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1 According to PLANET's Quality Assurance Process

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PI	Physical Internet
PoE	Point of Entry
IoT	Internet of Things
EPCIS	Electronic Product Code Information Service
VRP	Vehicle Routing Problem
OLI	Open Logistics Interconnection
DSS	Decision Support System
OD	Origin Destination
LSP	Logistics Service Provider
ETA	Estimated Time of Arrival

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In this report Physical Internet services are presented that cover three specific supply chain domains:

- Intercontinental corridor integration to PI Hubs
- Warehouse Operations for Physical Internet enabled hinterland transportation, and
- Last mile urban distribution

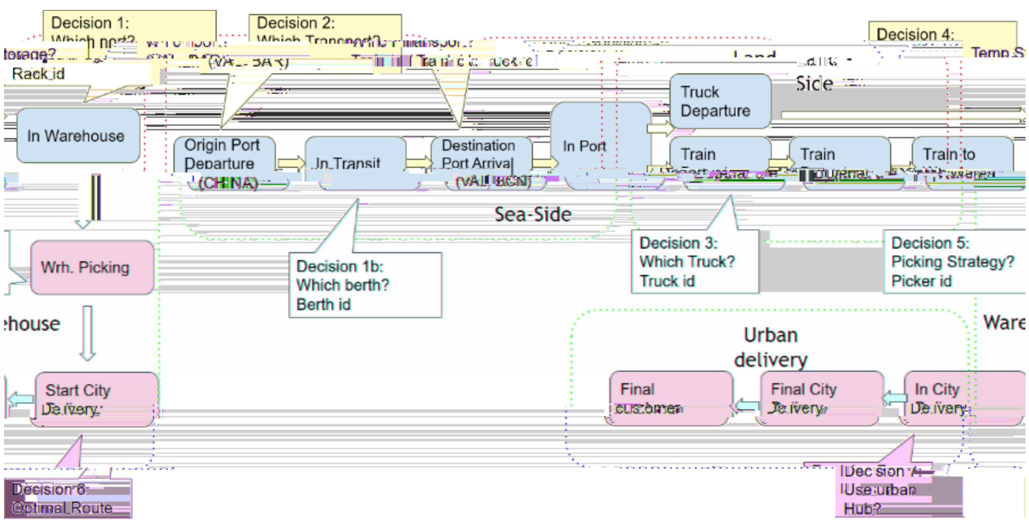
The PI services are designed to align with the PI principles and have been generalized to fit into the Physical internet paradigm. In the context of intercontinental corridors, Port of Entry PI Hub clusters are considered, and utilizing information on the destinations of the PI containers onboard a PI Mover, an optimal discharge PI Hub is identified for each container. In the context of hinterland transport, an automated capacity pre-booking solution is provided, that utilizing prediction confidence intervals and inventory replenishment theory, is found to deliver a 6.25% cost reduction for the tested OD pair. In the context, of last mile delivery, a dynamic parcel reshuffling algorithm is proposed, that can identify and utilise vehicles that are running ahead of schedule to micro-consolidate cargoes and expedite deliveries, alleviating parcel returns to the distribution center due to delays.

All services have been designed to utilise multiple information sources, and network up-to-date status updates, integrate standardized encapsulation and smart decision making, and promote operator collaboration. A collaborative marketplace is proposed in the last mile logistics context, that utilises criteria identified during the MAMCA workshop, to characterize all operators. Individual operators are then able to filter out operator profiles that they would not like to share loads with. Accommodating such operator constraints, enables the promotion of collaboration with last mile delivery operators that operate sustainable vehicles further enhancing the operational efficiency of the network.

In the context of the PLANET project and its Living Labs, multiple alternative technologies, infrastructures, and policies are considered. The aim of all alternatives is to drive operational efficiency in a Physical Internet enabled supply chain. The planning impact horizon of the decisions' considered in PLANET project living labs ranges from operational to strategic levels. The three PLANET Living Labs investigate three unique aspects of technological and infrastructural development. Focusing on the connectivity of the TEN-T network to global trade corridors:

- LL1 examines how new technologies (IoT, AI and blockchain) and concepts (such as Physical Internet) can improve processes, operations and efficiency along the door-to-door transport chains linking the Maritime Silk Road with EU internal corridors.
- LL2 examines how synchro-modal dynamic management of TEN-T & intercontinental flows promoting rail transport and utilizing the Port of Rotterdam (PoR) as the principal smart EGTN Node coordinating the rail focused transport chains linking China through Rotterdam to/from USA, and Rhine-Alpine Corridor destinations, and
- LL3 examines streamlining logistic processes in flows from China to Europe along the Silk Road by implementing IoT technologies (based on the EPCIS platform) and GS1 standards that facilitate transmission of data between the partners involved in the e-commerce operations.

All PLANET Living Labs investigate the integration of TEN-T operations as hinterland to global corridors as illustrated in Figure 2.1 for LL1. As part of this exercise, three types of use cases are defined. The first concerns the sea-side collaboration, between ocean liner operators, and port operators. In a more generic sense, this represents the operators of a global corridor, irrespective of the mode. The second concerns long-haul hinterland connections, between port and terminal operators, LSPs and warehouse operators. The third concerns urban distribution and the collaboration between regional warehouse operators and last mile logistics companies.



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The deliverable proposes methods and algorithms, that adapt legacy T&L practices to the operational principles of the Physical Internet. The proposed methods have been identified based on the challenges identified in the Living Labs but have been developed in a Living Lab agnostic way into services, as part of a more generalized framework of T&L solutions. The deliverable focuses both on the algorithms and their performance, as well as the EGTN platform that embodies the algorithms, their interactions with other EGTN services and where applicable with the interaction with the user.

Purpose of this section is to map PLANET's Grant Agreement commitments, both within the formal Deliverable and Task description, against the project's respective outputs and work performed.

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D2.14 Intelligent PI Nodes and PI Network services final version	Intelligent PI Nodes and PI Network services final version using D2.3 – D2.10 as well as the DSS tools. Final design and implementation of PI Nodes and Network services and deployment to the EGTN infrastructure.	Chapters 3, 4 and 5 describe the final versions of PI Nodes and Network services.	The Network services considered range from Intercontinental flows Point of Entry to last mile routing decisions. The Node services decisions integrate with prediction models developed in D2.9 to deliver smart functionality for smart contracts.
T2.4 Group multi criteria DSS for transport and PI Networks	This task develops: Intelligent PI Nodes and PI Network services to optimise the efficiency of the whole transport system whilst reducing emissions	Section 3, 4,and 5.	Section 3 presents PI Network algorithms for PI Node choice. Section 4 covers the last mile parcel reshuffling, and PI Node algorithms for trucking capacity booking are described in Section 5. In each section, data handling, mathematical modelling and calibration are considered.
ST2.4.2 Intelligent PI Nodes and PI Network services	Performing intelligent forecasting and planning, intelligent and automated operations, and real time reporting of operations and the status of the nodes and the network utilising outputs from T2.2 and T2.3 as well as the DSS tools.	Sections 3.4, 4.4 and 5.3	For each contextual service, integration with other WP2 services, implementation in the EGTN platform and dashboard interaction are described.

The deliverable is the final and updated version of deliverable "D2.13-Intelligent PI Nodes and PI Network Services". The algorithms and methods presented in this deliverable build on and complement the models presented in the interim version, and an effort has been made to be present the updates here in a full and coherent manner. However, to avoid repetition, it is often the case that background material presented in D2.13 is omitted, and any interested reader can use the interim material for further investigating the background and sources of inspiration for the models presented in this deliverable.

In Sections 4 and 5 the PI services are presented in each section starting from a brief model description of the model and its functionality, covering mathematical formulations where applicable, and investigating model performance. As per the PLANET projects main objectives, the models presented cover three specific supply chain domains:

- Intercontinental corridor integration to PI Hubs
- Warehouse Operations for Physical Internet enabled hinterland transportation, and
- Last mile urban distribution

In all three contexts, the PI principles of improving on critical variables such as cost, utilisation rates, and emissions through improved multi-modal integration and open accessibility to static and mobile infrastructures are promoted through open and standardized interfaces, monitoring and data sharing, smart decision making and modularized encapsulation.

Sections 3, 4, and 5 focus on PI solutions associated to each specific context respectively. For intercontinental corridors the proposed services focus on Point of Entry Hub identification for container routing. At the hinterland, the PI service focuses on appropriate, reliable tracking capacity pre-booking while at the last mile a collaborative parcel reshuffling solution is proposed.

For each context, the data requirements and data preprocessing of the models are discussed. The algorithmic approach or where applicable the mathematical model is presented, and a use case implementation is discussed, based on real data for calibrating the model. The interfaces and integration with other EGTN services is presented for addressing specific user needs, as well as the dashboard implementation and GUI features are discussed.

The deliverables findings are summarized and reported in Section 6, with the concluding remarks of the deliverable and suggestions for further work.

The PI Node and Network services described in this report are based on the supply chain operational questions illustrated in Figure 2.1. The Physical Internet’s Open Logistics Interconnection (OLI) and NOLI models and their functionalities are considered in the definition of PI services [5, 6]. In the definition of the PI layers the differences between data and physical goods transfer are considered, such as the fact that instead of just one kind of physical objects in data networks, there are actually three kinds of physical objects in physical networks: the physical means (as in data networks), the containers (that are just additional bits in data networks), and the goods (that are also just bits in data networks) [6].

