination terminal d;

$$\sum_{j\in\mathcal{O}_s} \left(\sum_{\ell\in\mathcal{C}^{jp}} x_{is}^{jp\ell} + \sum_{\ell\in\mathcal{R}^{jp}} y_{is}^{jp\ell} \right) = \sum_{k\in\mathcal{D}_s} \left(\sum_{\ell\in\mathcal{C}^{pk}} x_{is}^{pk\ell} + \sum_{\ell\in\mathcal{R}^{pk}} y_{is}^{pk\ell} \right), \quad \forall i \in \mathcal{J}_s, \forall s \in \mathcal{S}, p \in \mathcal{P} \tag{22}$$

which guarantees that any PI-container passes through only one PI-hub, unless it is delivered by direct truck;

$$\alpha_s \le \sum_{j,k\in\mathcal{N}} \left(\sum_{\ell\in\mathcal{R}^{jk}} \left(d^{jk\ell} + t^{jk\ell}\right) \cdot y_{is}^{jk\ell} + \sum_{\ell\in\mathcal{C}^{jk}} \left(d^{jk\ell} + t^{jk\ell}\right) \cdot x_{is}^{jk\ell} \right) + \sum_{j\in\mathcal{O}_s} \left(\sum_{k\in\mathcal{D}_s} \sum_{\ell\in\mathcal{T}^{jk}} t^{jk\ell} \cdot z_{is}^{jk\ell} + \sum_{k\in\mathcal{P}} \sum_{\ell\in\mathcal{R}^{jk}\cup\mathcal{C}^{jk}} \tau_p \cdot (y_{is}^{jk\ell} + x_{is}^{jk\ell}) \right), \quad \forall i \in \mathcal{J}_s, \forall s \in \mathcal{S} \tag{23}$$

$$\omega_s \ge \sum_{j,k\in\mathcal{N}} \left(\sum_{\ell\in\mathcal{R}^{jk}} \left(d^{jk\ell} + t^{jk\ell}\right) \cdot y_{is}^{jk\ell} + \sum_{\ell\in\mathcal{C}^{jk}} \left(d^{jk\ell} + t^{jk\ell}\right) \cdot x_{is}^{jk\ell} \right) + \sum_{j\in\mathcal{O}_s} \left(\sum_{k\in\mathcal{D}_s} \sum_{\ell\in\mathcal{T}^{jk}} t^{jk\ell} \cdot z_{is}^{jk\ell} + \sum_{k\in\mathcal{P}} \sum_{\ell\in\mathcal{R}^{jk}\cup\mathcal{C}^{jk}} \tau_p \cdot (y_{is}^{jk\ell} + x_{is}^{jk\ell}) \right), \quad \forall i \in \mathcal{J}_s, \forall s \in \mathcal{S} \tag{24}$$

which define, respectively, the delivery time of the first and last module of a PI-container.

Constraints in Eqs. (23) and (24), which were not considered in [12], have been introduced here to determine the arrival time at the destination distribution centre of the first module and the last module, respectively, thus enabling the calculation of the delivery gap in Eq. (5).

4. Robustness analysis

In the model described in Section 3.2, the values of the operational times at the PI-hubs (τ_p) and the number of modules (n_s) in which a PI-container is divided are assumed to be known in advance. However, such a condition does not always hold in real cases, where these values may be affected by uncertainty. Therefore, it is important to assess the variability introduced by the uncertainty of the parameters within the PI logistics framework considered.

To this end, a robustness analysis is performed, with the goal of understanding how the considered PI framework (and the related optimisation model) reacts to a variation of the PI related input parameters; in doing so, the parameters having the highest influence on the solution found are also identified. With respect to these parameters, the PI framework is less robust than with respect to parameters that have lower influence on the solution.

To achieve that, in this work a variance-based GSA has been conducted; its main theoretical concepts are summarised in the following section. For further details on this topic, the reader can refer to [44].

4.1. Variance-based global sensitivity analysis

Variance-based GSA aims at decomposing the variance of a considered model output into fractions that can be attributed to the uncertain input parameters that may vary.

From a formal point of view, the input–output dependence can be expressed as a scalar function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ that produces a scalar random output Y given a vector of n random inputs $X = \{X_1, X_2, \ldots, X_n\}$.

Then, let V_Y be the total variance of the output Y when all the random inputs X are allowed to vary, and let $V_{\sim X_i}(Y|X_i)$ be the variance when all the random inputs in X except for X_i, are allowed to vary. With these definitions, $\mathrm{E}_{X_i}(V_{\sim X_i}(Y|X_i))$ represents the expectation of the residual variance $V_{\sim X_i}(Y|X_i)$ "weighted" by the distribution of X_i and can be considered a measure of the influence of the variable X_i on Y. Specifically, if $\mathrm{E}_{X_i}(V_{\sim X_i}(Y|X_i))$ is small, meaning that the variance of Y is small when X_i is fixed, then the variability of X_i has a significant influence on V_Y. In fact, since

$$V_Y = \mathrm{E}_{X_i}(V_{\sim X_i}(Y|X_i)) + V_{\sim X_i}(\mathrm{E}_{X_i}(Y|X_i)), \tag{25}$$

if X_i is greatly influential, then $V_{\sim X_i}(\mathrm{E}_{X_i}(Y|X_i))$ tends to coincide with the total variance V_Y. Thus, it is possible to define the sensitivity index

$$S_i = \frac{V_{\sim X_i}(\mathrm{E}_{X_i}(Y|X_i))}{V_Y}, \tag{26}$$

which is known in the literature as the *Sobol first-order index*, *main effect*, or *importance measure*. This index represents the expected reduction in the variance of the output that could be obtained if an individual factor X_i were fixed. S_i is scaled in the range $[0, 1]$ and approaches 1 as X_i becomes more influential on Y.

Note that, given its definition, S_i describes only the *individual* effect of a single input on the output variance. However, it may happen that a given input is relevant to the output (e.g., it determines extreme output values) only when it is combined with a specific value of another input. These combined effects, called *interactions*, describe the synergistic effects that could be associated with particular combinations of two or more model inputs. Interactions become relevant if all the first-order indices are very small and thus are not able to explain the majority of the output variance. Such interactions can be evaluated by calculating the so-called *total-effect* terms, which, however, are more complex and computationally hard to determine.

It is important to note that different values of the indices must be calculated separately for each different output. In addition, the values of the first-order index are typically estimated numerically by generating an appropriate number of input parameter samples using Monte Carlo methods and approximated formulas. However, these methods require evaluating the function f (i.e., running the optimisation model) multiple times, which becomes a limitation when the model takes a significant amount of time for a single run. Additionally, if more than one KPI is considered as output, the number of required executions increases proportionally to the number of outputs considered. To address this issue, in this paper the values of the first-order index are estimated using a more advanced method that applies the same basic GSA idea by combining Random Balance Design with the Fourier Amplitude Sensitivity Test, as described in [45]. Moreover, this method has been adapted to compute the values of the sensitivity indices without having to run the model a proportional number of times. Consequently, the number of required model runs is always equal to N, where N is the number of samples of the inputs generated, independently of the number of outputs considered in the analysis.

