Progress towards Federated Logistics through the Integration of TEN-T into A Global Trade Network

D2.9 EGTN Support Services based on Big Data analytics models

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[1] According to PLANET's Quality Assurance Process

Table of Contents

List of Figures

List of Tables

Glossary of terms and abbreviations used

Abbreviation / Term	Description
AI	Artificial Intelligence
API	Application Programming Interface
AEM	Asia Europe Maritime
ANN	Artificial Neural Network
CO2	Carbon dioxide
DSS	Decision Support System
EGTN	EU-Global T&L Networks
ETA	Estimated Time of Arrival
EPCIS	Electronic Code Information Services
IoT	Internet of Things
LL(s)	Living Lab(s)
LMD	Last mile delivery
LSTM	Long short-term memory
LR	Linear Regression
MLP	Multi-layer Perceptron
ML	Machine Learning
OLI	Open Logistic Interconnections
PI	Physical Internet
RNN	Recurrent Neural Network
SotA	State of the Art
SLA	Service Level Agreement
SVM	Support Vector Machines
T&L	Transportation and Logistic Networks
VRP	Vehicle Routing Problem
WaaS	Warehouse as a Service
WP	Work package

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1 Executive summary

This deliverable describes the preliminary results of experimentation on AI based predictive models, using data made available in the project, to forecast the in-flow of pallets and containers to warehouses. The presented outputs reaffirm the feasibility of building forecasting models for the relevant considered applications and set the basis for using machine learning based AI models for potential future implementations across use cases, for which further time-series data resources will be utilized for validation.

The report also includes additional descriptions regarding ongoing collaborative tasks currently taking place for sharing and utilising expert domain knowledge to better understand the nuances of the available data. This is to enable the predictive models as services and determine their role in the Living Labs and within the currently ongoing development of the respective use cases. These data and predictive-model related tasks are the basis of the analytics-driven cognitive decision support systems that are focused on automating applications ,such as the blockchain-driven smart contracts for payments. The data analytics research conducted to date is also reported which covers both predictive and prescriptive models that enable accurate and responsive information workflows. The models and future services addressed in this report are described in the context of the Living Labs (LLs) current requirements and characteristics for future applications to be enabled, such as the re-routing optimization service.

In addition, the contextual descriptions are presented for the scenarios and use-cases for the analytics' models and future services being developed as part of applications of the corridor route optimisation, supplier collaboration and warehousing management. IBM will conduct further research and implementation developments to update the current identified requirements across all the deployments customised for the European Global Transportation Network (EGTN) stakeholders. The PLANET project employs 3 EU-global real-world corridor LLs that include sea and rail for intercontinental connection to establish the experimentation environment for designing and exploiting the future PI-oriented Integrated Green EU-Global T&L Network that is to be advanced within the project.

The collaborative efforts taken between IBM and the Living Labs project partners are solid and represented in the current descriptions of the use cases. These use cases form part of the basis for further development of models to complete and deploy the required services. The relationship between WP1 and WP2 is pointed out in the report since it describes how models could (to maximise their combined functionalities) interact with each other, and with other services part of the EGTN platform.

These new Physical Internet (PI) inspired EGTN services are designed to optimise the usage of available resources, increase operational efficacies, and encourage collaborations across regions and supply chains. The services developed are envisaged to be part of a set of configurable computing resources and components that can be rapidly provisioned, managed and deployed in line with versatile cloud capabilities inspired design principles.

The research outputs and developments obtained regarding forecasting pallets and containers are preliminary but indicate the feasibility of the approach for using data driven solutions. These and other predictive models required will evolve towards other implementations and deployments to be reported in the next iteration of this deliverable, D2.10.

2 Introduction

The present report describes work carried out under task T2.3 and its subtasks related to AI-based predictive models for supporting the development of information services to enhance the integration of the supply chain and the transport logistics network scenarios under consideration in the LLs. The first service is based on predictive models for network corridor optimization for dynamic route planning. This includes current perspectives on functionalities and high-level initial components which are described in following sections. A second service is supplier collaboration and warehouse analytics, for which two forecasting models were built and tested. The performance of the forecasted results is also quantified and reported in this document. A third service is the predictive transport service which aims to make use of data sensed along the cargo route using IoT technology. These models and services aim to help with the integration of the transport network and supply chain by two methods as described below.

The first method is the automated calibration and direction of the flow of the shipments across the nodes in an intelligible fashion. The second method regards the automated and intelligible allocation of resources and management of operations within the warehouses. Related R&D will also be conducted with regards to the use of containerization technologies for the deployment of the predictive models, to standardize the deployment, accessibility and manageability of the services within the EGTN platform. This represents the scope of the approach and methodology taken to achieve the EGTN Support Services based on Big Data analytics models that are the focus this deliverable.

The main goal of the data analytic models is to facilitate higher automation levels to create a network of shared resources and information along the entire supply chain [1]. This ambition requires the creation of more intelligent and cognitive software components that are capable of automatically leveraging data collected along the logistics supply chain to provide insights about network performance and the future demand and usage of available resources [2].

IBM is currently collaborating with the other project partners on innovative approaches to enable future models and services that could demonstrate added value to business partners within the LLs. This report details the machine learning models for the prediction of stock and containers flowing into warehouses and into the Spanish port of Valencia. It also details the integration capabilities of these services with other additional services developed, or to be developed, within the PLANET project to enhance intelligent decision-making capabilities.

Also presented are the current requirements provided by the LLs partners for the operation of the services within their use cases scenarios, which will be prototyped using the data resources that are currently available and that will be made available in the near future. This includes historical data that can be used to train, test and validate the models that provide forecasted information on the movements of shipments for the optimization of their related processes.

The forecasting models developed so far made use of the datasets provided by COSCO and DHL which represent a unique and significant amount of data for research. Access to these datasets has allowed for the application of the most current machine and deep learning techniques for time series such as Long Short-Term Memory Neural Network models. These models were used to conduct preliminary experiments which provided promising high accuracy in their forecasting and flexibility towards handling the statistical characteristics of the datasets and multiple relevant variables. The experiment results are presented in the section 3.3.

2.1 Mapping PLANET outputs

The below listed task descriptions (Table 2.1) highlight the software components/services. These software components in the form of predictive models and ultimately optimization services aim to be validated further in the different LLs scenarios as required.

PLANET GA Component Title	PLANET GA Component Outline	Respective Document Chapter(s)	Justification
Deliverable			
D2.9 EGTN Support Services based on Big Data analytics models	Specifications of BDA algorithms for corridor route optimisation, supplier collaboration and warehousing as a service	Chapter 3 Chapter 4 Chapter 5	This report gives a description of the predictive models built using available
Tasks			
T2.3	This task will leverage the complex (Big) data sets that are collected from T&L processes in order to analyse them for key business insights and as a starting point for supporting new T&L business models and services under the Physical Internet paradigm. The task will utilize data collected by the EGTN IoT and Connectivity infrastructure (T2.2) to create the following analytics-based services: • Corridor route optimization analytics, i.e. more efficient route planning for complex and dynamic routes through to town/city hubs utilising the new corridor connectivity index • Warehousing as a service, that allows warehouses along a transport route/corridor to be utilised on demand by T&L operators. • Supplier collaboration analytics that leverage Big Data generated along the cargo routes.	Chapter 3 Chapter 4	The report gives a description of the predictive models to be used as the basis for the services to optimize the cargo monitoring and routing and warehouse operations and how these align to the current LLs scenarios.
T2.3.1	Corridor route optimisation analytics: Big data augmented by detailed corridor transport models and real time IoT sensor information will be used to develop effective routing that is based on accurate real time information rather than static data.	Chapter 3 Chapter 4	A description of the route optimization service based past EU research
T2.3.2	Supplier collaboration and Warehousing analytics: Coordinated supply & demand planning together with accurate cargo visibility from suppliers on transport routes will make synergies possible between suppliers, customers and transporters. Warehouses along the route from factory to retail will be used as buffers to smooth the flow of goods and to enable just-in-time delivery and other similar policies. Warehouse status information (capacity,	Chapter 3 Chapter 4	Description of the pallet and containers predictive models and preliminary results on their performance.