This challenge is primarily associated to the NOLI Network Layer, that is responsible to receive loads of pi-containers from the Transport Layer and to create "blocks" from the loads. The Network Layer defines a path across the network for each block. The Network Layer computes and manages the routing of each block from its initial starting location to its final ending location. The Network Layer manages and maintains the data structures necessary to compute the best paths for the blocks.

This routing decision is also captured in Figure 2.1, in the sea-side operation, the land-side operation as well as last-mile delivery. The pi-choice model presented in Section 3 deals with the sea-side and hinterland transport operations, while Section 4 focuses on last mile routing decisions and handling uncertainty.

In terms of PI Node services, each warehouse, or consolidation center operator is required to provide sufficient outflow capacity considering the anticipated demand. This functionality is currently handled separately for each individual node. However, in cases where scheduled services are not available or do not provide sufficient volume that meets node outflow demand, additional transport capacity requires to be booked. The service provided in Section 5, focuses on undertaking this task cost efficiently in a PI setting. The service integrates forecasting capability, with smart decision making, and smart contracts to facilitate the efficient allocation of transport capacity where needed which is fundamental for the efficient functionality of the PI.

In a PI enabled global transport network, the integration of intercontinental transport corridors to the existing infrastructure network is a fundamental supply chain component. It represents the handover of cargo by intercontinental route operators to European hinterland operators and vice versa. The transition is currently limited in terms of efficiency by lack of up-to-date information, inadequate corridor and Point-of-Entry infrastructures and operational capabilities. This intercontinental corridor to EU network transition is present in all PLANET Living Labs albeit in their different contexts.

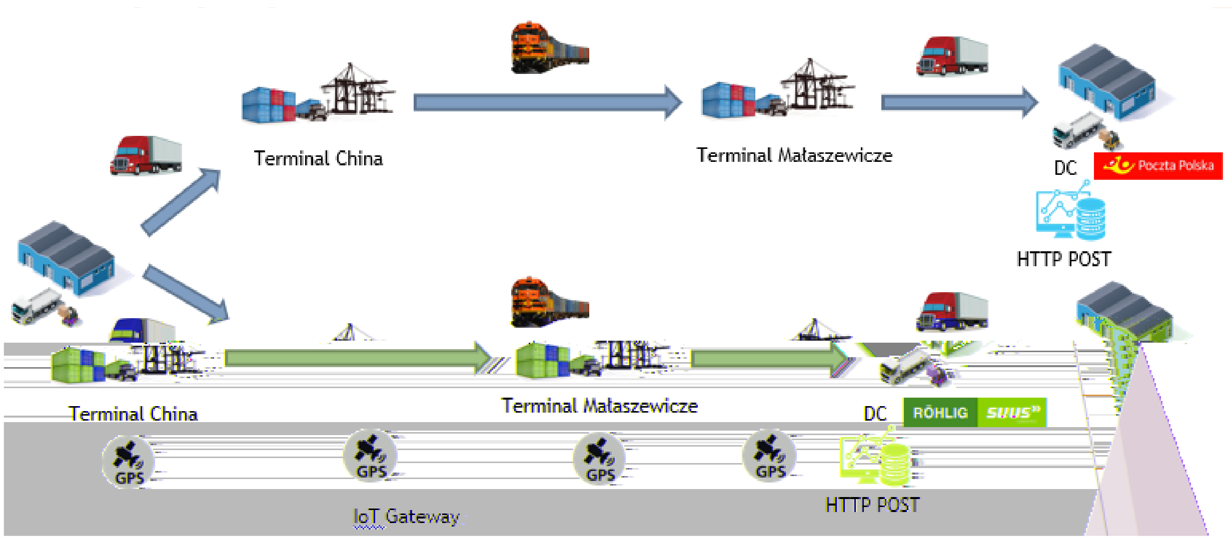
It is found in sea-side collaboration, between ocean liner operators, and port operators. As discussed in D2.13 [2] , container vessels operate fixed schedules between South-Eastern Asia and South Europe as illustrated for COSCOs aem1 and aem2 in Figure 3.1. Uncertainties in this context are typically associated with adverse weather conditions, delays due to strikes, and port congestion. Operators are therefore required to make marginal calls, and last-minute alterations to vessel schedules, that are difficult to manage, process and implement as alternatives routing options need to be established and booked for all cargo on-board the vessel whose discharge port requires to be changed. Operators and LSPs tend to avoid such last-minute alterations to only the absolutely essential cases, as for example to avoid a long-port strike.

Figure 3.1: East Asia to Mediterranean container ship routes

Intercontinental rail corridors such as the Silk Route interact with the European transport network through multimodal terminals such as the one in Malaszewicze, Poland (see Figure 3.2. In such cases cargo transported by rail, must travel through multiple countries and therefore undergo multiple equipment and infrastructure changes as various types of rails widths, locomotives and electrification currents are required. Increasing traffic along the route also implies higher delays and uncertain ETAs that significantly limit receiving LSPs ability to plan ahead and optimize their operations within the EU network.

Similar issues arise in smaller intercontinental corridors such as the connection between continental Europe and the UK, where alternating policies as well as proximity have an impact on the added value of various operational solutions and propositions. In such cases, the short travel duration, does not allow for significant dynamic operational changes to take place efficiently. However, automated processes for handling cargo documentation have a significant impact on customs processing efficiency.

Another significant aspect of the transition between intercontinental corridors and the EU transport network is the multiple stakeholders involved. In all three contexts LSPs, customs, one or more operators, intermodal terminals are involved in operating the supply chain.



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Therefore, for a feasible and impactful implementation of the Physical Internet principles, all stakeholders must be considered and a context-agnostic generalized solution is required, that involves, information standardization and exchange between stakeholders, as well as analytic and decision-making capabilities. The PI Hub Choice model algorithm is presented in Section 3.1, and the information standardization and processing is discussed in Section 3.2, while a performance assessment of the model is considered through a Use Case presented in Section 3.3.

The PI Hub Choice Model focuses on the containers loaded on a specific PI Mover. As a PI Mover is approaching a single Point of Entry to the European transport network (e.g. TEN-T), information on the final destination of containers is collected and combined with information on network status. The scope of the model considers network status, to identify the optimal Point of Entry for each of the containers, and therefore dynamically update the routing schedule of the PI Mover.

For example, consider a vessel that is scheduled to call at Valencia and Barcelona, as COSCO's aem2 route illustrated in Figure 3.1 and some of the containers loaded on the vessel are destined for the European hinterland. The PI choice algorithm considers:

- the two ports of the route as well as additional ports in the Iberian peninsula such as Algeciras,
- the infrastructure available at each port,
- weather conditions,
- sea-side congestion,
- hinterland connectivity for both ad-hoc (trucks) and timetabled services (rail).

In a generalized context, the algorithm considers alternative PI Hubs that belong to the same Point of Entry PI Hub cluster. Then if a delay is identified in the original PI Mover schedule, which may be caused by weather, strike action or simply high congestion, it seeks better performing alternatives. The algorithm therefore attempts to utilise hinterland transport connections, through alternative Points of Entry, if the PI Mover schedule originally navigates through a congested PI Node.

A mixed-integer linear program has been developed for determining the route of a PI Mover through appropriate PoE PI Hubs. In the formulation presented below, the PoE PI Hubs that belong to the same cluster are provided in advance.

The program determines if a PI Mover M should call the originally scheduled PoE PI Hub, or other PI Hubs that belong in the same cluster, aiming to optimize the operational costs of getting all containers currently on board M, to their individual destination. A binary decision variable y_P is defined for every PoE PI Hub P in the cluster $P \in C$ of size n, that represents the decision to call or not to call P. The PI Hub Choice model determines whether to call the originally schedule Pi Hub, or any other or any combination of more than one PoE PI Hub, or all of them.

$$y_P = \begin{cases} 0 & if\ M\ goes\ to\ P \\ 1 & otherwise \end{cases}$$

$$\sum_{y} y_P \leq n$$

The latter constraint is not limiting. It ensures that the decision variables can all be equal to 1, and the PI Mover calls all PI Hubs in the cluster. Further binary decision variables are defined that capture if a specific cargo shipment is discharged in Pi Hub P or not. To this end, x_{Pi} resembles the PoE of discharge and $i \in \{1, \dots, m\}$ is the container identification defined for m containers on board to be discharged at any of the ports in the cluster, which is further tied to a specific destination. Therefore, for any container i, we have that:

$$\sum_{P} x_{Pi} = 1$$

The above constraint ensures that PI container is discharged at exactly one of the PoE PI Hubs P in the cluster. Then the binary variable indicating whether a port will be called, y_P is equal to 1 if at least one container is discharged there. The point of having a y decision variable is to allow for additional operating costs of calling an additional PI Hub to be represented. Then, the problem can be formulated as follows:

Assuming a set of n candidate discharge ports $P \in C$ and a set of containers to be delivered $i \in \{1, \dots, m\}$ at specific customers location j, a binary decision variable x_{Pi} is equal to 1 if container i is discharged at PI Hub P, and 0 otherwise. A matrix l_{ij} captures the relationship between containers and final destinations. An additional binary variable y_P is equal to 1 if at least one container i is discharged at PI Hub P, in which case a fixed port calling cost f_P applies. A logistic cost proportional to the distance d_{Pj} from port P to customer location j is also considered. A sufficiently large number M is considered. Then, a cost minimizing problem can be defined with the following objective function.

$$\min_{x,y} \sum_{P} \sum_{j} (d_{Pj} x_{Pi} m_{ij} + y_P f_P)$$

Subject to constraints:

$$\sum_{P} x_{Pi} = 1$$

$$y_P M \geq \sum_{i} x_{Pi}$$

$$x_{Pi}, y_P \in \{0,1\}$$

The first constraint ensures that each container on-board will be discharged at one of the PI Hubs. The second constraint ensures that even if the optimizer decides to discharge at least one container at PI Hub P, the decision variable for calling PI Hub P, y_P will be equal to 1, and the corresponding costs for calling the port will be considered in the cost function. Finally, the binary nature of the container and port call decision variables is defined.