5. Case study and results

The robustness analysis is applied to a case study, described in Section 5.1, which includes both realistic and assumed data. The results of the optimisation model for the deterministic case, i.e., without variability in inputs and parameters, are presented in Section 5.2. Finally, Section 5.3 discusses the results of the robustness analysis.

5.1. Case study description

The considered case study consists of a PI logistic network with $|\mathcal{O}| = 5$ origin terminals, $|\mathcal{P}| = 13$ PI-hubs, and $|\mathcal{D}| = 2$ destination terminals, along with one origin and one destination distribution centre, as depicted in Fig. 3. The origin and destination distribution centres are located in Nantes and Moscow, respectively. The origin terminals, depicted in green, are situated in Rotterdam, Paris, Lyon, Brussels, and Bern. The PI-hubs are located in Hamburg, Mannheim, Berlin, Munich, Stuttgart, Milan, Turin, Genoa, Naples, Prague, Zurich, Vienna, and Warsaw. Additionally, there are two destination terminals in Budapest and Kyiv.

Regarding the freights to be delivered, $|S| = 20$ PI-containers are considered, each consisting of a fixed number of modules in the range $[1, 10]$. Then, concerning the transportation modes available in the considered network, the PI-containers can be transferred from the origin terminals to the destination terminals either by direct trucks or via the PI-hubs using a combination of trains and trucks. In this context, $|\mathcal{R}^{jk}| = 3$ trains and $|\mathcal{C}^{jk}| = 15$ trucks are considered for each link $(j, k) \in \mathcal{L}$, and $|\mathcal{T}^{jk}| = 20$ direct trucks are available to transport modules from the origin terminals to the destination terminals. The network extension (i.e., number of nodes) and fleet size were chosen as a compromise between case study representativeness and computational efficiency, to allow the computation of the sensitivity indexes in reasonable times and with the optimal solution values.

Finally, the departure times and the available capacities for all transportation modes are reported in Tables 4, 5, and 6.

The price for shipping one container by truck or train in Europe varies depending on several factors, including country, fuel costs, container size, etc. Based on scholarly references, like [46], the transportation cost of one 20ft PI-container is estimated at 1.2 €/km for trucks and 0.62 €/km for trains. Additionally, the cost is estimated at 3.78 €/km for direct trucks. Similarly, travel times were estimated using Google Maps, with the "transit mode" applied for trains and the "driving mode" for trucks and direct trucks. These estimates account for the specific network configuration and typical travel conditions across Europe.

Finally, the operation times required at the PI-hubs for transferring modules from the incoming vehicles to the outgoing ones are provided in Table 7.

5.2. Optimal results in deterministic case

In order to test the optimisation model and provide evidence of its effectiveness, the problem in Eqs. (1)–(24) was first solved under the assumption that all the parameters introduced in the previous section were constant and known. The problem was solved using CPLEX′ on a workstation equipped with an Intel™ Core i7-CPU (3.30 GHz) and 16.00 GB of RAM, providing the solution in approximately 4 min.

For the sake of brevity, the main characteristics of the obtained solution are reported in Table 8 for the case of J_2 minimisation, which

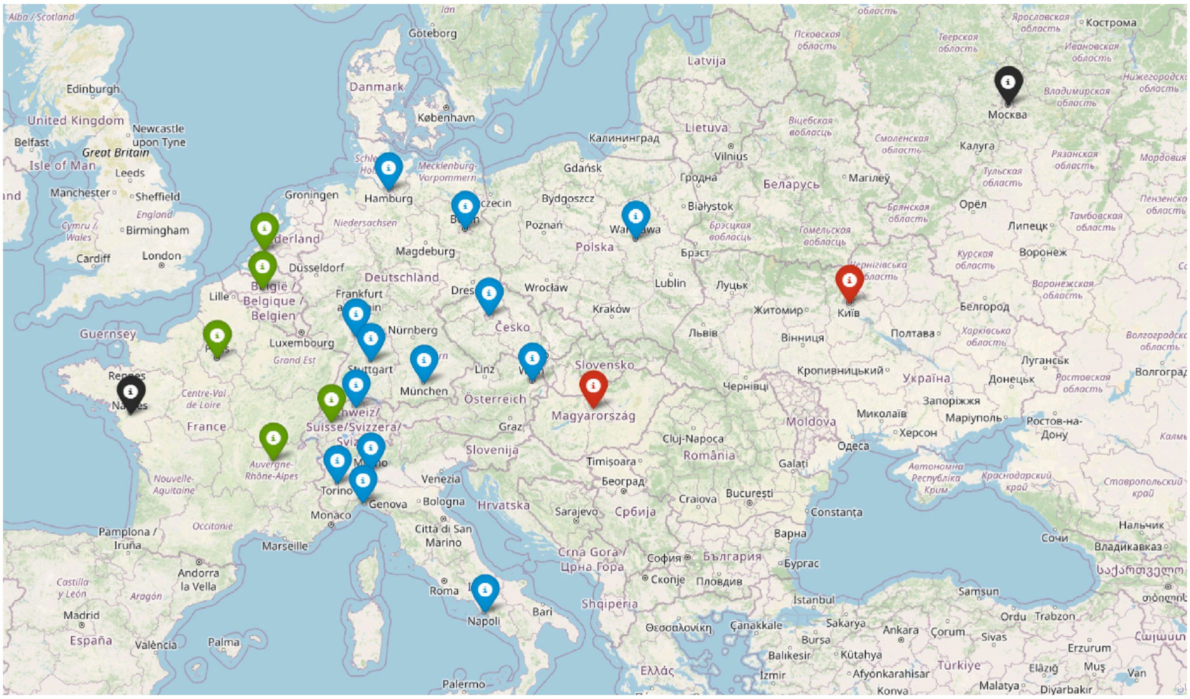

Fig. 3. Location of the terminals and PI-hubs in Europe: distribution centres (black), origin terminals (green), PI-hubs (blue), and destination terminals (red). Map source: OpenStreetMap.

Table 4
Data regarding trains that commute daily between terminals and PI-hubs.

Train	Train in link (j,k), $j \in \mathcal{O}_s$, $k \in \mathcal{P}$			Train in link (j,k), $j \in \mathcal{P}$, $k \in \mathcal{D}_s$		
	1	2	3	1	2	3
Departure time $(dp^{jk\ell})$	9:00	13:00	20:00	9:00	13:00	20:00
Capacity $(\Gamma^{jk\ell})$ in m^3	21	18	26	25	21	27

Table 5
Data regarding trucks that commute daily between terminals and PI-hubs.