	availability, other SLAs) will be available in real time as a feed to the EGTN Cloud platform and integrate with the Blockchain distributed ledger (Task 2.5).		
T2.3.3	Predictive Transport Models will provide Transport Models focusing on Transport Gravity Models and Transport Corridor and Network Data Models. Key transport gravity models corresponding to international trade routes (US-China, EU-China, etc.), following the guidelines of T 1.5.3 (EGTN technological layer specification) will be used in simulation tasks and in the DSS tool developed in T2.4 to predict the change in the volume of freight that might result from interventions on a given trade route or corridor. Transport Corridor and Network Data Models (mesoscopic and microscopic) will be developed based on relationships between Principal Entry Nodes (PEN) and TEN-T corridor Intermediate Nodes and Urban Nodes.	Chapter 4 Chapter 5	A description of the transport models required according to the current LLs scenarios.
T2.3.4	Predictive and optimisation component packaging and deployment will involve packaging the above analytics models as Cloud services so that they can be used in the as-a-Service format by processes such as synchro-modal booking, cargo management systems etc.	Chapter 3	A description of the techniques, approaches and frameworks to deploy models and services to be made available.

Table 2.1 Description of tasks of WP2. Adherence to PLANET's GA Deliverable & Tasks Descriptions

The validation of the above-described software components as predictive models within the LLs relies to a considerable extent on the close collaboration between the consortium LLs partners. Such collaboration includes the providing data accordingly and determine specifications and requirements for the use cases considered, and feedback based on their expertise within the domain of transportation and interconnection of supply chains. Such feedback is a critical component for IBM's development of enhanced predictive and optimization models using data from more realistic instance scenarios.

2.2 Deliverable overview and report structure

This report provides overall updated descriptions on the work carried out so far for task 2.3 and provides a view on potential future work regarding the enhancement of the predictive models presented in this deliverable. It provides information on how these models could deliver value within the different scenarios of the LLs. Also highlighted is the importance of a systematic evaluation and improvement, by the LLs and business partners, of the performance of the models and how information on the predictive models could possibly be interconnected to other services to provide enhanced supply chain optimization. And, how the models could be made available and accessed within the EGTN network in the event the predictive information output is required individually or together with other predicted information outputs.

This deliverable report is structured in the following way. The section 3 contains a description of the predictive models and their considered enablement as services within Work Package 2. In this section also the requirements from the consortium project partners are provided as well as the accomplishments so far regarding possible future implementations, connectivity, and deployments. Section 4 provides further description of the predictive models developed within the context of the LLs and the different use cases. Section 5 describes the ongoing collaboration with project partners in order the determine and understand further the descriptions of the LLs and use cases. Also, in this section five additional descriptions on the current understanding of the connectivity and interoperability of the predictive models' outputs is provided. Sub-section 5.4 describes the future work and section 6 provides the conclusions.

3 Prediction and optimisation models

This section describes the research on data analytics that enables the cognitive capabilities of the EGTN platform, enabling predictive and potentially future prescriptive models to enable accurate and responsive workflows across the relevant use cases and applications. These applications include intelligent transport routing, corridor route optimisation, and warehousing for supplier collaborations. The ultimate outcome of the predictive analytics aims to contribute to enabling stakeholders within EGTN networks to optimise planning and re-planning of the pre-defined goals based on a variety of considerations such as low-carbon routes, fastest routes, and low-cost routes. The analytics developed within T2.3 will harness the transparency and traceability of applications such as the smart contracts. In this scenario, the data is delivered from IoT sources and is inputted to a blockchain where the integrity of the data is ensured. In this way visibility of the data could be further developed, creating more trusted innovative technologies across different aspects of the integration of the transport and logistics network.

The potential value to the T&L industry, to the environment and to the overall European economy that could result from the application and adoption of such analytical models is extensive. One of the primary drivers of supply chain logistics is the ability to accurately forecast demands and to be able to meet those demands. Failure to achieve this basic requirement could result in lost revenue and loss of competitive advantage. However, as it stands today it remains massive potential to achieve improvements in this area, by applying technology to enable more accurate predictions than could surpass those made by human operators, and by introducing intelligent automation to replace time consuming and error prone operational processes. Therefore, data science will support improvements to inventory management, demand prediction, route planning and higher levels of intelligent automation is vital to the sustainability of future T&L business models. Not just in the European context, but also in the context of the global intermodal route corridors being considered and modelled in the PLANET project. The business benefits of introducing increased efficiencies into the supply chain in the areas of route optimisation, warehouse optimisation and supplier collaboration include faster delivery times, higher levels of customer fulfilment, reduced occurrences of stock-outs, better transport utilisation, reduced operating costs and increased business revenue. Another overarching benefit of the utmost importance is the environmental and societal impact. Better inventory management and route planning would result in a crucial and positive shift towards more sustainable and greener logistics. For example, better warehouse and route planning means fewer unnecessary transport vehicles on the road resulting in reduced Co2 emissions and leads to traffic congestion improvements due to less vehicles having to pass through cities and towns. The end result being an improvement in the health and safety of the citizens living in those areas.

In this section we discuss further details of the subtasks in T2.3 for route optimisation, supplier collaboration, warehousing as a service and predictive transport modelling. For each of the subtasks a description is given that aligns with the task core definition in the PLANET Descriptions of Actions, its scope and requirements. Also, accomplishments are described on this proposed work that set the basis for the development of further analytic application.

The ICONET project seeded the development of the route optimisation service. The route optimisation applications being developed as part of T2.3 have evolved from the ICONET project and include the use of AI based predictive models to enable a core capability to ingest multivariate streams of data to build forecasted information. The summarization of several variables to infer future information enhances the analytic capabilities of the predictive models. This expanded capability allows the predictive model-based routing service to assess different events and their impact across routes and therefore make use of a more robust criterion, to make more informed and better decisions in adjusting previously set routes.

The evolution of the ICONET routing application within the PLANET project aligns with the multi-user and multi-criteria models to be developed in task T2.4 for the enablement of smart nodes for the optimization of the network transportation corridors. This multivariate and robust decision approach is particularily relevant in the last mile delivery scenario, where there are more dynamic and changing urban conditions that might increase uncertainty for a timely delivery. This includes sharing information regarding routes changes with additional vehicles to allow a collaborative re-design of the routes. Such a collaboration as pointed out in the deliverable D2.13 enables more flexibility when a parcel is required to be transferred from one van or method of delivery to another.

The routing service architecture overall will avoid any design element that would limit in a considerable manner its capabilities to connect with other services or software components for scalability purposes of any application.

3.1 Route optimisation service

The development of the corridor route optimization-based analytics requires Big Data augmented by detailed corridor transport models and IoT sensor information. The data will be used to develop and enable more effective optimisation of routes. Such changes could be determined based on a set domain expert criterion accurately enabled by real-time information rather than static data. The application focuses on real-time dynamic routing of cargo traveling throughout the network to reduce its dependencies on predefined routes. By avoiding such dependencies in the cargo flow, it is enabled a more flexible and efficient transport network which aligns with the Physical Internet (PI) concept of digital internet inspired protocols on adaptive routing, at each node, for information networks.