From the formulation presented in the previous section, the PI Hub Choice model inputs include the containers on board a PI Mover and their delivery information, as well as port congestion and hinterland transportation costs.

The data available does not always match model requirements and therefore additional harmonization prior to running the model is applied. For example, in the context of seaborne transportation, the data provided by one of the Living Lab partners was in .json format as illustrated in Figure 3.3. A similar dataset is available for every container on board a PI Mover, which in this case is a Cosco vessel.


```
{
    "terminal": "T073",
    "date": "2021-08-10T15:22:42",
    "status": "COMPLETE",
    "operation": "IMPORT",
    "transportType": "CARRIER_HAULAGE",
    "isRail": "false",
    "BLnumber": "9015247950",
    "ReleaseCompanyCode": "TTCV",
    "ReleaseCompanyName": "APM TERMINAL VALENCIA S.A.",
    "AcceptanceCompanyCode": "MVAL",
    "AcceptanceCompanyName": "CSP IBERIAN VALENCIA TERMINAL S.A.U.",
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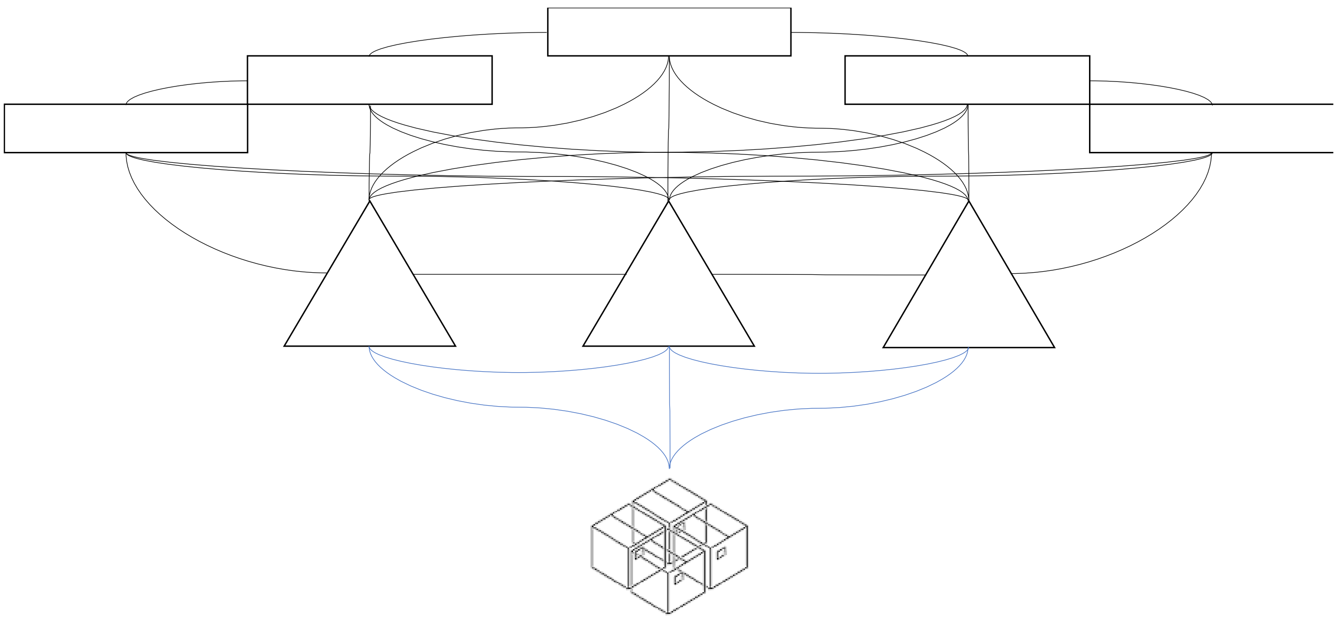
The dataset contains information on the final customer; however, the PI Hub Choice model requires information about the transport cost for all PI containers, from any possible discharge port to their respective destination. This is essential to construct a network, as port congestion and hinterland transportation are represented through a graph of nodes and link as illustrated in Figure 3.4.



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The links and node of the network are developed depending on the mode of transport. For hinterland transportation, road transport distances are identified using an OpenStreetMaps API. Rail transport links are estimated to have a longer loading time due to transshipment, but a lower handling cost. Intercontinental link duration is identified based on historical data where available. Short sea links are estimated based on straight line distances and vessel speed, while an additional port entry link is considered to represent port entry congestion.

Additional data was provided with scheduled services for hinterland transport such as for rail. Considering that scheduled hinterland services often offer viable and efficient alternatives to road transport, an amendment of the mathematical formulation is anticipated to handle this routing capability.

The PI Hub Choice model was embedded in a simulation environment to test its performance. The simulation focused on the Iberian Peninsula, and more specifically the Point of Entry ports of Algeciras, Valencia and Barcelona that form a cluster and the hinterland transport serving and connecting them to the rest of Spain. To represent realistic conditions, the simulation considered 3 competing vessel operators with each having a daily service (one vessel) calling all three ports sequentially. The simulation assumed different port entry dwelling times per company, to account for port ownership schemes, as vessel operators are increasingly vertically integrating their operations.

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PI Hub 1	PI Hub 2	PI Hub 3	day	company	vessel

As illustrated in Table 3.1, 21 vessels with varying numbers of containers loaded on them were considered for seven consecutive days. It is observed that one of the three PI Hubs is consistently omitted from each vessels schedule, with company 0 and company 1 vessels omitting PI Hub 3 and company 2 vessels omitting PI Hub 2. This behaviour is most probably associated to the company specific port entry costs. Table 3.1 illustrates the containers discharged per PI Hub, however, the model's output is provided per container, rather than per vessel. Therefore, individual container routing instructions can be generated, once the discharge port and mode to destination are provided by the model.

The PI Hub Choice model has been implemented as an EGTN service through an API that returns optimised PI container and PI Mover routing decisions. The PI container information is not digested directly by the PI Hub Choice model, but rather pre-processed to identify:

1. accurate coordinate information for each PI Container destination based on the description provided by the PI Mover operator,
2. identify alternative PI Hubs that belong to the same Point of Entry cluster,
3. to establish road and rail hinterland connections between each candidate discharge PI Hub to every PI Container destination,
4. and to populate a complete OD matrix of candidate routes to be considered by the PI Choice Model service.

Additionally, a database of information on the anticipated Point of Entry congestion and queues is maintained in Kafka DB, that are retrieved by the PI Choice Model as input in its cost function. The congestion database is in the current implementation of the EGTN platform updated by the respective user querying the service. The output of the service is provided as a .json that contains two dictionaries, one containing each PI containers discharge port and route to the destination, and one containing the PI Hubs that the PI Mover is scheduled to discharge containers at.

The Track & Trace service monitors the location of PI Containers and the EGTN Knowledge Graph service tracks which parcels, and delivery addresses are contained in each PI Container. The two services operating together maintain the information of PI Containers on board a PI Mover.

Containers are moved on pre-defined routes established at the beginning of the process and following strict regulations and procedures. Each logistics node is under control of single company with no visibility of its supply and next nodes, therefore shipments can follow not optimized routes and can be affected by heavy delays.

The PI network will expect to build flexible and resilient door-to-door services, in which all logistics nodes have the intelligence to identify optimized dynamic routing of containers through the network considering capacity, level of service and cost of transport modes available. Logistics services are visible and digitally accessible by all actors involved. This way user identifies his requirements in terms of origin and destination of goods and leaves the execution of the transport to the PI network, based on secure protocols and services to guaranteed trust and transparency.

The tool enables the identification of optimal container forwarding options, bypassing congested ports and while considering hinterland transportation options and their capacity. The service integrates well with existing COSCO processes, as it can be run while a vessel is on-route and prior to reaching the first Iberian Peninsula port. Currently, the system is manual and responsive only to port strikes. Congestion and hinterland transport alternatives are not considered.

The congested urban environment and the multiple different functionalities it accommodates, impose significant uncertainty in last mile delivery operations. Uncertainty is observed in travel times due to road congestion, parking availability in proximity to the delivery location, information accuracy associated with package drop off location, as well as when applicable uncertainty about the presence of the recipient at the time and location of the drop-off. Last mile operators frequently assume a unilateral travel speed and drop-off duration in their planning process. Depending on the conditions encountered during the delivery round, last mile operators frequently need to dynamically redesign urban delivery rounds, to alleviate delivery delays. This challenge is highly relevant to the concept of the Physical Internet and EGTN as it utilises the benefits associated to dynamic tracking of parcel deliveries and vehicle fleet. The problem focuses on decision-making at an operational level.

Delivery rounds, that are typically fully designed prior to initiating their implementation every day, consider the delivery locations, fleet availability (i.e., the number and capacity of delivery vehicles available) and local accessibility constraints such as Low Emissions Zones (LEZs) or Zero Emissions Zones. When delays arise, in order to expedite a late delivery round completion time, operators sent assistance vehicles, that share the delivery load.

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As discussed in the interim deliverable D2.13, the visualisation of the delivery rounds enables the manual tracking of delivery progress, and the identification of severe delays, when a delivery round is considerably behind schedule. The red vertical line at 3pm in Figure 4.1, captures the current time, and enables progress inspection. For example, route C17 (first row) seems to be roughly on-time, while round C24 (last row) seems to be running slightly late.