Truck $\ell \in \mathcal{C}^{jk}$ in link (j,k), $j \in \mathcal{O}_s$, $k \in \mathcal{P}$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Capacity $(\Gamma^{jk\ell})$ in m^3	8	9	6	8	7	8	11	10	12	10	9	10	6	15	11
Departure time $(dp^{jk\ell})$	6:30	7:30	8:30	9:30	11:30	12:30	13:30	14:30	16:00	17:30	18:30	19:30	20:30	21:30	23:30
Truck $\ell \in \mathcal{C}^{jk}$ in link (j,k), $j \in \mathcal{P}$, $k \in \mathcal{D}_s$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Capacity $(\Gamma^{jk\ell})$ in m^3	8	7	5	9	6	8	8	7	9	7	8	10	11	12	10
Departure time $(dp^{jk\ell})$	6:30	7:30	8:30	9:30	11:30	12:30	13:30	14:30	16:00	17:30	18:30	19:30	20:30	21:30	23:30

Table 6
Capacity of the direct trucks in each link (between terminals) that can commute daily $(\Gamma^{jk\ell})$.

Direct truck $\ell \in \mathcal{T}^{jk}$	1	2	3	4	5	6	7	8	9	10
Capacity $(\Gamma^{jk\ell})$ of direct truck in link (j,k), $j \in \mathcal{O}_s, k \in \mathcal{D}_s$	10	9	6	12	7	8	6	8	4	5
Direct truck $\ell \in \mathcal{T}^{jk}$	11	12	13	14	15	16	17	18	19	20
Capacity $(\Gamma^{jk\ell})$ of direct truck in link (j,k), $j \in \mathcal{O}_s, k \in \mathcal{D}_s$	10	9	6	12	7	8	6	2	4	5

Table 7
Average operation time (τ_p) of each PI-hub for transferring the modules from the incoming section to the outgoing one.

PI-hub $p \in \mathcal{P}$	Hamburg	Mannheim	Milan	Berlin	Prague	Munich	Zürich
Average operation time (τ_p) (hr)	2	1	1	2	2	1	2
PI-hub $p \in \mathcal{P}$	Stuttgart	Turin	Genoa	Naples	Vienna	Warsaw	
Average operation time (τ_p) (hr)	2	3	1	1	2	1	

Table 8
PI-containers and modules transferred through PI-hubs and via direct trucks.

PI-container s	$s=1$	$s=2$	$s=3$	$s=4$	$s=5$	$s=6$	$s=7$	$s=8$	$s=9$	$s=10$
Number of modules n_s	$n_1=3$	$n_2=5$	$n_3=2$	$n_4=6$	$n_5=7$	$n_6=8$	$n_7=8$	$n_8=9$	$n_9=10$	$n_{10}=5$
Routed via PI-hub										
Train/Train	1, 2, 3	–	1, 2	4	2, 3	4, 6	1, 3, 5	2	1, 2, 8	2
Train/Truck	–	1, 4	–	2, 5	1, 7	5	–	–	–	3
Truck/Train	–	2	–	3	6	8	7	1, 8	3, 5, 7	4, 5
Truck/Truck	–	–	–	–	4	2	–	–	–	1
Routed via Direct trucks	–	3, 5	–	1, 6	5	1, 3, 7	2, 4, 6, 8	3, 4, 5, 6, 7, 9	4, 6, 9, 10	–
PI-container s	$s=11$	$s=12$	$s=13$	$s=14$	$s=15$	$s=16$	$s=17$	$s=18$	$s=19$	$s=20$
Number of modules n_s	$n_{11}=6$	$n_{12}=4$	$n_{13}=3$	$n_{14}=7$	$n_{15}=5$	$n_{16}=4$	$n_{17}=6$	$n_{18}=9$	$n_{19}=10$	$n_{20}=8$
Routed via PI-hub										
Trains/Trains	2, 4	1, 2, 4	1, 2, 3	5	5	1	5, 6	1, 9	2, 3, 4, 5, 6, 8	–
Trains/Trucks	–	3	–	7	1, 4	2, 3	–	–	10	2
Trucks/Trains	1, 3, 6	–	–	6	3	–	–	5	–	1, 5, 7
Trucks/Trucks	–	–	–	1	–	–	4	–	7	–
Routed via Direct trucks	5	–	–	2, 3, 4	2	4	1, 2, 3	2, 3, 4, 6, 7, 8	1, 9	3, 4, 6, 8

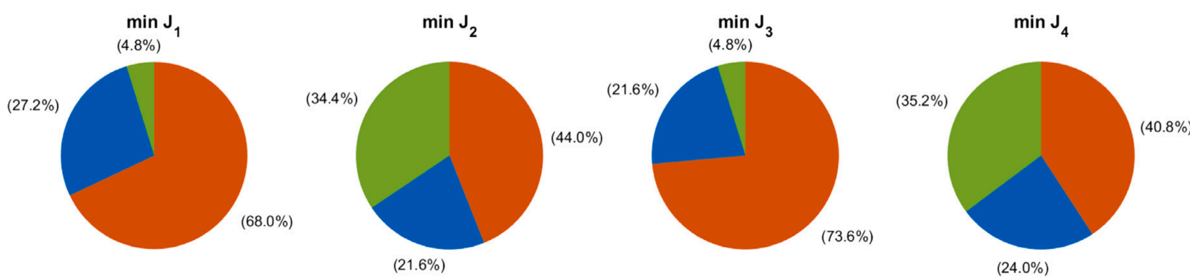

Fig. 4. Modal split of modules leaving the origin terminal. Legend: Direct trucks; Trucks; Trains.

is the most common objective in logistics optimisation [7,47]. This table shows the modules of each PI-container transported from the origin terminals to the destination terminals using either direct trucks or various combinations of vehicles (trains/trucks) through PI-hubs.

To assess the individual effect of each objective on the solutions obtained, the optimisation problem was solved by considering one of the four objectives at a time. The resulting ratio of transportation modes (modal split) varies with the different objectives, as expected, thus validating the effectiveness of the problem formulation considered.

The modal split, depicted in Figs. 4, 5, and 6, was derived from the optimisation problem described in Section 3.2. The optimisation model was solved by separately minimising each objective, resulting in a different allocation of modules across the available transportation modes. These objective-specific allocations explain the variations in the modal split across different scenarios. In more detail, Fig. 4 shows the modal split of the PI-containers when they leave the origin terminal. In such graphs, it can be observed that the direct truck usage is effectively minimised, as expected, when it is the main optimisation goal (J_1) and when the transportation costs are minimised (J_3). Therefore, these two optimisation goals result in similar modal splits. In contrast, minimising the delivery time (J_2) or the delivery gap (J_4) leads to an increase in the use of direct trucks, as they are faster than the passage through the PI-hubs.