The scope of the present subtask covers the exploration and experimentation with innovative analytical services that could be integrated with the EGTN platform, enhancing routing decisions for transport and logistics actors. To achieve this, completer descriptions of the business use cases and the methods for gathering and analyzing relevant data from the partners are required. The identification of such relevant data is critical for implementing and experimenting with various machine learning methods/models to validate and improve the routing decisions, within the LLs scenarios.

3.1.1 Living Lab requirements

Some of the project requirements identified and gathered from project partners for this subtask include:

- Advancing the current state-of-the-art in PI methodologies and route optimisation techniques and data driven approaches such as machine learning based predictive models.
- Contributing to improvement of the integration of the transport & logistics and geo-economic operations across routes between China and EU, by evaluating relevant outcomes within the LLs.

Some of the LL's requirements for work package 3 within LLs for this subtask are:

- For LL1 & LL3 the aim is to achieve greater efficiency and cost saving by using state-of-the-art technology for routing, which can contribute to more efficiently forwarding pellets across alternative network transportation routes.
- For LL1, COSCO has specified research is required into re-routing shipping topics.
- Tasks within LL1 & LL3 include Polish Post and CityLogin aiming to make Last Mile Delivery (LMD) more efficient.
- In LL3 ILIM aims to review and specify how the China-EU End-to-End transport process via rail, road and sea could become more integrated.

To build feasible and implementable route optimisation services, there is a strong requirement for relevant data and information on the current routing systems available for their validation. It is essential to clearly determine the processes involving routing, where are the bottlenecks and overall opportunities for improvements on the operational KPIs that are relevant for a range of different type of users. There is a need for historical data with enough time resolution regarding the journey origin and destination locations for delivery, available modes of transportation, transport capacity, availability of alternative routes are required. Furthermore, data regarding relevant external factors such as traffic, weather and news data need to be considered as requirements for developing more effective routing services or predictive models with the PLANET LLs scenarios.

3.1.2 Proposed Solution

Considering the current LL scenarios described for route optimisation services it might be required to examine multiple solutions and approaches given their complexity. For example, CityLogin use-case demands delivery of ~3000 parcels from one central location to customers in a single day. On a typical day, ~30 vehicles are available, and parcels are sorted before they are sent out for delivery. Another example is the COSCO use-case which has a pre-determined ocean route but having a real-time information decision making tool would facilitate the transportation when a container arrives at a dry-port. More specifically, the schedule of a container arrival at the sea terminal needs to be synced with in-land transportation services to enable more continuous seamless transportation. The solutions to these two scenarios require quite different approaches. The CityLogin scenario falls under the category of a generic last mile delivery problem known as Capacitated Vehicle Routing problem[3] whereas the COSCO problem needs to be formulated as a schedule synchronization[4].

Moreover, considering the different LL scenarios and the type of data to be available within, the algorithms are to perform route optimisation tasks, which can be categorized as classic operations research-based optimisation and data-driven learning-based optimisation.

3.1.3 Accomplished work

IBM has been actively engaging with the project partners and current LLs participants to understand their requirements for route optimisation models. It is recognised that the usual practice is that important routing decisions are taken manually, at times relying on a single individual to make choices who may have very basic information at hand. This is not the most efficient way to save time and cost for the transport and logistics industry applications. IBM and consortium partners identified the importance of exploring ways in which more automated ways can be implemented using machine learning to provide more reliable alternative, cost-effective and timely route optimization decisions tools that make the process more efficient.

Considering routing applications in the Digital Internet (DI) domain, it is possible for route optimization in logistics networks problems, within Physical Internet environments, for them to be described and modelled similarly. For instance, the routing in DI is controlled by routers by means of routing tables which contains the forwarding path each TCP packet must take depending on its intended destination. The key element in routing in DI is the concept of encapsulating data packets in a datagram and datagrams into frames for transportation purposes and then decapsulation or re-encapsulation by routers which makes it analogous to logistics networks. In fact, a model for encapsulating freight in standardized containers has already been proposed in previous state-of-the-art works[5][6][7]. In this new model for logistics network, PI is conceptualized as consisting of PI-Hubs or nodes that receive PI-Containers, and possibly sort and recompose them to optimize the transport in each segment.

For a routing service, it can be assumed that encapsulated PI-containers are standardized and ready to be transported at the PI-Hub terminal. A set of PI-containers obtained are then to be transferred according to the destination to the next PI-hub. Each Pi-Hub may maintain a routing table that can be used to determine the next hop for the PI-containers based on a set preferred criterion, for example transport cost, delivery time and/or CO_2 emissions. However, there are very distinctive differences between routing in DI and PI. The first difference is the transit time: in DI data packets travel almost at the speed of the light and their lags are, in most scenarios, negligible. However, flow and arrival time of PI-containers in the PI are dependent on many factors such as transportation modes, availability of locomotives and labour, handling time at the PI-hub, etc., which makes transit time not negligible since vary significantly impacting optimal routing decisions. Secondly, in case of disruption in DI transmission process, the delay in rerouting data packets is negligible, which means for most users of the DI the scheduling of information deliveries is not generally a concern. However, delays in scheduled delivery of PI-containers or physical goods due to disruption and finding alternative route of delivery are concerning for shippers, customers, and service providers as they may generate penalties, lead to lost business and other additional costs. For routing there are two key objectives. The first objective is minimizing the total distance travelled from source to destination as it is related to transportation cost and CO_2 emission. And the second one regarding delivery time information from the moment a container departs it is monitored until its arrival to its destination. This includes delivery time on road, handling time to load and unload from transportation means, and waiting time at ports and other facilities.

Existing research outputs, on PI routing and cargo loading optimisation services, developed by IBM in the EU funded project ICONET, will further evolve in the context of PLANET.

The routing service, to some extent, can be formulated as Vehicle Routing Problem (VRP) and Travelling Salesman Problem (TSP) with some modifications to consider the aspects of the PI such as intermodal transportation and real-time changes in the PI network. The TSP is subset of VRP and deals with one route whereas VRP can handle multiple routes. The TSP and its more generic form, the VRP are classic combinatorial (NP-hard) problems in operations research (OR) and these are formulated as integer constrained optimization, i.e. with integral or binary decision variables[8][9]. The theory and algorithm design communities have typically used graphs to formulate these problems. Classically, approaches to tackling an optimization problem can be categorized into exact, approximation, and heuristic algorithms. Exact algorithms are based on enumeration or branch-and-bound with an integer programming formulation, and they guarantee to find optimal solutions but are not feasible for large instances. On the other hand, polynomial time approximation algorithms are tractable for large instances, but may suffer from weak optimality guarantees or empirical performance[10]. Finally, heuristics are fast and effective algorithms but require problem-specific knowledge and manual design of mathematical model for the solution.

To reduce the effort of manual mathematical modelling for solutions to *OR* problems optimization, researchers had looked at machine learning and reinforcement learning based approaches. These approaches are trained on large number of problems instances and have been shown to be fast with reasonable performance for some applications when sufficient data resources are available, producing more automated solutions. However, when compared with the same benchmark instances, these learning-based methods cannot, in most cases, outperform state-of-the-art TSP solvers such as LKH3, which is a penalty-function-based extension of the Lin-Kernighan [11].

An effective routing service is one of the best ways to provide value to the transport and logistics networks by adopting big data and analytics. This to be able to make an informed timely decision to adjust a pre-determined route, which might require different sources of data to form a more solid criterion. The data is not only used by the predictive models, but also required to better understand the dynamic evolution of the network flow. An optimal re-routing dynamic depends directly on the behavior and evolution patterns of transportation towards an equilibrium. But since this state of network equilibrium is inherently unseeable and bottle necks constantly arising, a dynamic constant switch is in the routes is required to narrow the gap between the estimated preferred arrival time and actual delayed times provide by congestions in the network.