It is also worth noticing that the sequence at which van drivers choose to implement the delivery round does not always align with the delivery planned route, as experienced delivery drivers have tacit knowledge about the complex operational environment in which they serve customers daily. They know which roads are hard to navigate, when traffic is bad, when and where they can easily find parking, which stops can be conveniently served together, and many other things that are difficult, if not impossible to formalize in an optimization model. This tacit information is therefore not contained in most route planning tools used in the industry, causing drivers to frequently deviate from originally planned route sequences. Considering their tacit knowledge, drivers follow a deviated actual route sequence instead, which is potentially more convenient under real-life operational conditions.

As delivery round delays arise, the original planning and design of the rounds might need to be updated. This is because delivery operational constraints, such as delivery time windows (no deliveries past 9PM) and driver shift hours, cannot be violated. In such cases, a fleet operator tries to identify delivery rounds that might finish early or be ahead of schedule and dispatch them for helping the round running late. The process of identifying van availability, van suitability and then redesigning the delivery rounds, that involves identifying which parcels will be moved from the original van to the helping van, and where the two should meet for the parcel exchange will take place is currently undertaken manually.

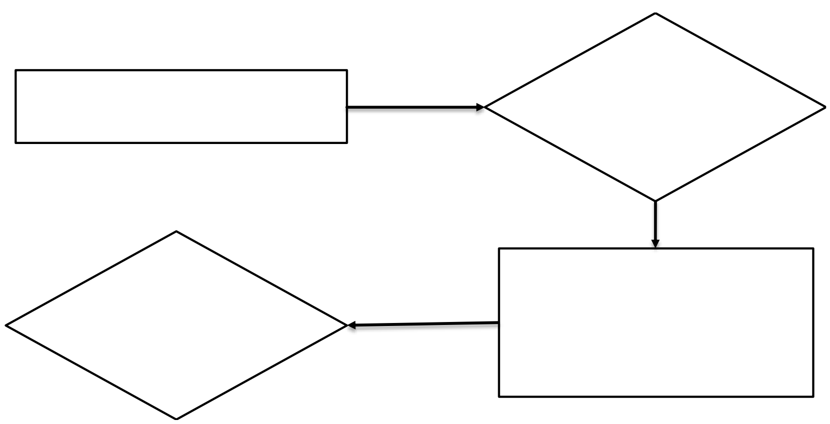
The aim of the Last Mile Dynamic Reshuffling service is twofold: firstly, it aims at automating the process of identifying a vehicle that can share the delivery load with the late running vehicle, hereafter called the help vehicle and managing the operational parameters for materializing the exchange. This procedure involves identifying:

- which vans can be sent for assistance without inflicting severe delays in their delivery obligations,
- how many and which parcels require to be transferred from the late vehicle to the helping vehicle,
- a common meeting point for the two vans, and
- the dynamic redesign the delivery round for both vehicles featuring the common meeting point.

Secondly, a critical constraint for effectively addressing delivery delays, is the availability of helping vans, which are typically limited as operators aim to utilise all their resources in the planning phase. Offering fair and balanced criteria for determining helping rounds contributes to promoting collaboration between otherwise competing operators. However, operators tend to seek solutions internally, rather than handing over their deliveries to other operators. A collaborative DSS is therefore provided to offer fair and balanced alternatives for collaboration to last mile operators. The service exposes the help request and then it applies filtering criteria as defined by the operator posting the request, in search for qualifying help rounds.

When an alert for a late running delivery is raised, the automated reshuffling model is initiated to assess possible options for assisting the van that is running late and optimise the process. The process is designed to run in two stages, with the first stage identifying the nearest available help rounds, and the second stage dealing with the redistribution of parcels, and redesign of the delivery routes.

As illustrated in Figure 4.2, the first step of the process involves identifying all the delivery rounds operating in proximity. Following the openness principles of the Physical Internet, the proposed algorithm can consider the delivery rounds of one or more operators as candidates for helping the delivery round that is running late. The process firstly filters the rounds in terms of ETC, to identify the ones with higher availability, and then undertakes the more computationally intensive process of identifying the centroid for each round. The round centroid calculation considers all pending delivery locations for each round separately.



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The collaborative marketplace functionality for delivery assistance is an enhancement to this process that instead of considering a single operator’s vehicles, considers all vehicles operating in proximity and applies an operator customized filtering process. The marketplace functionality is presented in Section 4.2.

Once the optimal help round has been identified, and it is confirmed that it is operating in proximity to the late running round, and it has sufficient spare time for handling additional parcel deliveries, the task of reshuffling the pending parcels is initiated. The aim of this task is to identify which of the pending parcels of the two rounds should be delivered by which vehicle, to alleviate overall delivery delays. The late running round meeds to share some of its load with the helping round, however up to this point it is not clear which ones should be transferred.

A Machine Learning clustering algorithm is applied to the dataset, that divides the pending delivery parcels to two roughly equal in size clusters using their centroids [7]. The algorithm compulsorily assigns all nodes to one of the two clusters, leaving no nodes unassigned. The algorithm has been applied using a travel-time matrix as the criterion of vector separation of a node to the cluster centroid obtained by an Open Street Maps API.

The output of the clustering algorithm is a tag for each node of the population, that corresponds to a unique delivery round. Each tag is then associated to each of the two delivery rounds, by using a simple linear optimization model that minimizes the number of parcels to be transferred to the help vehicle. The parcels are therefore, classified into the ones remaining in the late running round, the ones remaining in the help round, and the ones moving from the late running round to the help round.

After reshuffling the parcel delivery locations, and establishing the area moving to the help round, it is required to convert that information to instructions for the two vans and drivers. In effect, this includes the new routes for both vehicles, that incorporate a meeting point, and the information on which parcels require to be transferred from the one van to the other.

The meeting point can be determined prior to addressing the vehicle routing decision. The meeting point necessitates proximity of the two vans, as well as limiting the waiting time involved in the process. To identify two locations with proximity that are suitable for serving as the meeting point, the locations of the parcels remaining on the late running round, and the location of the parcels remaining on the help round are considered. The locations of the parcels moving from the late running round to the help round are excluded from this process, as prior to the exchange at the meeting point, they are loaded on the incorrect van. The travel distances between all locations are considered and the two points with the closest distance are identified. This location is then added to the locations the help round requires to visit.

The meeting point represents a proximity location suitable for the two vans to visit, however there is no guarantee up to this point that the two vans arrive there simultaneously. To address this, a common time window is set on both vans for reaching the meeting point. Depending on the position of the vehicles in comparison to the meeting point and the time available until the 9pm cut-off, the time window start time and duration are appropriately adjusted. If no solution can be found the meeting point time window is relaxed, by either delaying its start time, or expanding it, or both.

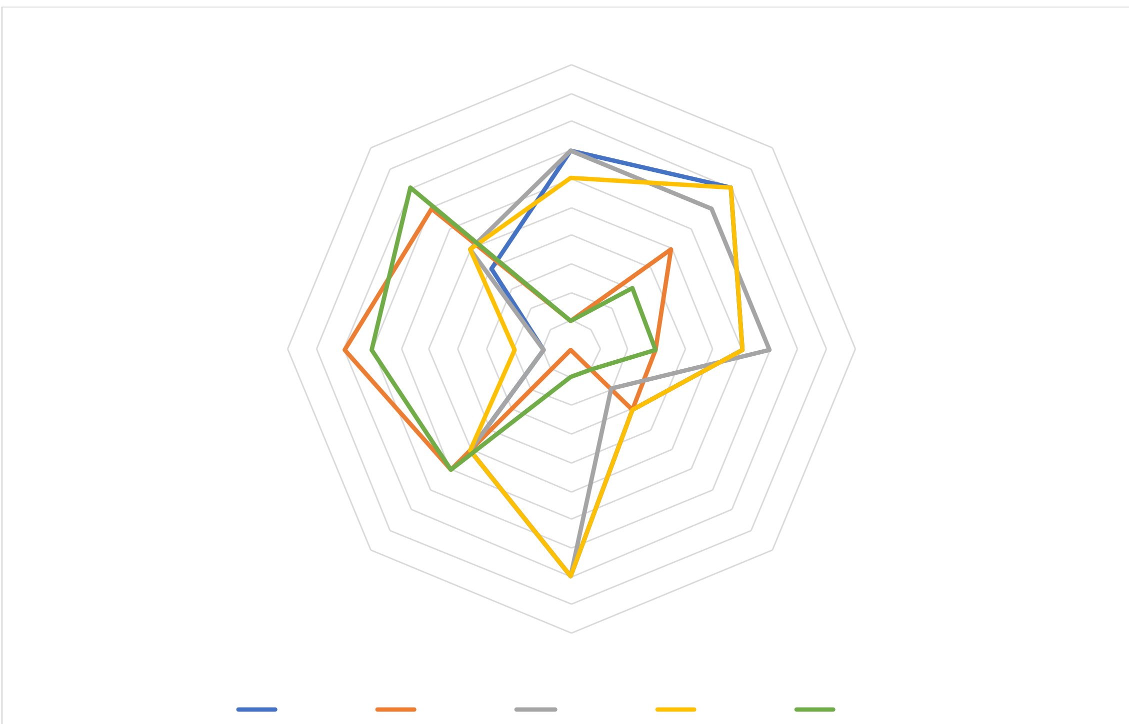
A Travelling Salesman Problem with time-windows is then solved, including a common time window for reaching the meeting point, while no time window constraints are considered for all other locations.

The collaboration between last mile operators is a functionality that is yet to be unlocked in a practical perspective. Collaboration in the last mile can be performed in multiple contexts ranging from warehouse and consolidation location sharing to dynamic re-routing solutions. Last mile operators avoid collaboration for parcel deliveries, typically claiming fear of losing delivery volumes to competitors, poor service quality of other operators, as well as lack of brand recognition.