Figs. 5 and 6 show, respectively, the modal split of modules arriving at the PI-hubs and leaving them. In particular, trains are always the most utilised mode, with 31%–39% of modules arriving by train and 33%–42% departing by the same mode. However, similarly to the previous case, truck usage decreases when transportation costs are minimised (J_3) and increases when the delivery time (J_2) or the delivery gap (J_4) is minimised.

5.3. Robustness analysis results

This section presents and discusses the results of the robustness analysis conducted on the network shown in Fig. 2, whose optimised dynamics are dictated by the mathematical programming model in Eqs. (1)–(24). In particular, the global variability of the system performance, when all input parameters vary, is first investigated (Section 5.3.1). Secondly, the results of the GSA, which analyses *the individual sensitivity* of each input parameter, are presented (Section 5.3.2).

In this analysis, the uncertain input parameters are the processing times τ_p at each of the PI-hubs and the number of modules in each PI-container n_s. Specifically, this analysis evaluates how robust the PI logistics framework is with respect to the division of PI-containers into modules and their processing times at the PI-hubs.

The input parameters are assumed to be stochastic, independent variables with the following uniform distributions, which were chosen to represent a situation of complete uncertainty. Specifically:

- $\tau_p \sim \mathcal{U}_{[1,3]}$, $\forall p \in \mathcal{P}$, i.e., the processing time for each module at the PI-hubs is modelled as a random variable with a uniform distribution in the range $[1, 3]$ hours;
- $n_s \sim \mathcal{U}_{[1,10]}$, $\forall s \in \mathcal{S}$, i.e., the number of modules per PI-container is modelled as a random variable with a uniform distribution in the range $[1, 10]$.

Regarding the output variables for the GSA, four KPIs are considered, each corresponding to one of the objective functions to minimise (i.e., $KPI_i := J_i$, $i = 1, \ldots, 4$). Each KPI represents a different performance measure of the PI logistics framework considered.

Additionally, four different configurations of the problem are considered, as follows:

- **C1**: In the first configuration, the use of direct trucks (J_1) is minimised;
- **C2**: In the second configuration, the total delivery time (J_2) is minimised;
- **C3**: In the third configuration, the total transportation costs (J_3) are minimised;
- **C4**: In the fourth configuration, the total delivery gap (J_4) is minimised.

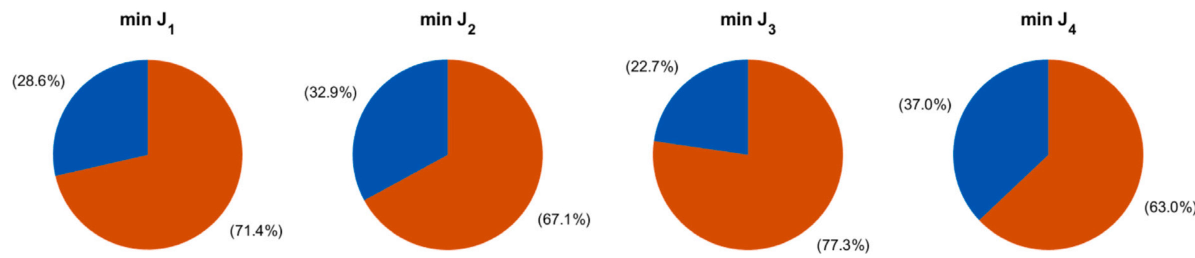

Fig. 5. Modal split of modules arriving at the PI-hubs. Legend: Trucks; Trains.

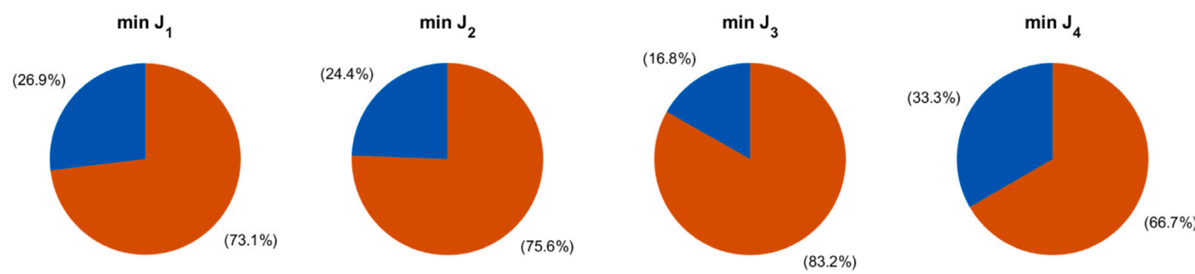

Fig. 6. Modal split of modules leaving the PI-hubs. Legend: Trucks; Trains.

The goal of these four configurations is to assess the impact of the selected objective function on the robustness of the PI logistics framework. It is important to emphasise that, while each configuration optimises only a single KPI, all KPIs are evaluated. For instance, configuration C1 represents the scenario in which the effect of uncertainties is analysed for all KPIs when the PI framework operates with the sole objective of minimising the number of direct trucks.

5.3.1. Analysis of the KPIs variability

As discussed in Section 4, the GSA aims to evaluate the fraction of variance associated with the variation of an input parameter. In other words, it provides a ranking of the most influential input parameters but does not provide information about the magnitude of the variance. For example, an input parameter may be among the most influential, but if the total variance is small, the system is still sufficiently robust, as the performance would not change significantly. Additionally, the magnitude of the output variance should also be related to the output mean values, as high variance on low mean values indicates greater variability compared to high variance on very high mean values. Therefore, to fully evaluate the robustness of the PI logistics framework, a preliminary analysis is performed to assess the ratio between the standard deviation and the mean (hereafter indicated as the relative standard deviation) of the above-mentioned KPIs. This measure is chosen as representative of the output variability. In this context, Fig. 7 shows the results for each KPI and configuration. The values shown have been calculated from the results obtained from several executions of the model (each performed with a different sample of PI input parameters, generated according to the uniform distributions previously introduced); in particular, 1000 executions were found to be sufficient for achieving convergence of the KPI variability.

Regarding the results, KPI_1 (direct trucks usage) exhibits very high variability when minimised (configuration C1), and relatively high variability when any of the other objectives are minimised. This result suggests that variations in input parameters can significantly impact the usage of direct trucks.

As for KPI_2, i.e., the total delivery time of the PI-containers, its variability is significantly lower than that of the other KPIs, especially in configurations C2 and C3. This indicates that the delivery time exhibits higher variability when the direct truck usage or the delivery gap is minimised.

The total transportation costs, addressed by KPI_3, are characterised by high variability across all configurations.

Lastly, KPI_4 exhibits very high variability in configuration C4, when the total delivery gap is minimised, and high variability in configuration C1, when direct truck usage is minimised.

Therefore, by examining the effects of the different minimisation goals (i.e., the different configurations) on the KPIs, it can be observed that minimising direct truck usage (C1) leads to high variability in the model outputs for delivery time, total cost, and the delivery gap (blue bars in Fig. 7). In contrast, minimising the delivery time (orange bars) or the transportation costs (yellow bars) leads to lower variability in the model output, especially in delivery time.