This delivery route optimization is probably most critical in the last phase of the delivery known as LMD, since unexpected events arise constantly such as traffic jams, car accidents road closures and other unforeseen events that could escalate in a type of domino effect, impacting the delivery scheduled and becoming more difficult to solve when managed manually. Handling a change of route effectively has several benefits such as fewer vehicles on the road, fewer kilometers traveled, lower costs and delivery times, better service quality and customer satisfaction, lower C02 emissions and better working conditions for drivers. A dynamic routing service could impact across the different transportation use cases for maritime and inland transportation since in both modes of transportation it is possible to have congestion and bottlenecks related to ports and warehouses. It is in this sort of routing optimisation scenarios where machine learning models can be used to handle data from different continuously monitored events to infer relevant incidents to avoid while the transportation is taking place.

In multivariate time series forecasting two signals if correlated can be modeled to infer each other when one of them is not present. In a similar fashion different signal from sensors available within the LLs scenarios and correlated to traffic congestions could be used to provide information on the risk for a route to be congested and be required to be avoided to keep the journey within schedule. The use of forecasting models provides ways to handle large amount of data within a more decentralized approach for making decisions, since different sources of information might need to be considered at the same time.

The routing service models for LMD routing operations for centralized and decentralized delivery of goods, are a type of scenarios for which the project partners including CityLogin, consider use-cases and solutions. Solutions such as the centralized delivery ICONET PI Routing service whose design considers designating a distribution centre for a set of orders to be fulfilled and allocate them across an available set of PI-Means[12] and calculates the optimal route for each PI-Mean to service the required delivery destinations. For the decentralized delivery of goods, multiple distribution centres can be designated from which orders can be collected. This in addition to the last mile delivery to reach the final destination for an existing order. The PI Routing service has the capability to consider delivery time-windows for delivery destinations when calculating the optimal route for PI Means to fulfil orders. The APIs use JSON data formats for both inputs and outputs, with inputs being the distribution centres, order details and available PI-Means. The output is the optimised delivery route for each destination. The ICONET PI Routing service can optimise specific attributes when determining optimal routes. PI-Mean cost, carbon footprint, delivery time and delivery distance can be chosen as the parameter to be optimised. The routing optimisation provided by the ICONET PI routing service can be beneficial to LMD operations by improving efficiency while maintaining customer satisfaction with delivery assurance. The PI paradigm goal of achieving the seamless transport of goods requires the efficient orchestration of cargo being conveyed and the PI-Means required to transport it. The ICONET PI Routing service contributes to this goal through the automation of the orchestration process.

In PLANET, IBM builds upon this PI routing service to help solve the dynamic vehicle routing problem by considering real-time data from IoT sensors, and other factors such as traffic intensity and density, weather along route, relevant news and holiday data to further improve real-time routing models. To progress with this objective, we have collaborated with project partners including COSCO Shipping, DHL and CityLogin from LL1 to gather real world data required for routing. IBM has also led discussions with the PLANET project partners for their support in gathering external data whose characteristics are discussed more in detail in Section 4.

3.1.3.1 Capacity Optimization in fixed route environments

In PLANET, the train loading optimisation service can be used in conjunction with the predictive services to plan the transport capacity required to book in advance, and in this way, help make planning more efficient and cost effective. Other sources of information that could be used in conjunction include the IBM model to predict container flow for the Valencia port, which could be part of novel pipeline that integrates modelling capabilities for maritime routes optimisation. This service is discussed in more detail in section 5.1.

The ICONET Train Loading Optimisation service models PI Containers, PI Means (in the form of train wagons) and rail Shunting/Marshalling Yards. The service contains APIs that facilitate applications and information for a more optimised loading of PI Containers to PI Means and the optimised formation of trains in Shunting/Marshalling Yards. The PI paradigm proposes introducing an expanded set of standardised shipping containers to convey cargo. It is expected that along with existing monolithic containers, such as the 40-foot and 20-foot shipping containers, a range of smaller, modular containers will be introduced. These modular containers could be stackable or un-stackable. Stackable containers could be composed into larger units for transport.

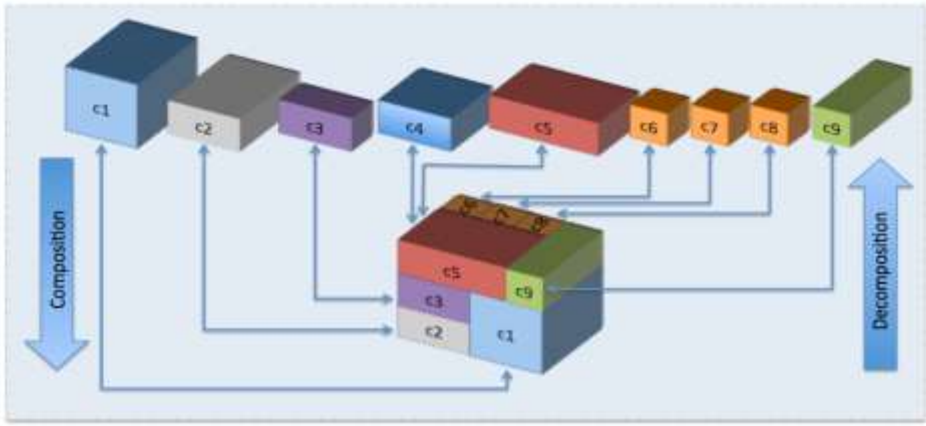

Figure 1 The ICONET Train Loading optimisation service

The ICONET Train Loading Optimisation service (see Figure 1) represents PI Containers in a simple JSON data format containing dimension and weight properties. Similarly, train wagons are represented in a JSON format with maximum dimensions and weight capacity. There are sources of monitoring information to allow allocate the input PI Containers to the available train wagons. This can be done in two-dimensional (2D) or three-dimensional (3D) space. The information in form of applications and enabled by APIs produce a JSON data format could produce a loading plan. The loading plan lists the train wagons with their allocated PI Containers and gives exact placement coordinates for each container. The Train Loading Optimisation service also provides a data generator API that produces randomly generated sets of PI Container objects and train wagons to be loaded. As the modular PI Container concept is still a proposal, no real data for these containers exist. This data generator API is a convenience feature for simulation and can be configured to produce representative synthetic data while real-world data is still emerging.

The ICONET Train Loading Optimisation service also provides an API to optimise the formation of trains from incoming train wagons in rail Shunting/Marshalling Yards. Rail Shunting/Marshalling Yards are a series of parallel rail tracks used to sort train wagons by destination to form outgoing trains. Shunting/Marshalling Yards are found in PI Hubs such as ports and rail terminals. The service represents the Shunting/Marshalling Yard as a JSON document containing the number of parallel rail lines and the max train wagon capacity for each line. Train wagons are represented in a JSON data format with destination and capacity properties. The optimisation API for sorting the incoming train wagons across the available rail lines accepts a JSON data format arrival schedule that lists the times at which train wagons arrive. The optimisation API outputs an optimised allocation plan, in JSON data format, that specifies the rail line each train wagon should be directed to and when to dispatch formed trains. The ICONET Train Loading Optimisation service aims to assist the automation of rail operations like loading containers to train wagons and sorting wagons across Shunting/Marshalling Yards. This kind of automation is needed to achieve the goals of the PI paradigm in seamless transport networks. The efficiency improvements that result from these optimisation efforts can reduce costs, such as reduced energy consumption and lower carbon footprint, associated with operating rail infrastructure.

3.1.4 Proposed work for route optimisation service

A first implementation instance for the proposed work in routing services aligns within the supplier collaboration warehouse application which makes use of blockchain ledgers to improve the traceability and visibility of the import/export door-to-door transport chain of containerised cargo. Moreover, a blockchain service provides transparency across services by enabling the recording of end-to-end transactions. The recording of transaction also enables an improved traceability of the items across the network; this information regarding the different journey stages for which a particular pallet or items travel could also be relevant in making better decision to adjust its routing.