In the context of the dynamic parcel reshuffling algorithm described in Section 4.1, operator collaboration leads to the identification of more candidate help vehicles and can significantly impact positively solution efficiency as discussed in further detail in Section 4.3. As part of the PLANET MAMCA Workshop undertaken in Poznan during the projects GA meeting in October 2022[2], the project partners worked together to identify the most significant last mile delivery stakeholders and performance criteria, also ranking them in terms of significance. When asked specifically about last mile delivery, the most significant criteria identified were:

- sustainability
- transport cost
- congestion
- service quality
- emissions
- driver availability (human resources)
- delivery time
- profitability

Using a standard scale of performance for each of the criteria, a comprehensive characterization of each operator can be achieved. For example, Figure 4.3 presents a mapping of five last mile operators based on synthetic data, where Operators 1, 3 and 4 are conventional van operators while operators 2 and 5 and cargo bike operators, scoring higher in low emissions and sustainability performance.



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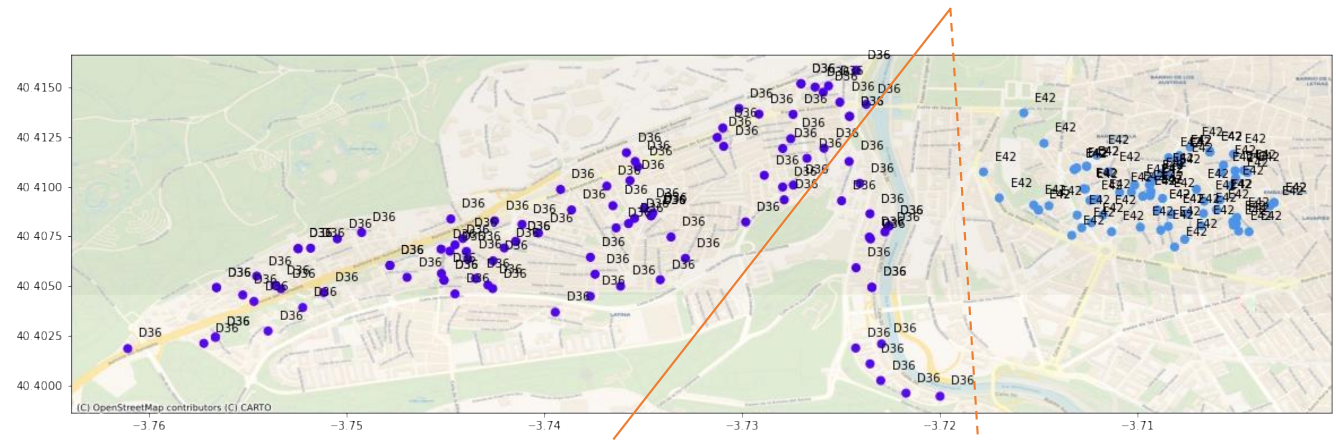
Maintaining a comprehensive multi-criteria performance characterization for each operator as the one illustrated above, enables a collaborative filtering process to take place. Each operator can pre-define acceptable performance criteria for collaboration. For example, a mainstream operator that uses vans, may specify emissions and sustainability performance for collaboration to be at least 7, in which case only the two cargo-bike operators would qualify. Then, after respecting operators' collaboration preferences, the nearby delivery rounds identification algorithm can be executed (as described in Section 4.1.1), considering only the last mile operators that qualify after applying the multi-criteria filtering process. Note that the collaborative filtering service is not

[2] A detailed description of the Workshop and its proceedings is available in PLANET Deliverable D2.12 [3]

yet implemented as part of the EGTN parcel reshuffling service due to the limited last mile operators available in each Living Lab.

In D2.13 an initial implementation of the parcel reshuffling algorithm was presented. The algorithm was applied on a dataset provided by Living Lab 1 partner CityLogin describing the morning delivery plan for more than twenty delivery rounds on 10 July 2021. A simulation capability was also developed and integrated with the parcel reshuffling algorithm, as delivery round progress data during the day were not made available. As described in D2.13, the simulation imposes traffic, parking and handover delays, around the network. If a delivery round experiences delays, and a delivery is scheduled beyond 9pm, a late running flag is raised, and the parcel reshuffling algorithm is initiated. An additional dataset was made available describing the morning delivery plan on BlackFriday 2021. The original algorithm described in D2.13 used a K-Means clustering approach for parcel reshuffling, and routing based on straight line distance. The algorithm originally performed well and yielded satisfactory results for the parcel reshuffling component, however, the routing solution using the straight-line distances illustrated significant link overlapping, and was therefore amended to use city grid distances, and travel times utilizing an Open Street Maps API.



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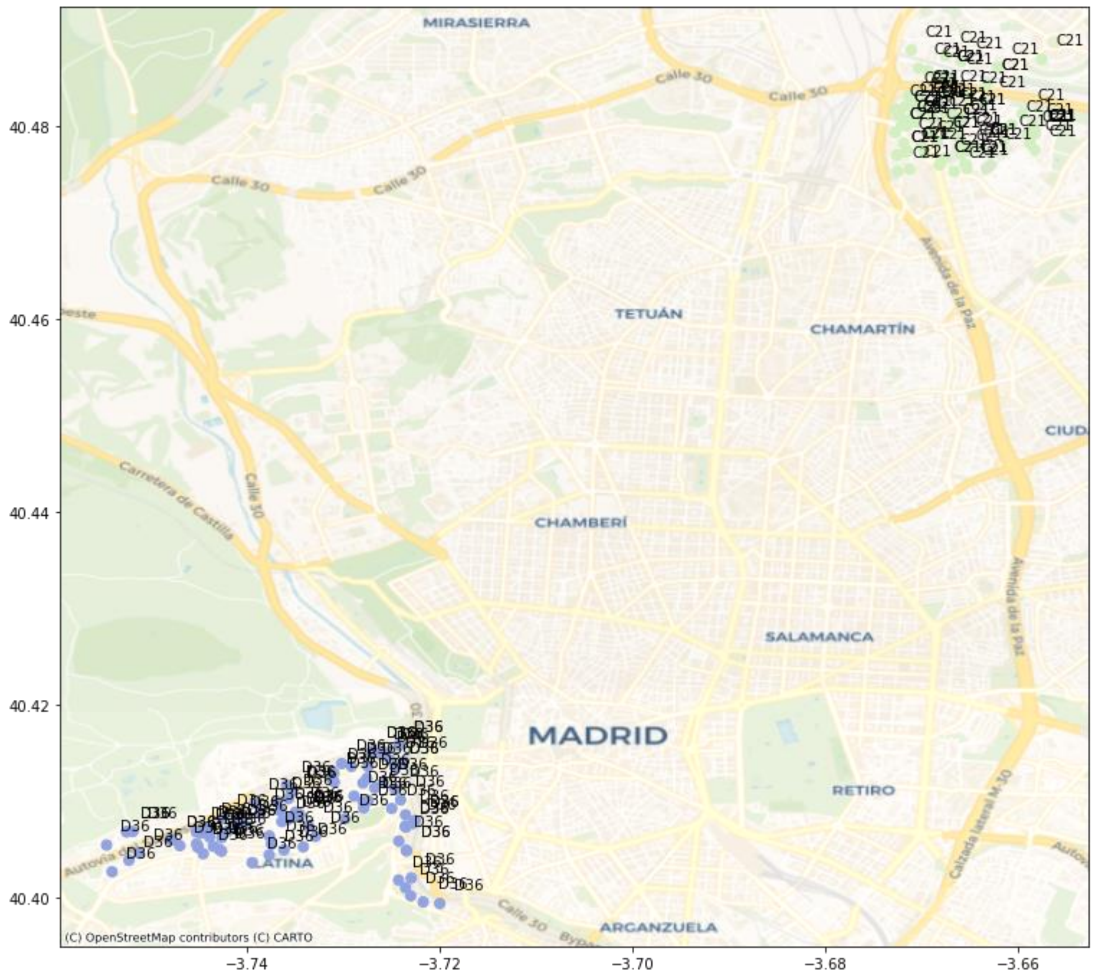
When testing the multi-company feature of the algorithm to assess how performance changes when operators choose to collaborate or not, three scenarios were defined:

1. The scenario assumes that there is no collaboration between last mile distributors operating in proximity and that parcel reshuffling does not takes place. When a delivery round is delayed beyond 21:15, it returns to the distribution centre carrying any undelivered parcels, and a new dedicated delivery is scheduled for those parcels the following day.
2. The scenario assumes that each last mile distributor operates in isolation, however parcel reshuffling is possible between the same company's vehicles. When a vehicle is estimated to make a delivery beyond 21:15, the parcel reshuffling algorithm is initiated, and a nearby vehicle (of the same company) is identified, to share the load.
3. The scenario assumes that last mile distribution companies can collaborate. When a vehicle is running late and there are estimated deliveries beyond 21:15, the parcel reshuffling algorithm is initiated taking into consideration all vehicles operating in proximity.

Due to the lack of availability of a multi-company dataset that is required for analyzing the scenarios described above, a copy of the CityLogin's dataset was used to create a multi-company dataset. To achieve this, the

CityLogin delivery rounds where evenly and randomly subdivided into four 'imaginary' companies. The companies were assumed to handle equal volumes of traffic, and therefore the delivery rounds were evenly divided, however an un-even subdivision of delivery rounds may enable an analysis of the impact of the algorithm for different company sizes (i.e. larger operators have more reshuffling opportunities than smaller operators). An un-even subdivision of delivery rounds has not been considered and analysed in the context of this simulation analysis. In the multi-company scenario, the availability of help rounds is much sparser. Figure 4.5 illustrates the later running round (D36 shown in light blue at the bottom left) and the optimal same company help round C21 (shown in green on the top right). When compared to the multi-company scenario that yields E24 as the optimal help round (as illustrated in Figure 4.4) it is evident that the same-company collaboration is considerably less feasible and efficient.



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Furthermore, in cases where the distance between the delivery rounds operational areas is significant, as the one presented in Figure 4.5, it was observed that the K-Means cluster algorithm was not reshuffling any parcels. The K-Means clustering algorithms quantifies the centroid for all delivery locations of each delivery round and sets it as the centroid of the cluster gradually extending its region. It is, therefore, the case that when there is a significant distance between the vans, all nodes are assigned to a cluster prior to the two clusters sharing a common border. To address this behavior, and to enable parcel reshuffling even when the help van is not operating in proximity, the parcel reshuffling algorithm was adjusted to a constrained K-Means clustering algorithm, that yields equal cluster sizes [4].

The EGTN implementation of the parcel reshuffling service, involves interoperation with other EGTN services. In a PI enabled context, all PI containers are monitored and tracked by the PI Networking Service. The OLI PI Shipping service acts as an orchestrator and raises a late running flag when a vehicle round is delayed, and the latest delivery is beyond 21:15.

In the last mile parcel reshuffling use case, the Track and Trace service monitors the location of PI containers. The EGTN Knowledge Graph service is responsible for tracking individual parcels within PI Containers, and PI containers within PI Movers, and consolidating both historical as well as the current location and containerization data.

Furthermore, the last mile routing service solves variations of the Vehicle Routing Problem (VRP) in efficient computational times. The VRP is typically solved by operators during the morning design of their daily delivery rounds. In the morning round design the shortest/ fastest route is identified and therefore a sequence for visiting all delivery locations is established. Depending on the nature of the products being distributed vehicle routing can be with or without time windows. In the context of parcel reshuffling, the VRP is solved for two vehicles with separate starting locations, and time windows, that ensure that both vehicles will visit the meeting point simultaneously.

The parcel reshuffling service is accessible through the EGTN user interface. The core functionality involves a choice of source data for the parcel reshuffling service, however extended functionality is anticipated for integrating parcel tracking capability either by using the PI container track and trace service data, or by individual operators connecting their existing tracking infrastructure with the EGTN platform. Last mile operators typically track van movements as well as parcel barcode scanning, which enables comprehensive and instantaneous tracking capability.