In conclusion, the analysis of KPI variability shows that the considered optimised PI logistics framework is quite robust for the delivery time (KPI_2) across all the optimisation goals (i.e., in each configuration), and for the delivery gap (KPI_4) when either the delivery time or transportation costs are minimised.

The above general analysis shows the variability of the model outputs when all the selected model inputs vary. To isolate the effect of individual inputs, the output variability was further investigated by analysing the results obtained when either the number of modules per PI-container, n_s, or the processing time, τ_p, of a single PI-hub p was allowed to vary at a time. This additional analysis was performed only for configuration C2, as the total delivery time was found to have the lowest output variability in the previous analysis. The relevant results are reported in Fig. 8, where the ratios between the standard deviation and the average values of the four KPIs are depicted. In this figure, it can be observed that all KPIs, except KPI_2, exhibit higher variability when n_s varies and τ_p is fixed, compared to the opposite case. This highlights the importance of the number of PI-container modules with respect to the processing times in the PI logistics framework optimised as per the model in Eqs. (1)–(24). Regarding KPI_2, it is worth noting that its output variability is lower because it is the minimisation goal.

5.3.2. GSA results

The last analysis performed on the considered PI network consists of the application of the GSA tool, briefly introduced in Section 4.1. Based on the results discussed in Section 5.3.1, the objective of this analysis is to identify the input parameters that contribute most to the observed variability and to estimate the relevant sensitivity indexes. To this end, the function f, mentioned in Section 4.1, is provided by the optimisation model defined in Eqs. (1)–(24), which governs the considered PI logistics framework. Regarding inputs and outputs, the

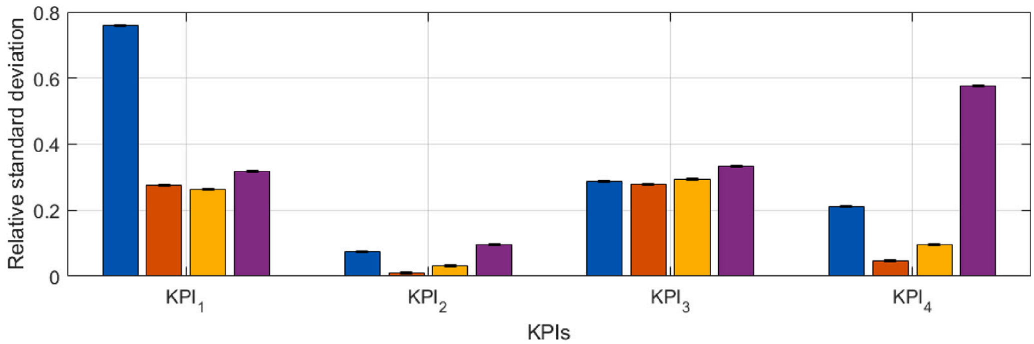

Fig. 7. Ratio between the standard deviation and the mean (calculated over 1000 samples) of the KPI values for the four considered configurations. Legend: ■ C1 ($\min J_1$); ■ C2 ($\min J_2$); ■ C3 ($\min J_3$); ■ C4 ($\min J_4$).

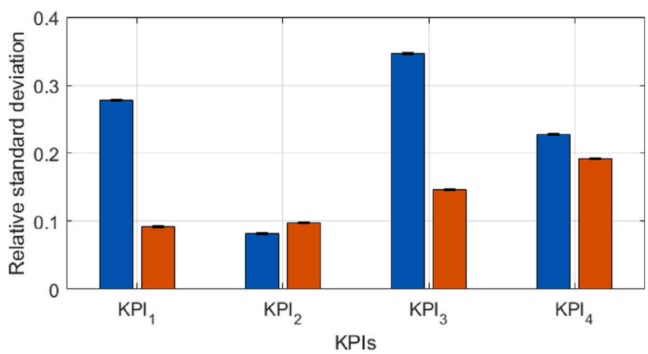

Fig. 8. Ratio between the standard deviation and the mean (computed over 1000 samples, for configuration C2) by varying only the number of modules n_s (■) or the processing time τ_p at one PI-hub (■).

vector X gathers the operational times τ_p at the PI-hubs and the number of modules n_s in each PI-container, while Y consists of one of the KPIs J_i, $i = 1, \dots, 4$, at a time.

The first step of this analysis consisted of the identification of the number of samples needed to compute the sensitivity indexes, which depends on the number of selected inputs, their probability distribution, and the model. In this regard, consider the graph in Fig. 9, where the sensitivity index values are plotted as a function of the number of samples. All indexes converged after 300–400 samples, so 1000 samples were considered sufficient to estimate the sensitivity index values for all the input parameters.

Next, regarding the resulting sensitivity index values, consider the radar graph in Fig. 10, where the rows correspond to the configurations and the columns correspond to the KPIs.

In particular, attention is given to the cases where the PI system performance exhibited more variability in the analysis performed in the previous section, namely, for KPI_1 (first column), KPI_3 (third column), and KPI_4 (fourth column), with the latter only in configurations C1 and C4. In these cases, the sensitivity of the number n_s of modules per PI-container is significantly higher compared to the other parameters. This indicates that n_s plays a key role in determining the performance of the PI system, or, in other words, that the system is less robust with respect to variations of this parameter. Specifically, n_s accounts for nearly all the variability in direct truck usage and transportation costs when the delivery time is minimised (Fig. 10e–g). Therefore, this analysis suggests that n_s should be considered a variable to be optimised within the model.

Conversely, the sensitivity values are significantly low for the operational times at the PI-hubs, indicating that the considered optimised PI scheme is robust with respect to individual variations of these parameters, regardless of the objective being minimised. However, there are some cases (e.g., KPI_4 for C1) where the sum of all the indexes is significantly lower than 1. This means that, in such cases, the performance variability is driven by second- or higher-order effects, i.e., by interactions between the PI parameters, which cannot be captured by the computed first-order sensitivity indexes.

From a practical point of view, this implies that a single PI-hub can be characterised by high variability in processing time without significantly impacting the overall PI network performance. In other words, if the processing time of a single PI-hub is affected by high uncertainty (e.g., due to regional or national conditions), assuming its average processing time in the network's optimal programming would not significantly affect overall logistics operations. On the other hand, if, for example, all the PI-hubs in the network were affected by high uncertainties, fixing all their processing times to average values would not be recommended. In this case, it cannot be concluded that the PI system is sufficiently robust with respect to their interactions. This result suggests that, even with a centralised optimisation approach, a rolling horizon approach to module delivery should be considered. For example, split and routing decisions could be periodically revised to incorporate the most up-to-date information on the problem inputs.