The objective of this proposed work is to contribute to the overall improvement in managing the transport chain network. From this angle IBM aims to evaluate the state-of-the-art DVRP solutions with emphasis on innovative machine learning based approaches. IBM also aims to build on the Distance and Time optimisation direction of the deliver path using the ICONET routing service, which could help reduce the C02 emission problem this by considering extra input of real-time IoT based data variables such as environmental and bump/damage. The below work items are proposed to be advanced and further evaluated.

- An implementation of a real-time PI Route Optimisation service based on the results of the Dynamic Vehicle Routing Optimization (DVRP) solution evaluation results.
- A deployment of the implemented PI Route Optimisation DVRP solution in a simulated environment, and a LLs environment.
- An evaluation of the performance of the PI Route Optimisation DVRP solution and applicability in meeting use cases identified by the project and LLs.
- To include factors external to the PI Network that affect real-time routing
    - Weather
    - Social
    - Future considerations –as transport moves to cleaner energy CO2 becomes less of an issue
    - Financial cost minimisation
    - Socio-economic route balancing

3.1.5 Routing service and carbon footprint

The Routing Service is the first and most relevant application of time series forecasting in PI scenarios. The PI concept defines a specific series of layers in the supply chain in an analogy to digital internet e.g. the Open Logistic Interconnections (OLI) layers; from the routing it is possible to leverage information insights regarding the future demand and distribution of goods. The routing layer, in fact, is the layer responsible for identifying the suggested route for each PI-Mover. Therefore, if a trained machine learning forecasting model is employed as part of the optimisation service and the gathered insights are published, the routing service will calculate the route and can consider the most probable distribution of goods, resulting in an optimal outcome in terms of time and mover's utilization. The final result of sending the PI-Mover to the right PI-Node[12] to collect a PI-Container is an important goal of the PI. One of our research aims is to employ the forecasting models we have developed as part of the routing service we are developing so that more efficient routing decisions can be made.

IBM plans to also develop Estimate time of Arrival (ETA) forecasting and carbon footprint forecasting services for the EGTN Platform. Estimated time of arrival accuracy is hugely important for transport and logistics partners as it can save a lot of time and money while also making the whole process more efficient. By incorporating IoT real time location data along with weather, news, traffic along route data and using a machine learning model such as support vector machine or decision trees we can create a novel way of improving estimate arrival time accuracy. Similarly, by utilising information about transport modes and routes we can predict carbon footprint and help businesses make more informed decisions to reduce their carbon footprint.

3.2 Supplier collaboration and warehousing as a service

The applicability of the supplier collaboration and warehousing services has been determined so far within the smart contracts which are based on block chain technologies for the further automation of payments. This applicability has the potential to be extended in its usage in several ways for the PLANET project as required. For instance, for the overall clearinghouse duties in terms of expanding the interoperability of the blockchain to other external ledgers, which could benefit added members of the supply chain companies with more flexible ways of interaction without acquiring additional blockchains or the need of porting data to external additional ledgers.

Such an extended coordination between suppliers and increased automaton of the warehousing tasks has the potential of generating the synergies required between suppliers, customers and transporters. The warehouses along the route, from factory to retail, will be used as buffers to smooth the flow of goods and to enable just-in-time delivery and other similar policies. The warehouse status information (capacity, availability, other SLAs) will be available in real time as a feed to the EGTN Cloud platform and integrate with the Blockchain distributed ledger (Task 2.5).

3.2.1 Project and living labs requirements

Some of the identified project requirements are:

- Achieve enhanced integration to the global T&L network.
- Provide secure, trusted, and easy collaboration with digital mediation.
- Develop a collaborative model within Europe and with intercontinental transport service providers.
- Build a PI model for Warehousing
- Employ SOTA ML research in the Warehouse Recommendation Engine.
- Consider Sustainability and Standards Compliance.
- Integrate with the Prediction and Optimization Analytics tasks in T2.3.
- Integrate points with the other tasks in WP2 –Blockchain, HMI, IoT, Connectivity.

Some of the LL requirements are listed below

- LL 1 UC2 (DHL) - communication channel is required between DHL, COSCO and CityLogin. The communication channel will be used to agree delivery by COSCO to DHL Warehouse and to agree delivery to City Hub with CityLogin
- LcL 2 (Panteia) - Infrastructure analysis (LL2 ST2) will aim to organize delivery processes within the different rail systems along the corridor that need to be investigated to provide more fluent and swifter services than the currently available.
- Regarding the Blockchain T&L Solution (LL2 ST5) it was determined these technologies would require reaching synchromodality over the various geographic areas and supply chain actors. To acquire this capability a system would be needed to support coordination without the need of a dominant member.

Considering the above listed requirements research was conducted to determine suitable technical approaches and solutions to address the objectives of the task 2.3. Such approaches are described in the section below.

3.2.2 Current work

Several discussions have taken place with some of the Transport and Logistics partners in PLANET, which has revealed that there is keen interest in having a type of supplier collaboration tool which can automate some of the booking processes with other suppliers. IBM has developed a warehouse flow prediction model to forecast the volume of pallets coming into the warehouse within 24 hours in advance. The pallet forecast will further consider developing an AI enabled smart contract service. IBM initiated and continues conversations with project partners to ideate how to merge the predictions generated by this model with aspects of the blockchain capabilities currently under development as part of T2.5, with the aim of collaborating on the innovative idea of creating an AI enabled smart contract service which we will describe in further detail in Section 5.

3.2.3 Proposed further work

A first implementation instances for the proposed work in supplier collaboration warehouse application is the use of blockchain to improve the traceability and visibility of the warehouse operations and how predictive analytics can contribute to the development of intelligent logistic nodes. An example of this is the usage of the volume flow forecasting service that can help companies with the inflow and outflow of pellet movement. As part of the work proposed for the supplier collaboration and warehousing-as-a-service task, a service is proposed that optimizes the space utilization and resource planning by providing predictions for volume regarding inbound and outbound of pallets the next day or week. By predicting the relevant quantities for product demand and supplier resources collaboration information input data could be generated with enough information to trigger a smart contract application for the further automation of payments and allocation of resources to fulfil such a product demand.

The current high-level architecture and implementation of the smart contract application is described in detail in section of 5.2 of this report. Once the smart contract is triggered and ongoing demand and resources for its transportation determined and possibly quantified, external tasks such as the LMD through the routing service could be fed with this quantified information to collect items in a more timely manner from the local distribution centre, enabling an improved warehouse management system and transportation planning of the network.

Many marketplaces for storage space sell on a basis of “space-as-a-Service” and collect commissions for securing the sale. This method has one common flaw as it must manage and synchronise the multiple inventory systems and while updating the marketplace accordingly. To achieve this the warehouses must ensure that, if running out of stock, then every marketplace (and there could be many marketplaces which list items in their catalogues) needs to be updated. Currently drop shippers do it manually or there are services that automate this process. However, the problem is pronounced when e-commerce traffic is exceptionally high. There is no dominant storage-space inventory management service due to the technical limitations of legacy server-side WaaS solutions. Furthermore, there is no coordination between warehouses and affiliate marketing services since the legacy affiliate system requires a storage-space seller to already have an interface to direct consumers. Also, in decentralized warehousing, stockout is another challenge that requires synchronization between marketplaces and inventory. Stockout represents a loss of an order if space is rented out.

To mitigate this, an initial solution was considered based on using a smart contract application, which is described next. Using the data available by the DHL Warehouse Management System (WMS), predictive models would output forecasted data regarding the future demand for transportation resources. Such a demand could automate the initialization of a contract in the Blockchain with a transportation company such as CityLogin. A similar model for the prediction of availability of transportation resources could determine whether CityLogin will have the required transportation resources available. Based on these two sources of information an automated contract could be issued with an already scheduled collection route set.