Higher first attempt delivery success is key for all the stakeholders involved. Each package returned to the warehouse due to a failed or out of time delivery, generates economic, social, and ecological costs. It is, therefore, key for Last Mile delivery companies to save the costs associated with having to do a second try. Currently, second delivery attempts represent around 20% daily extra cost for operations due to the additional amount of kilometres needed to either come back and try delivery on the same day or to return to base and plan the delivery for the next or a later date. It is also key for the cities to avoid additional runs by delivery vehicles operating, as they contribute to road occupation and pollution emissions.

The use of the algorithm to support decisions in real time allows decisions to be made in the time and moment necessary so that they do not have a negative impact on the service, complying with the restrictions agreed in the SLA in a totally optimized way, avoiding the error of decisions out of time or not correctly valued by the head of traffic. The decision support provides notice regarding a future problem in the operation by analysing the data in real time and allows the correction of the deviation in an optimized way.

In the case of use studied, the current situation of the operation, these aids are managed by the traffic manager based on his experience and supported by reserved assistance vehicles to be used in case of need if any delivery person suffers a mishap or delay. This implies an oversized cost for emergencies in terms of retention or activation of a resource to prevent service problems.

The use of algorithms for decision support allows optimizing the resources available to the traffic operation by providing information on routes with problems in advance. It also provides the best possible solution by determining the vehicle that can help, the time, the place and the number of packages that must be transferred from one route to another and that allows the daily objective to be met at the lowest possible cost.

The transmission of packages would take place within the track and trace system, so that the traceability of the package would be guaranteed, allowing to know in real time when it has been carried out and, based on the plan, to know the estimation of completion.

For the end customer, as far as the service is concerned, it would allow a more faithful adjustment to the estimated delivery time, increasing the perceived level of service and avoiding the implications for it of delays and cancellations.

It allows increasing the % of services delivered on the first attempt, reducing the average cost per delivery, using the available resources, both human and vehicles, in a more optimized way, reducing their under-use or over-exploitation and, therefore, allowing better working conditions for the while increasing productivity.

In a more holistic version of the market, it also allows the interaction between several logistics operators, being able to integrate these solutions between several operations in order to optimize the global transport resources in a specific place and time, in an interoperable concept of digital solutions, such as, for example. a city would allow the operator to resort to the underutilised resources of the competition in order to meet its agreed level of service and in turn increasing the optimization of the competitor's resource creating value for both and for the entire context of the city by optimizing the use of everything possible of the resources available for last mile deliveries.

The Automated Capacity Pre-Booking service is a novel Decision Support System (DSS) service that determines the capacity that requires to be pre-booked for outbound shipments for a specific warehouse and route. The service aims to disrupt current practice in warehouse and terminal outbound capacity booking, aligning with the principles of the Physical Internet and utilizing advanced analytics.

Current warehouse operations are based on pre-agreed contracts with freight forwarders or carriers for a fixed number of trucks. However, unexpected demand at specific moments or other events often creates the need for the booking of extra trucks. Several parameters may affect the demand for trucks in a warehouse. These include the following:

- Periods of increased shopping
- Events affecting routes and truck availability
  - Strong weather conditions. E.g., the Filomena Storm caused chaos in transportation of goods due to traffic cuts.
  - Transport strikes.
- Current affairs and their effects on the economy
  - The pandemic. For instance, lockdowns cause an increase in online shopping.
  - International conflicts (e.g., the Ukrainian war)
  - Fuel prices. Price increases often cause strikes.
- Day of the week. Warehouse flows typically follow a weekly seasonality. For example, there are no operations on Sundays, and there is therefore an increased workload at the start of the week.
- Continuous growth of e-commerce.

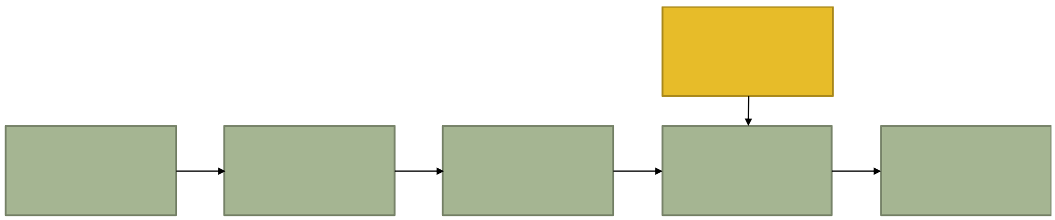
These parameters cause uncertainty and sudden variations in warehouse flows, that the fixed contracts in place with freight forwarders or carriers are difficult and costly to adapt to. Auxiliary trucking capacity is booked one day ahead of execution based on expected outbound demand. One day ahead, warehouse operators hold definitive bookings and outbound traffic information, and are therefore fully aware of what requires to be shipped, enabling them to make the appropriate trucking capacity bookings. Changes on the day of execution are also possible either in the form of booking additional capacity or as a cancellation. In case of last-minute alterations, a premium or cancellation fee is paid for booking more or cancelling some capacity respectively.

The pricing structure of cancellations and bookings are dependent on the planning horizon of the operator and how many days ahead of execution the booking or cancellation is made. A discount can be associated to the booking price and the cancellation fee if made “early”. When capacity is booked several days prior to execution, carriers can better optimize their operations, and therefore can offer an improved rate. A similar logic applies to early cancellations, as the carrier can still search for alternative cargoes.

The automated capacity pre-booking is a service that is relevant to every PI Node and PI Hub in the T&L network, as it utilises historical data to make short-term predictions and makes pre-bookings in a cost-efficient manner. The predictions are made separately for each delivery route originating from the PI Node, as each destination serves unique customers with unique demand characteristics.

The “Automated Capacity Pre-Booking” DSS is a sub-component of a series of EGTN services that are designed deliver smart contracting functionality, which is described in additional detail in Section 5.3. The core concept of automating the smart contracting capability, lies in utilizing early predictive capability and the confidence intervals produced by predictive models.

In the context of booking PI Node outflow trucking capacity, predictions need to take place within 10-day as well as 3-day windows. Predictions become less accurate, the further ahead in the future they look. Therefore, for regular daily operations, 3-day predictions provide a sufficient time frame for truck bookings which allows to account for up-to-date information on weather. In addition to this, unforeseen events may occur that may be known only a few days in advance (e.g., strikes). In such situations, the warehouse operator follows a contingency plan. This is a manual process which requires the booking of extra trucks a few days prior to the event to ensure that pallets will reach their destination on time. On the other hand, 10-day predictions become valuable from a business perspective as we are approaching periods of increased shopping (e.g., Christmas or Black Friday). For instance, an increase in bookings due to a special event such as Black Friday, can be predicted at least a week in advance. In such an occasion, truck bookings can be made several days ahead of the event and better prices can be negotiated.