5.3.3. Summary of results and practical implications

To summarise, the results present several strengths: the first is the determination of the PI logistics framework's robustness with reference to the total delivery time (KPI_2). This outcome, derived from the KPIs variability analysis discussed in Section 5.3.1, shows that, regardless of the objective being minimised, the total delivery time in the system is not significantly affected. This is an interesting result since low delivery times are among the most common goals in logistics.

The second strength is the clear determination of the high relevance of the number of modules n_s into which PI-containers are divided. This is derived from the high sensitivity associated with this parameter, especially in determining direct truck usage (KPI_1) and transportation costs (KPI_3). From a practical perspective, this suggests that optimising n_s within the model (instead of treating it as a given parameter) could further reduce KPI values.

The third strength lies in the determination of the systems' robustness with respect to processing times at single PI-hubs, derived from the low sensitivity associated with these parameters. From a practical perspective, this result guarantees that the performance of the system would not be compromised if a PI-hub experienced processing times higher than those considered when solving the optimisation model (e.g., due to a peak in demand or a failure). In other words, if the PI-hubs are sufficiently reliable in terms of processing times, their average values can be considered in the optimisation problem without significantly affecting the system's performance if one of them encounters non-forecasted higher values.

On the other hand, the weakness of the results lies in the inability to conclude that the PI framework is robust with respect to the interaction

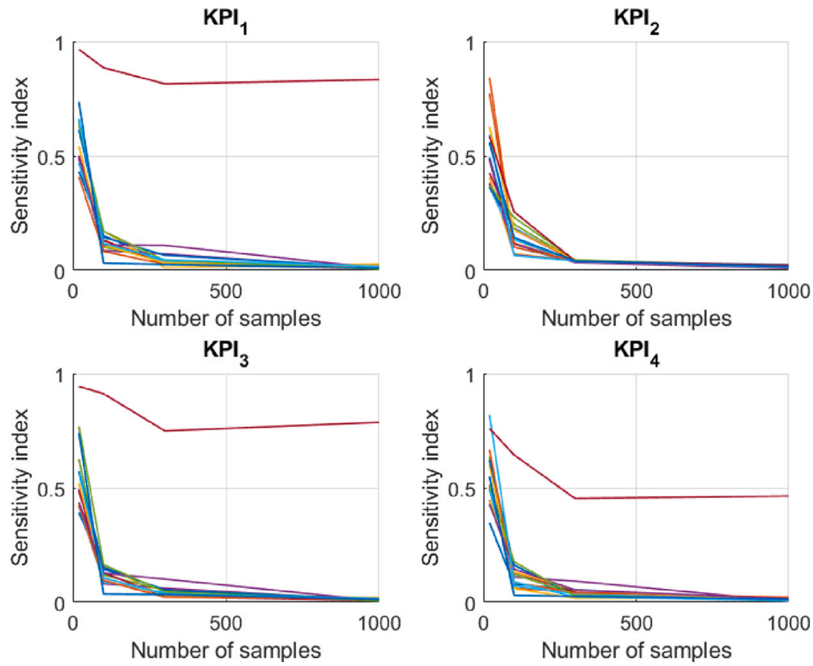

Fig. 9. Sensitivity of the 14 inputs for the 4 KPIs in configuration C2 as a function of the number of samples. Legend: τ_1; τ_2; τ_3; τ_4; τ_5; τ_6; τ_7; τ_8; τ_9; τ_{10}; τ_{11}; τ_{12}; τ_{13}; n_s.

of processing times at many PI-hubs. This is due to the fact that the computed sensitivity indexes only describe first-order effects. From a practical perspective, this means that, in cases of low reliability in the PI-hubs, uncertainties in processing times should be modelled, or decentralised routing approaches would be needed.

6. Conclusions

In this paper, a robustness analysis was conducted on the optimised PI logistics framework to better understand its behaviour and assess the impact of the processing times at each PI-hub and the number of modules in each PI-container. Specifically, after analysing the variability of the system's performance, summarised by four KPIs, sensitivity indexes were computed to quantify the relative influence of each input parameter on the PI logistics framework.

According to the analysis of the variability in system performance, the PI logistics framework was found to be quite robust with respect to all input parameters when the total delivery time was optimised. This is a notable result, as delivery time is one of the most common performance goals in logistics.

According to the GSA, the sensitivity indexes of the processing times at each PI-hub were very low, indicating that the considered PI logistics framework is robust to individual variations in these parameters across all the considered KPIs. On the contrary, the sensitivity index for the number of modules per PI-container was significantly greater than 0. This indicates that this parameter plays a crucial role in determining performance and that the considered PI logistics scheme is not robust with respect to how the PI-containers are divided into modules. Hence, this parameter should be carefully considered in real applications and, possibly, included as an optimisation variable.

The main limitation of this study is that, due to the required intractable computational effort, GSA was applied to evaluate only the individual (first-order) effects of each PI parameter. However, there are some cases (e.g., KPI_4 in C1) where the interactions (second- or higher-order effects) among PI parameters dominate, making it difficult to conclude that the PI logistics framework is robust with respect to these interactions. In such cases, all PI parameters should be treated as relevant, and further analysis should be conducted to evaluate the total effects.

The outcomes of this research align with those outlined in the PI roadmap [10], which anticipates significant benefits for all stakeholders in the freight and transport industry operating within the PI framework. Leveraging opportunities such as utilising existing idle capacities by adopting open and interconnected logistic services increases efficiency across the logistic network. The findings of this study are valuable to a wide range of stakeholders. Logistics service providers and freight operators can leverage these insights to identify potential sources of operational inefficiencies and reduce costs by optimising module configurations and routing strategies while considering the most relevant variables. Policymakers and environmental agencies can benefit from the demonstrated environmental advantages, such as reduced carbon emissions, which align with sustainability goals. Additionally, businesses relying on logistics networks will able to better estimate the average delivery times and the cost-effectiveness, thus enhancing their market competitiveness. In all cases, the proposed robustness analysis provides a framework for assessing the reliability of the results. Therefore, these findings lay the foundation for the development of robust, adaptable logistics systems that can meet future demands with greater efficiency and sustainability.

To conclude, from a research perspective, future studies will explore incorporating the way PI-containers are divided into modules as a decision variable in the optimisation model. This approach holds promise for further reducing direct truck usage and transportation costs, as the PI framework exhibits lower robustness concerning the number of modules in each PI-container, with variations significantly impacting KPI values. Therefore, optimising this variable is expected to enhance overall KPI performance. Additionally, rolling-horizon strategies will be investigated to dynamically update module-splitting and routing decisions based on real-time system conditions. Furthermore, a heuristic solution approach will be developed to efficiently solve larger problem instances within a reasonable timeframe, enabling a more comprehensive evaluation of the overall impacts.