These functionalities could provide enhanced logistics for warehouses and transportation services based on future information, impacting such aspects of the warehouses as space planning and the warehouse inventory management system by optimising the coordination the inflow/outflow cargo. A preliminary implementation architecture for the above-described smart contract application is provided in section 5.

A second solution described below will be considered for inventory applications provided that relevant data resources are made available that could be used and accessed by IBM for validation purposes. The solution is proposed for warehouse-as-a-service applications where a space owner (individual or enterprise storage provider) can remove the need of a middleman (marketplace) to directly reach the consumers, while retaining some of the benefits of selling through conventional retail platforms.

A blockchain based warehouse “space-as-a-service” is proposed which addresses the inventory synchronization challenge and removes the need of marketplace and allows space providers to reach consumers directly. The novel aspect of the system is a tokenizer module which converts physical space into a non-fungible token (NFT– a digital twin of physical object/item that has unique characteristics, value, that are not interchangeable) and links with a smart contract. These NFT are unique identifiers (assigned to each inventory), and are stored on the blockchain (Hyperledger fabric, or any open-source chain), making them immune to duplication and tamper proof. Other modules of the proposed system include a connector which allows warehouse space provider to import its inventory and create NFTs.

This method can be generalized to any type of inventory. Its advantages are that it removes the need of manually updating inventory across multiple marketplaces, allows end-users to buy and sell directly, each inventory item is unique and cannot be tampered with. Collaboration with project partners to jointly develop this proposed system will aid in implementing and defining further the innovative elements of this idea in PLANET’s EGTN platform.

3.3 Implementation of predictive models

Predictive models have become hugely important in today's world where there is a plethora of historical data available. This historical data can be used to train models that can identify and forecast values which follow trends and patterns not easily noticeable using manual non-automatic means. Predictive modelling can enable smarter decision making as they give us a near accurate forecast of the future thus making planning in advance more efficient. By having future information about potential scenarios, a delivery strategy could be adjusted to reach the desired scenario in a timelier manner and perhaps be faster than other delivery companies acting as competitors. The predictive models built in this section by providing accurate forecasted information could contribute at improving the planning and agility of processes and their relationships within the supply chain, that required manual, constant, and time-consuming management. Since big data is produced from these processes, it appears that data driven solutions are natural fit to further automate and integrate key processes and reduce costs from 20 to 50 percent [13]. By predicting accurately useful information regarding individual tasks or events such as the number of pallets or containers arriving at a particular time could impact related activities in terms of allocating resources to handle such an event reducing waste, efficiency, or invertor costs.

Other tasks include gathering information directly from IoT sensors to identify additional relevant data which could also involve video images, shelf weight, temperature, type of materials arriving which can be used for warehouse operational efficiency, including inventory accuracy. This provision of information can be useful at three main different levels, the first one regards to descriptive information on what has happened in terms of previous activities in a way that recurring events can be identified and there is better preparation on future close enough related events. The second provision is at the level of predictive information, which could handle real-time data collected from current or past events to make inferences about the future. This type of information will be provided by the predicted models built so far and described in this section. The third type is the prescriptive type of information which enables additional analyses regarding a series of actions that when taken place can impact in a broader way key decision regarding the supply chain key processes.

In the below sections and subsections, it is described the use of the data available so far to build forecasting predictive models needed for the development of services determined so far within the LLs use cases and scenarios.

3.3.1 Acquired requirements

Some of the project requirements for the present 3.3.1 subtask are:

- Developing forecasting models which can be integrated with other services on the EGTN platform to aid intelligent decision making.
- Using machine learning models to make more accurate predictions.

Some of the LLs requirements for this subtask are:

- A warehouse volume flow forecasting model.
- A congestion prediction at seaport.
- Estimated time of arrival forecasting model.
- Carbon footprint prediction model.

3.3.2 Preliminary results

IBM investigated the possibility of using historical data of activities within a PI-Node to improve the efficiency of its operations. A PI-Node can be defined as a place that continuously receives PI-Containers and manipulates them to send them to their destination as efficient as possible. This information can be used to forecast future demands of consumer goods and to cluster PI-Containers on arrival to ensure their correct and optimal storage. In this deliverable, IBM introduces the concept of time series forecasting and its usage based on ANNs to make relevant predictions regarding storage quantities.

The timeseries forecasting is a well-known technique within the econometrics and statistics: there has been an increase of its application in several fields from Financial Markets [14] to Urban Traffic[15], mostly due to a significant increase in the volume of data recorded. Timeseries forecasting provides a solid basis for planning the future evolution of systems subjected to respective studies. For this reason, preliminary steps to apply timeseries forecasting techniques within the PI application will be carried out.

There are two main approaches to carry out forecasting tasks. The first approach is statistical orientated for which more standard techniques are considered. These techniques include the Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and the most well know Autoregressive Integrated Moving Average (ARIMA) models. These models are known in the literature due to their relative simplicity, robustness and efficiency across several forecasting scenarios. The second approach for forecasting is based on machine learning approaches of RNNs such as the LSTM [16][17][18][19]. Advances in the use of this second approach have been remarkable in the recent years due to the increase of computational power. Beneficing domains such as machine translation, speech recognition, generating image descriptions, video tagging, text summarization, and language modelling and generation. All these applications require forecasting tasks using time series (ordinal) structured data. Moreover, all the mentioned domains applications could potentially be relevant for the creations of RNNs based forecasting models services, additional to the currently identified for the PLANET project and in case data required is made available.

Results for the forecasting models built in this deliverable are presented below. Several parameter values were considered to train the forecasting model, but several more might be required, considered and evaluated in a more automatic way in future experiments. A relevant parameter to consider is the one for the specification of the time resolution of the forecasted information that the model provides. In the below results such a resolution is not visualized at different levels, which in most cases are determined or constrained by the user or the data available. The setting of the temporal resolution the model will output will be set in the PLANET LLs scenarios.

The Figure 2 represents a daily time series for the pallet quantity in storage, in each warehouse, at the end of each day. This information is used to predict the future evolution of this graph. In the Figure 2 above it can be perceived that there could be existent issues with some of the key features of the time series forecasting in that, autocorrelation might exist which makes standard econometric models unable to be applied, also when a seasonal trend exists, or the mean value is changing over time. For time series data to be predictable, it should satisfy the below two conditions:

1. A relatively low level of correlation between the numerous data points.
2. The time series should be stationary.

While the first condition above simply implies that the correlation between the time series and its lagged version is close to zero, the second condition is more complicated. Stationarity means that the time series should comply with the below characteristics:

1. The time series should have a constant mean across time.
2. The data should have a constant standard deviation across time.
3. And the time series should not have any source of trend in it.