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As illustrated in Figure 5.1, predictive models are developed either using supervised Machine Learning models or time-series analysis. In the context of this report, and based on the datasets considered in PLANET's Living Labs, only the latter option (i.e. time-series analysis) is considered, however, it remains valid for all types of statistical models, that confidence intervals can be exported. To address the issue of demand uncertainty, confidence intervals from the predictive models are considered.

Wikipedia describes a confidence interval (CI) as "a range of estimates for an unknown parameter. A confidence interval is computed at a designated confidence level; the 95% confidence level is most common, but other levels, such as 90% or 99%, are sometimes used". A CI is therefore a range of values (a lower bound and an upper bound), where we expect our prediction to fall in with a certain level of confidence. The size of the interval is directly proportionate to the level of confidence. Therefore, we can propose a narrow interval with low confidence, or a larger interval with higher confidence.

The aim behind the use of confidence intervals, is to ensure that when smart contracts are triggered, they will not book higher a truck capacity than is needed. Instead of using the actual prediction value, which might be either an underestimation or an overestimation, smart contracts may be issued using the 95% (or even 99%) confidence intervals. This provides meaningful information in terms of booking trucking demand using the lower CI value, given that there is a high confidence level that the actual demand will be above the lower bound, and therefore high degree of certainty in the outcome of the model. In this manner, the output of the models is a prediction range rather than a single number (i.e., the number of pallets). Confidence intervals are particularly meaningful in the case of the 10-day predictions, as they break down the prediction to levels of various degrees of certainty.

The proposed capacity pre-booking service is optimized for a specific cost structure, as it utilises features of inventory replenishment theory. Inventory theory is concerned with the design of production/inventory systems to minimize costs. Provided a level of demand expressed in the form of a demand distribution, and a given purchase, and holding cost structure, stochastic optimization is used or Monte Carlo simulation to identify an optimal order quantity, known as Economic Order Quantity. In the context of PI Nodes, the aim is not to figure out how much inventory to order, but rather how much capacity to order for a specific demand profile. Furthermore, inventory management uses holding costs and markdown prices, to capture the effect of time on the inventory quantity, while in a freight logistics context, this can be replaced, by early capacity booking discount and late cancelation fees.

The service therefore assumes a known pricing structure of the form illustrated in Table 5.1, where $b_{10} < b_3 < b_0$ and $c_{10} < c_3 < c_0$ are true. A more comprehensive pricing structure with booking and cancellation fee values for more prediction options ahead of execution can be considered.

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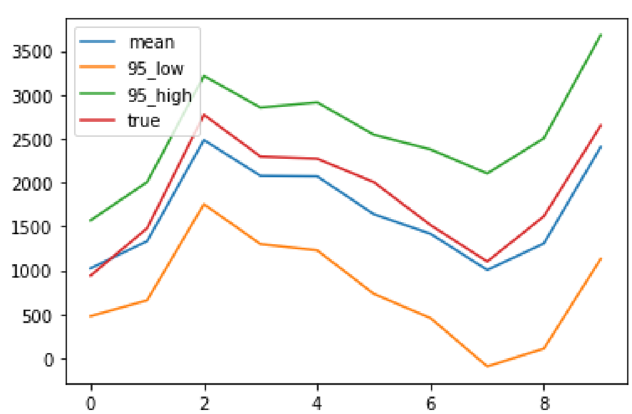
	b_0	c_0
	b_3	c_3
	b_{10}	c_{10}

In conjunction with the confidence intervals, and the pricing structure, the stochastic capacity order quantity, will provide a value of financially viable trucking capacity to book. This means that high certainty volumes can be associated to low booking prices, while low confidence predictions will be associated with higher booking prices. In such a scenario, should a prediction generate more bookings than needed, the warehouse operator will cancel the booking and pay the associated penalty.

The proposed DSS receives a 95% confidence interval, and a prediction-day tag. If the prediction tag indicates that the confidence interval provided is a 10-day one, then the DSS informs the smart-contract service to book the lower bound of the CI capacity. If the prediction tag indicates that the confidence interval provided is a 3-day one, the service considers the pricing structure and performs a Monte Carlo simulation with 1000 synthetic values. Then a linear optimization model is applied to the simulated cases to identify the optimal Economic Order Quantity, which is then communicated to the smart contract service to book. Finally, for a 0-day tag the model return the expected average of the prediction.

The automated capacity pre-booking services, relies on a prediction service using historical data and time-series analysis to provide an estimate for outgoing flow from the PI Node to a specific destination. The aim of the service is to ingest this prediction and propose a cost optimized capacity to the smart contracting service. Figure 5.2 illustrates a 1-to-10-day prediction using a seasonal ARIMA model as well as the 95% confidence intervals.



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		10	9	8	7	6	5	4	3	2	1	TRUE
truck_booking_rate (€)		548.2	553.7	559.3	564.9	570.6	576.4	582.2	588.1	594	600	
cancellation_fee (€)			78.6	87.3	97	107.8	119.8	126.1	132.7	139.7	147	150

Hki wtgB BR BP qf gB F Br ckBr tkekpi Buvtwevwtg BhqtBwr BvqB f c uBcj gcf Br tgf kevkqpuB

For the specific PI Nodes OD pair, a pricing structure is provided as the one illustrated in Figure 5.3. The pricing structure reflects Living Lab 1 operator DHL and truck services from a Madrid warehouse to a Barcelona warehouse.

To establish a rolling horizon prediction the same seasonal ARIMA model is applied daily to produce a set of daily predictions that consist of the average prediction (illustrated by the blue line in Figure 5.4), a 95% CI lower bound and higher bound. As illustrated in Figure 5.4, the simulated rolling horizon, yields various average prediction values ranging from as low as 60.89 for the 10-day prediction to as high as 71.88 for the 4-day prediction, while the actual capacity executed is 66.2.

		10	9	8	7	6	5	4	3	2	1	TRUE
0		23.62138										23.525
1		33.83996	33.88084									37.025
2		64.12899	64.97779	64.94969								69.3
3		54.08236	53.88789	55.15326	57.50043							57.4
4		51.04408	50.93834	52.50063	53.75662	53.54692						56.8
5		40.28462	40.5939	41.58104	43.013	43.3804	45.03475					50.125
6		35.40664	35.51556	36.72075	38.50133	39.1365	39.95201	44.43099				37.9
7		23.77807	24.28625	24.98032	27.328	27.26618	28.41198	32.88042	27.80834916			27.55
8		33.53593	34.10832	35.55896	38.14776	38.02003	39.27432	43.84561	38.33129811	37.10155		40.4
9		60.89138	62.5045	61.23281	66.0359	65.90646	67.57642	71.88478	66.27490424	64.70396	67.60259	66.2
10			52.42906	51.44898	55.4195	55.13963	56.90781	61.26696	55.63141664	53.99867	56.85584	66.825
11				51.61195	54.09171	54.09774	56.73482	61.37459	56.0695461	54.57862	57.76595	50.625
12					44.74446	44.85498	46.87506	53.54341	48.17777007	46.72349	49.87445	45.6
13						39.6651	41.39376	47.86791	39.80620082	37.85169	41.44054	33.9
14							29.95096	36.42156	28.98146188	27.02869	30.55749	24.2
15								46.27861	38.54837366	35.87257	41.04132	40.5
16									65.89276653	62.56312	67.98381	65
17										52.74739	58.34298	68.9
18											58.08659	56.175

Hki wtgB BTqmkpi Bj qtk qpBr tgf kevkqpuBhqtBuko wrcvkqpBf c B B

To identify the optimal pre-booking quantity, a reasonable, safe and cost-efficient capacity requires to be obtained. Furthermore, as the booking capacity action points are 10-days and 3-days prior to transport execution, the search is for two appropriate capacity figures, one for pre-booking 10-days ahead and one for 3-days ahead.

As discussed in the previous section one can use multiple confidence intervals as less or more confidence yields different CI ranges. Additionally, the inventory replenishment theory, utilises the pricing structure to identify as cost-efficient pre-booking capacity. Using the inventory replenishment theory, seems like a reasonable option as the confidence interval naturally shrinks as we approach the transport execution day, therefore influencing the proposed Economic Order Quantity value.

To test this hypothesis, originally three scenarios were tested: The was defined as booking the entire actual capacity on the execution day at the highest rate. The scenario assumed daily changes in the booked capacity using the new prediction available while the scenario assumed alterations in the booking capacity being made only 10-days and 3-days ahead and no action taken the rest of the days. In cases where a new prediction was lower than the already booked capacity, then if an adjustment was made, a proportional cancellation fee was applied. For booking 66.2 containers on the 10th day of the simulation, the baseline scenario cost was $40567, the daily average scenario cost was $37687, and the 10/3 average scenario cost was $36546. In this case the 10/3 average scenario is found to outperform the other two, as the daily average scenario frequently imposed cancellation fee costs making it slightly more costly.