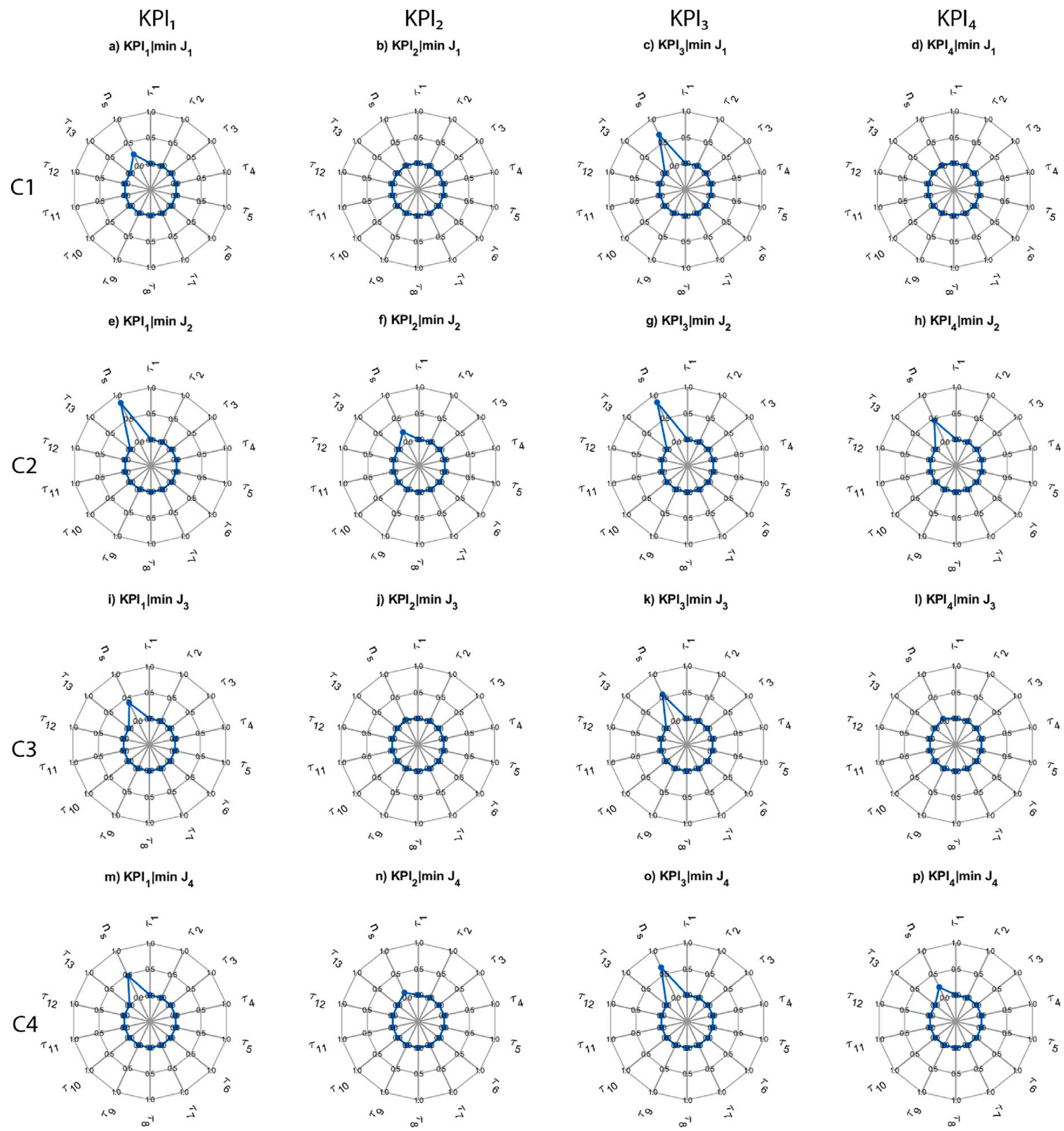

Fig. 10. Sensitivity indexes of the model inputs for the four KPIs (columns) and model configurations (rows).

CRediT authorship contribution statement

Federico Gallo: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Conceptualization. **Alireza Shahedi:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation. **Angela Di Febbraro:** Writing – review & editing, Validation. **Mahnam Saeednia:** Writing – review & editing, Validation, Supervision. **Nicola Sacco:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Nicola Sacco reports financial support was provided by European Union under the PNRR of NextGenerationEU, National Sustainable Mobility Center. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the European Union under the PNRR of NextGenerationEU, National Sustainable Mobility Centre (CN00000023, MUR Decree n. 1033—17/06/2022, Spoke 10). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or European Commission. Neither the European Union nor the European Commission can be held responsible for them.

Data availability

Data will be made available on request.