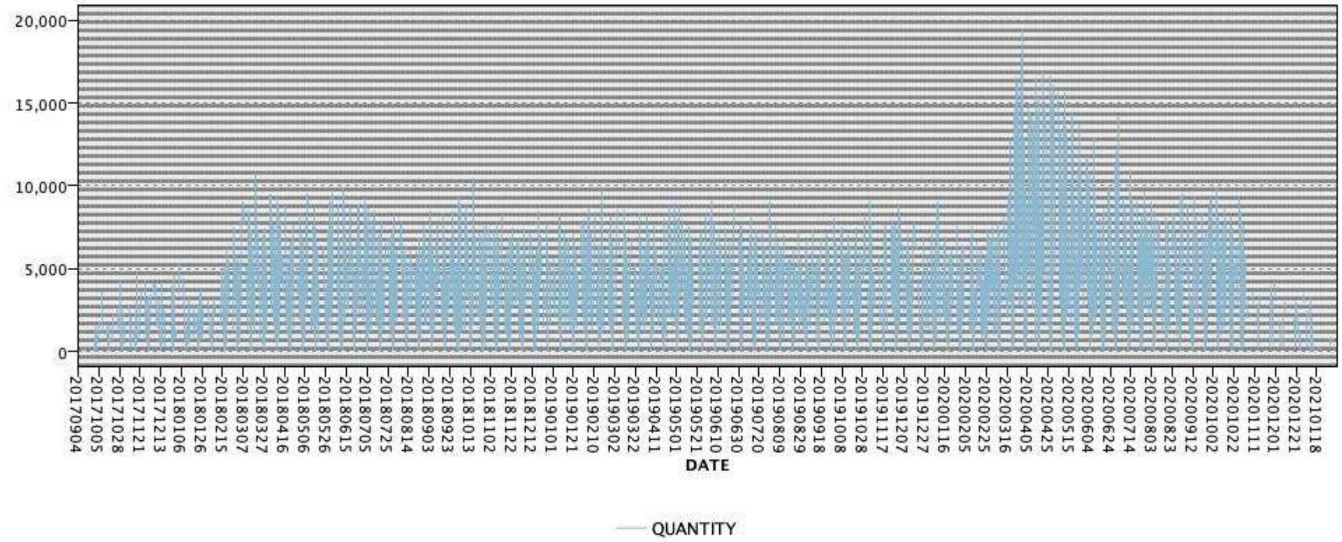

Figure 2 Change in stored number of pallets (date vs quantity)

If above conditions are met, the time series is stationary and can be forecasted. It is generally the case that these conditions are not present in real-world time series data, such as in the case the daily stocks. For this reason researchers have developed several techniques to overcome this issue [20][21]. ANNs models can make predictions without too much consideration in the stationarity of a time series.

The idea of adding time series forecasting to the Physical Internet context can be fruitful for supply chain optimization. In fact, the work presented in [22] proposes an approach to reduce the complexity of a Hub's connection by leveraging a predictive model of the demand. The approach is based on the concept of dynamic clustering for the retailers' demand, solving retailers to PI-hubs' clusters assignment problem, and then tackling a routing problem for each cluster. The dynamic clustering is based on a forecasted demand calculated using an LSTM network. The work presented in [23] investigates a dynamic pricing problem for less-than-truckload (LTL) carriers during several auction periods in PI applications, considering the peak demand forecasting.

Neural networks, particularly LSTM recurrent neural networks, can represent a solution to several computational problems for time series forecasting, particularly real time deployments in which it is impossible to make all the tests necessary to understand the statistical properties of the data. See Annex I regarding an overview of LSTM for a brief explanation of what LSTM models are and how they are used.

Our approach was to use the LSTM model to predict the next value of the stored quantity given *n* previous observations. To achieve this, the time series was split representing the quantity of a product in a series of sequences. Given that there are several products, instead of training a model for each product we decided to train only one. This is possible if we normalize all the time series to be constrained between 0 and 1.

IBM developed and trained two separate forecasting model. The first with regards to a warehouse volume flow forecasting model and a second with regards to the container flow forecasting model.

The warehouse volume flow uses a stacked multivariate LSTM architecture. This implies that the model consists of multiple LSTM and dense layers within the neural network architecture with varying number of neurons. It takes as input multiple variables, some of which are features extracted from the date and quantity values. The model outputs an integer value for the quantity of pallets forecasted to arrive in the warehouse the next day, i.e., in the next 24 hours. This model has been trained on historical data provided by DHL for the pallets flowing in and out of their warehouse.

Some of the LSTM model parameters used in its development include:

LSTM Model Parameter	Value
No. Of layers	5
Dropout	0.2
Optimiser	Adam
Activation function	Rectified linear unit (relu)
Epochs	1000
Batch size	7

Table 3.1 LSTM model parameters used

The historical data contained the date and one variable regarding the volume of pallets flowing for that date, we extracted other features such as week, month, quarter, weekday, year, rolling average mean for last 3 days, 5 days, 7 days and 14 days. Some of the results obtained in building the forecasting model are presented below.

We conducted several trial-and-error experiments to find the optimal parameters for our model so we could improve further its accuracy[24]. We tried a few variations of LSTM for example single variate LSTM, Bi-directional LSTM and convolution neural network combined with a LSTM, however when we tried the stacked LSTM architecture this gave us the best results and so it is included some of the experiments done on this particular stacked LSTM model considering different epoch and batch size as showed below tables (Table 3.2, Table 3.3, Table 3.4 and Table 3.5)

Epoch = 1000 batch size = 3

Train Score RMSE	172.94
Test Score RMSE	193.39
Test Score MASE	0.28
Test Score MAE	156.80

Table 3.2 Results in model performance using the parameters Epoch = 1000, batch size = 3

Epoch = 500 batch size = 7

Train Score RMSE	155.49
Test Score RMSE	191.70
Test Score MASE	0.28
Test Score MAE	158.86

Table 3.3 Results in model performance using the parameters Epoch = 500, batch size = 7

Epoch = 300 batch size = 7

Train Score RMSE	80.74

Test Score RMSE	123.05
Test Score MASE	0.15
Test Score MAE	85.89

Table 3.4 Results in model performance using the parameters Epoch = 300, batch size = 7

In the below Table 3.5 Results in model performance using the parameters Epoch = 1000, batch size = 7 the best results achieved are shown

Epoch = 1000 batch size = 7

Train Score RMSE	44.55
Test Score RMSE	143.55
Test Score MASE	0.15
Test Score MAE	83.56

Table 3.5 Results in model performance using the parameters Epoch = 1000, batch size = 7

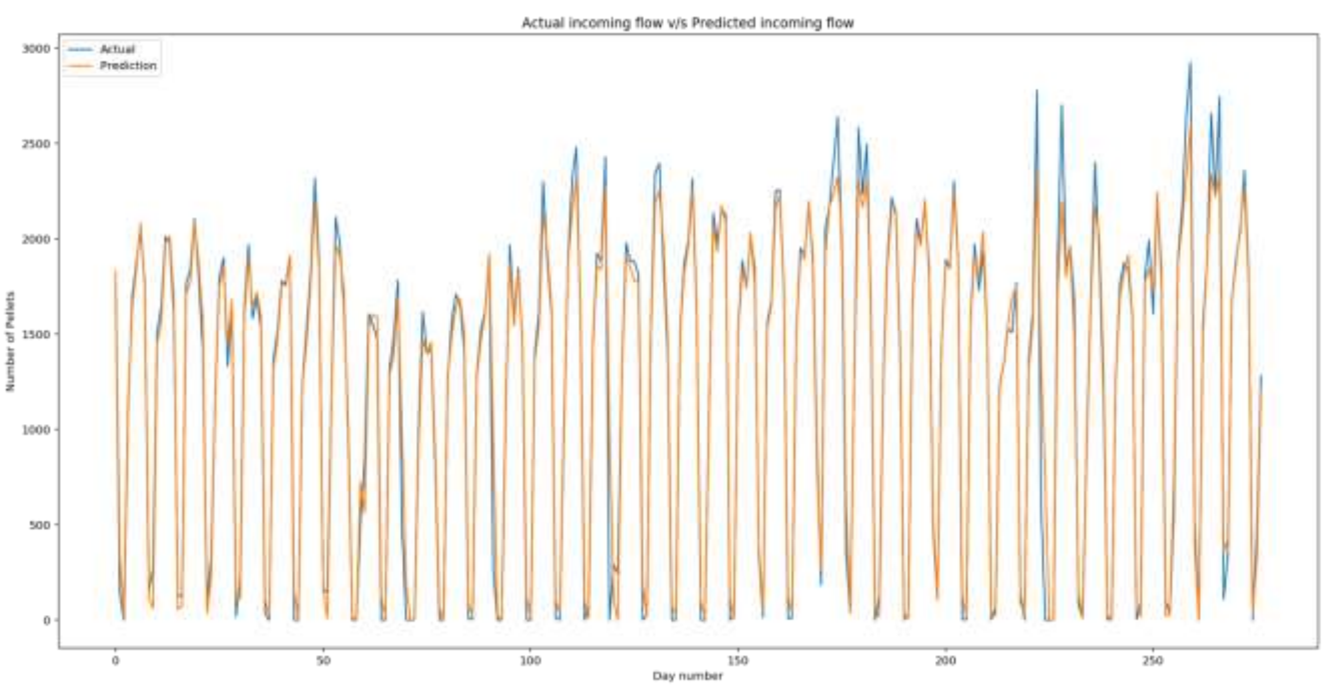

Figure 3 Visualization of the number actual number of pallets and the forecasted outputs