A further test is conducted to examine the long-term performance of various scenarios, considering 10-day prediction rolling horizons for 40 transport execution days in the simulated environment. Considering the findings of the first test, and the fact that the scenario that considered two days of action (10 and 3 days ahead) outperformed daily action scenario, the scenarios illustrated in Table 5.2 are considered.

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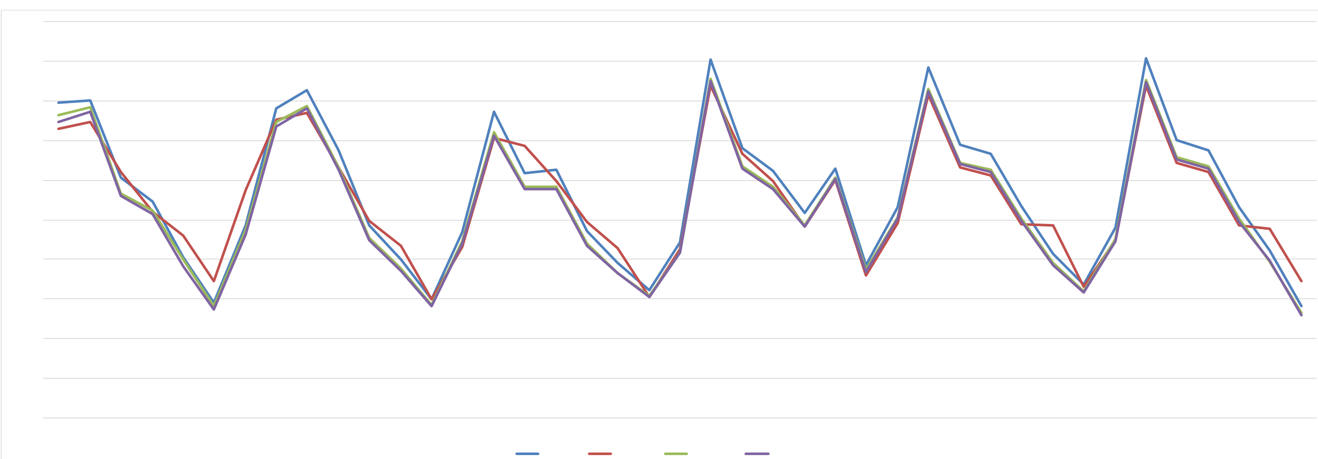
	0	0	Average
	Average	Average	Average
	95% CI Low Bound	EOQ	Average
		EOQ	Average

To assess the performance of the models 40 days are simulated and for each one of them a 10day rolling prediction is produced. Figure 5.5 illustrates the daily performance of all four scenarios. The blue line representing the baseline is most commonly the lowest performing option, except a few cases as in days 16, and 33 when the average (red line) performs worse due to high initial predictions. The red line is also found to perform poorly on consecutive days as in the case form day 4-8. Considering the entire 40-day period, the average model outperformed the baseline by 2.54%.

The green line representing the “start_low” and the black line representing the “start_EOQ” model always outperform the baseline, and consistently the average scenario as well. It is somehow difficult to differentiate them in Figure 5.5, and when considering the entire 40-day period, the “start_low” model yields 5.35% savings while the “start_EOQ” model yields 6.39% savings compared to the baseline. Therefore, the “start_EOQ” model is found to be the optimal scenario and has been implemented in the capacity pre-booking service.



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The combination of predictive models with smart contracts brings added value, as it enables a more efficient and smoother operation of the T&L workflow. By using the predictive models, the operator will know in advance the number of extra bookings needed, while the use of smart contracts will allow for the automated generation of paperless contracts. This automated and ad-hoc trigger of smart contracts normalises the engagement of resources, reduces the overall operational costs, but also creates opportunities for the establishment of new relationships with freight forwarders.

The number of truck bookings are calculated based on the number of outgoing pallets in the warehouse, which are predicted by the AI models in the context of T2.3. Using a historical dataset, as well as IoT data (depicting real-time trucks/cargo position and status) the models can perform rolling predictions. In this manner, continuous planning of future pallet quantities is based on historical data of the number of pallets. Past data (currently two years but to be investigated further) are used to create predictions for a rolling horizon of 10-days.

Taking all the above into consideration, the combined use of confidence intervals with a pricing strategy provides a dynamic solution for lower operational costs and a fair risk distribution between the service requestor and the service supplier. In this manner, the use of AI and Blockchain offer efficient and flexible services that enable the smooth and efficient coordination of different stakeholders across the supply chain.

The challenge of e-commerce growth increasing last-mile diversity and complexity, while simultaneously balancing fuel consumption, travel distance, traffic patterns or load capacity make the last mile difficult and costly for operators and push the logistics sector to continuously identify and embrace new trends. Predictive Logistics is finding strong adoption for industry professionals, given the abundance of supply chain data, as well as better machine-learning algorithms. The predictive capabilities of AI are helping logistics operators make precise decisions to proactively streamline operations thanks to the parallel progress of machine learning, computing power and big data analytics. As AI becomes more intelligent, predictive technology could take logistics players a step further by combining it with smart contracts and automating the truck booking process.

Instead of waiting for customers to order, this solution goes beyond same-day or same-hour booking process by supplying a proactive booking model, not only improving customer service/satisfaction, but bringing competitive advantage through data-driven decision making and the shift towards a predictive AI-powered supply chain.

The service utilises predictive capability and the output of confidence intervals in order to drive more efficient costing of trucking capacity. The solution reduces cost through a highly efficient and effective processes taking logistics players a step further into the territory of anticipatory booking model. This allows not only logistics providers but carriers and shippers to connect and determine cost-effective business models bringing a win-win situation to all parties by lowering cost, reducing management time and increasing business agility. In addition, the solution is highly scalable, and applicable to any logistics operation as it can be customized as per customer's needs.

The current report proposes PI services for transforming current T&L practices to the operational principles of the Physical Internet for three supply chain domains:

1. Intercontinental corridor integration to PI Hubs
2. Warehouse Operations for Physical Internet enabled hinterland transportation, and
3. Last mile urban distribution

The PI services designed and presented in this report, align with the PI principles and have been generalized to fit into the Physical Internet paradigm. In the context of intercontinental corridors, Port of Entry PI Hub clusters are considered, and utilizing information on the destinations of the PI containers on board a PI Mover, an optimal discharge PI Hub is identified for each container. In the context of hinterland transport, an automated capacity pre-booking solution is provided, that utilizing prediction confidence intervals and inventory replenishment theory, is found to deliver a 6.25% cost reduction for the tested OD pair. In the context, of last mile delivery, a dynamic parcel reshuffling algorithm is proposed, that can utilise early running vehicles to micro-consolidate cargoes and expedite deliveries, alleviating parcel returns to the distribution center due to delays. All services have been designed, to utilise multiple information sources, and network up-to-date status updates, integrate standardized encapsulation and smart decision making, and promote operator collaboration.

A collaborative marketplace is proposed in the last mile logistics context, that utilises criteria identified during the MAMCA workshop, to characterize operators. In a collaborative marketplace setting, individual operators are then able to filter based on operator profiles that they would not like to collaborate with, for example further promoting collaboration to foster the utilization of sustainable transport modes.

For all services presented in this report, a high-level context use case is provided. The services are designed for generic utilization, serving multiple use case needs. A service architecture is described, and where applicable a mathematical formulation of the DSS is provided. All proposed services integrate with EGTN databases to collect parameters for running the models, and up-to-date network status information. Furthermore, a detailed description is provided on the integration of the services with other EGTN services, such as:

- The track and trace capability, for monitoring the location of a PI Mover, or the progress of delivery rounds in the last mile context
- The knowledge graph capability that provides up-to-date information on the parcels included in each PI container on board a PI mover, therefore enabling establishment of a complete OD network in modelling PoE PI Hub choice.
- The last mile routing capability
- The predictive capability

In all three contexts, the PI principles of improving on critical variables such as cost, utilisation rates, and emissions through improved multi-modal integration and open accessibility to static and mobile infrastructures are promoted through open and standardized interfaces, monitoring and data sharing, smart decision making and modularized encapsulation.

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