References

[1] P. Arnold, D. Peeters, I. Thomas, Modelling a rail/road intermodal transportation system, Transp. Res. Part E: Logist. Transp. Rev. 40 (3) (2004) 255–270.
[2] L. Filina-Dawidowicz, S. Stankiewicz, K. Čižiūnienė, J. Matijošius, Factors influencing intermodal transport efficiency and sustainability, Cogn. Sustain. 1 (1) (2022).
[3] T. Platz, The efficient integration of inland shipping into continental intermodal transport chains, Meas. Decisive Factors (2009) URL https://api.semanticscholar.org/CorpusID:142850349.
[4] J.T. de Miranda Pinto, O. Mistage, P. Bilotta, E. Helmers, Road-rail intermodal freight transport as a strategy for climate change mitigation, Environ. Dev. 25 (2018) 100–110.
[5] S. Carrara, T. Longden, Freight futures: The potential impact of road freight on climate policy, Transp. Res. Part D: Transp. Environ. 55 (2017) 359–372.
[6] K.F. Turnbull, The role of freight transportation in economic competitiveness: Summary of the 8th university transportation centers spotlight conference, in: Transportation Research Board Conference Proceedings on the Web, 2015, no. 16.
[7] Y. Sun, C. Zhang, K. Dong, M. Lang, Multiagent modelling and simulation of a physical internet enabled rail-road intermodal transport system, Urban Rail Transit 4 (2018) 141–154.
[8] W.E. Forum, Supply chain decarbonization, 2009.
[9] B. Montreuil, Toward a physical internet: meeting the global logistics sustainability grand challenge, Logist. Res. 3 (2011) 71–87.
[10] E. Ballot, S. Barbarino, B. van Bree, F. Liesa, J.R. Franklin, D. 't Hooft, A. Nettsträter, P. Paganelli, L.A. Tavasszy, Roadmap to the physical internet, 2020.
[11] A. McKinnon, Innovation in road freight transport: achievements and challenges, in: Innovation in Road Transport: Opportunities for Improving Efficiency, 2009, Lisbon, Portugal, 2009.
[12] A. Shahedi, F. Gallo, M. Saeednia, N. Sacco, Lead-time-based freight routing in multi-modal networks considering the physical internet, J. Supply Chain Manag. Sci. 4 (3–4) (2023) 61–80.
[13] E. Ballot, B. Montreuil, R.D. Meller, The physical internet, in: La Documentation FranÇaise, 2014.
[14] X. Qiu, H. Luo, G. Xu, R. Zhong, G.Q. Huang, Physical assets and service sharing for iot-enabled supply hub in industrial park (ship), Int. J. Prod. Econ. 159 (2015) 4–15.
[15] C. Landschützer, F. Ehrentraut, D. Jodin, Containers for the physical internet: requirements and engineering design related to fmcg logistics, Logist. Res. 8 (2015) 1–22.
[16] H.S. Sternberg, M. Denizel, Toward the physical internet—logistics service modularity and design implications, J. Bus. Logist. 42 (1) (2021) 144–166.
[17] B. Montreuil, E. Ballot, W. Tremblay, Modular design of physical internet transport, handling and packaging containers, in: Progress in Material Handling Research: 2014, 13 of International Material Handling Research Colloquium, MHI, 2015, URL https://minesparis-psl.hal.science/hal-01487239.
[18] S. Onal, J. Zhang, S. Das, Product flows and decision models in internet fulfillment warehouses, Prod. Plan. Control 29 (10) (2018) 791–801.
[19] H. Treiblmaier, Combining blockchain technology and the physical internet to achieve triple bottom line sustainability: a comprehensive research agenda for modern logistics and supply chain management, Logistics 3 (1) (2019) 10.
[20] B. Montreuil, J.-F. Rougès, Y. Cimon, D. Poulin, The physical internet and business model innovation, Technol. Innov. Manag. Rev. 2 (6) (2012).
[21] Alice, Alliance for logistics innovation through collaboration in europe, 2017, http://www.etp-logistics.eu/.
[22] T. Chargui, A. Bekrar, M. Reghioui, D. Trentesaux, Multi-objective sustainable truck scheduling in a rail–road physical internet cross-docking hub considering energy consumption, Sustain. 11 (11) (2019) 3127.
[23] Y. Sallez, S. Pan, B. Montreuil, T. Berger, E. Ballot, On the activeness of intelligent physical internet containers, Comput. Ind. 81 (2016) 96–104.
[24] E. Puskás, G. Bohács, Concepting freight holding problems for platoons in physical internet systems, Acta Logist. 6 (1) (2019) 19–27.
[25] B. Karakostas, Modelling and simulation of a physical internet of transportation hubs, Procedia Comput. Sci. 151 (2019) 17–22.
[26] J. Zhang, S. Onal, S. Das, The dynamic stocking location problem–dispersing inventory in fulfillment warehouses with explosive storage, Int. J. Prod. Econ. 224 (2020) 107550.
[27] X.T. Kong, J. Chen, H. Luo, G.Q. Huang, Scheduling at an auction logistics centre with physical internet, Int. J. Prod. Res. 54 (9) (2016) 2670–2690.
[28] F. Walha, A. Bekrar, S. Chaabane, T.M. Loukil, A rail-road pi-hub allocation problem: Active and reactive approaches, Comput. Ind. 81 (2016) 138–151.
[29] T. Chargui, A. Bekrar, M. Reghioui, D. Trentesaux, Proposal of a multi-agent model for the sustainable truck scheduling and containers grouping problem in a road-rail physical internet hub, Int. J. Prod. Res. 58 (18) (2020) 5477–5501.
[30] S. Pan, M. Nigrelli, E. Ballot, R. Sarraj, Y. Yang, Perspectives of inventory control models in the physical internet: A simulation study, Comput. Ind. Eng. 84 (2015) 122–132.
[31] Y. Yang, S. Pan, E. Ballot, Innovative vendor-managed inventory strategy exploiting interconnected logistics services in the physical internet, Int. J. Prod. Res. 55 (9) (2017) 2685–2702.
[32] Y. Yang, S. Pan, E. Ballot, Mitigating supply chain disruptions through interconnected logistics services in the physical internet, Int. J. Prod. Res. 55 (14) (2017) 3970–3983.
[33] H.M. Wagner, Global sensitivity analysis, Oper. Res. 43 (6) (1995) 948–969.
[34] J. Kleijnen, J. Helton, Statistical analyses of scatterplots to identify important factors in large-scale simulations, 2: robustness of techniques, Reliab. Eng. Syst. Saf. 65 (2) (1999) 187–197.
[35] M. Baucells, E. Borgonovo, Invariant probabilistic sensitivity analysis, Manag. Sci. 59 (11) (2013) 2536–2549.
[36] J.C. Felli, G.B. Hazen, Sensitivity analysis and the expected value of perfect information, Med. Decis. Making 18 (1) (1998) 95–109.
[37] M. Strong, J.E. Oakley, An efficient method for computing single-parameter partial expected value of perfect information, Med. Decis. Making 33 (6) (2013) 755–766.
[38] A.B. Owen, Sobol'indices and shapley value, SIAM/ ASA J. Uncertain. Quantif. 2 (1) (2014) 245–251.
[39] A. Di Febbraro, N. Sacco, et al., Global sensitivity analysis of the optimal capacity of intersections, IFAC Proc. Vol. 47 (3) (2014) 8775–8780.
[40] F. Gallo, A. Di Febbraro, D. Giglio, N. Sacco, Global sensitivity analysis for the evaluation of the effects of uncertainty of transport demand and passenger behavior on planning railway services with variable train composition, in: 2021 IEEE International Intelligent Transportation Systems Conference, ITSC, 2021, pp. 2298–2305.
[41] I. Kioutsioukis, S. Tarantola, A. Saltelli, D. Gatelli, Uncertainty and global sensitivity analysis of road transport emission estimates, Atmos. Environ. 38 (38) (2004) 6609–6620.
[42] A. Saltelli, M. Ratto, T. Andres, F. Campolongo, J. Cariboni, D. Gatelli, M. Saisana, S. Tarantola, Global Sensitivity Analysis: The Primer, John Wiley & Sons, 2008.
[43] A. Saltelli, S. Tarantola, F. Campolongo, M. Ratto, et al., Sensitivity Analysis in Practice: A Guide To Assessing Scientific Models, Vol. 1, Wiley Online Library, 2004.
[44] A. Saltelli, M. Ratto, T. Andres, F. Campolongo, J. Cariboni, D. Gatelli, M. Saisana, S. Tarantola, Global Sensitivity Analysis, Wiley, 2008.
[45] S. Tarantola, D. Gatelli, T. Mara, Random balance designs for the estimation of first order global sensitivity indices, Reliab. Eng. Syst. Saf. 91 (6) (2006) 717–727.
[46] N.S. Kim, B. Van Wee, The relative importance of factors that influence the break-even distance of intermodal freight transport systems, J. Transp. Geogr. 19 (4) (2011) 859–875.
[47] R. Chen, S. Li, Minimizing maximum delivery completion time for order scheduling with rejection, J. Comb. Optim. 40 (4) (2020) 1044–1064.