The model was tested using the last 283 days of the historical dataset and can see in Figure 3 that our model makes predictions that follow the actual trend quite closely, this is also reflected in the root mean squared error values. This prediction model can be used for any distribution center or warehouse if it is trained on historical data from that specific warehouse.

3.3.3 Container flow forecast

The use of statistical models and AI in forecasting applications, such as is the case for containers, has remained an ongoing task for several decades, and considerable research has been carried out in this field since then.

However, most common forecasting methods such as Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA, regression analysis and exponential smoothing remain used under the assumption of a linear trend [25] within the data available. These are techniques for forecasting that uses values of previous series of observations to predict future values. They are used to forecast one point at the time adjusting the forecast as a new data point baceomes available. The ARIMA methods are useful in providing modeling trends and seasonal components, allowing the added benefit of including independent (predictor) variables in the model. This includes the specification of autoregressive and moving average orders and degrees of differencing[17]. The time series for container flow consists of nonlinear trends which makes it difficult to forecast effectively and so novel techniques are being explored to predict trends more accurately.

Genetic programming has been shown to outperform decomposition methods and SARIMA methods to forecast Taiwan's container throughput as is shown in the work carried out in [26]. A vector error correction method based on a vector autoregression to predict the container transportation volume was introduced in [27]. An improved gray Verhulst model proposed in [3] indicated that it is possible to achieved high prediction accuracy and also retained the strengths and characteristics of the gray system model. In [28] it is showed that multilayer perceptron (MLP) forecasting outperformed linear regression (LR) forecasting models with multivariate data to forecast cargo throughput; the models were compared in terms of their root mean squared errors (RMSEs) and mean absolute errors (MAEs)[29]. The MAE is a quite good KPI to measure forecast accuracy, as the name says it is the mean of the absolute error which is the absolute value of the difference between the forecasted and the actual value. The MAE tells how big of an error is expected from the forecast on average. If the error measure is too focus in the mean it could happened that an infrequent bf error is not detected. To adjust for possible larger errors the RMSE is calculated. It is possible to compare the RMSE and MAE to determine whether the forecasted information contains large but infrequent errors. This methods for measuring the errors have limitations since they are relatively simple tools for the evaluation of accuracy in forecasting.

The Mean Absolute Scaled Error (MASE) gives an indication of effectiveness of a forecasting algorithm according to a Naïve forecast. If its value is greater than one it indicates that the algorithm is performing poorly compared to a naïve forecast. The naïve forecast is a standard estimating technique in which the last period's actuals are used as this period's forecast, without adjusting them or attempting to establish any other causal factors. The results presented in the previous sections for the pallet flow prediction all the models evaluated provided a MASE score considerably lower that 0 which is an indication of the high forecasting performance of the models.

The data provided by COSCO Spain for daily container volumes at ports are a nonlinear time series as can be seen below, which makes it hard for regression and nonlinear fitting models to explore the time series relationship. However, RNN are a class of ANNs algorithms that can generate memory states of past values when learning temporal sequences with inherent dependencies. The LSTM models are an advanced type of RNN's which have capabilities to help overcome the vanishing gradients problem.

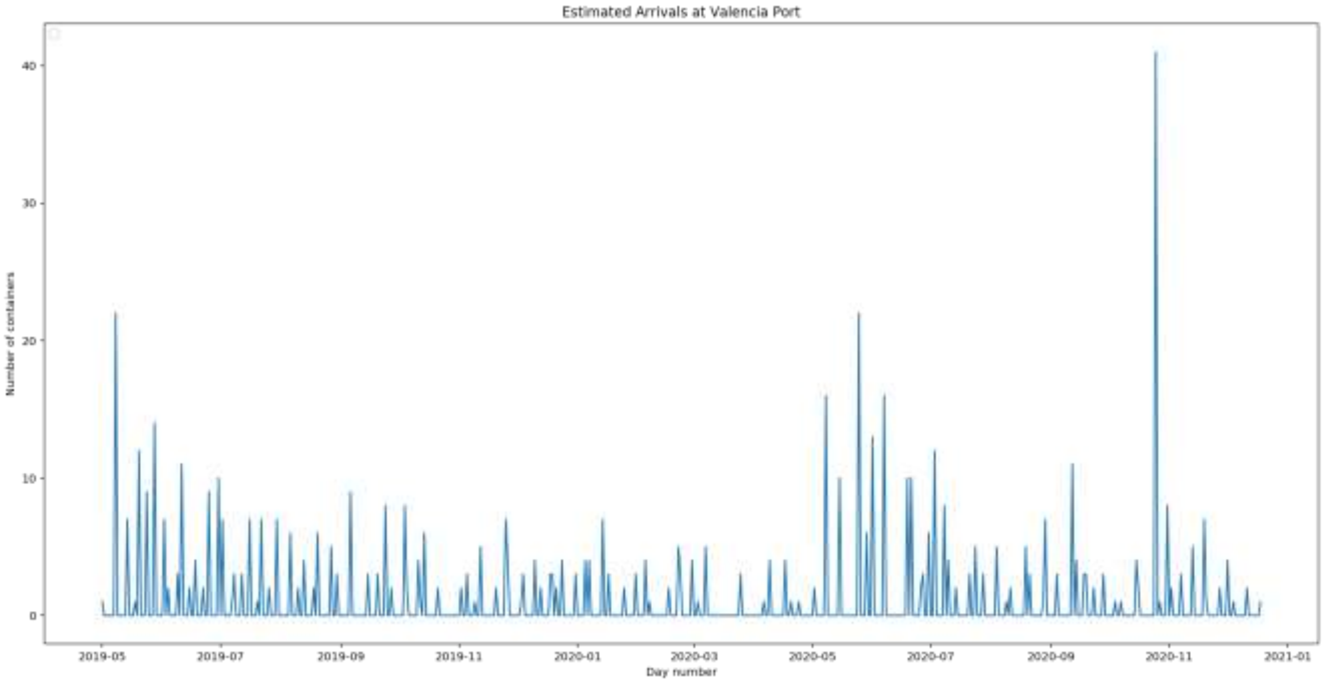

Figure 4 Container volumes at ports

The LSTM models are a popular approach for predictive modelling especially for sequential time series data. For instance, for the prediction of the volume of containers arriving at ports (see Figure 4), for the work presented in this report, a multivariate stacked LSTM model (see parameters in Table 3.6) was implemented using Python. This model is trained using historical data provided by COSCO Spain for the number of containers arriving at Valencia port from their vessels. It outputs includes the predicted flow of containers for the next day aiming to help improve further decisions on transport planning.

Some of the LSTM model parameters considered are enlisted below:

LSTM Model Parameter	Value
No. Of layers	4
Dropout	0.2
Optimiser	Adam
Activation function	Rectified linear unit (relu)
Epochs	300
Batch size	7

Table 3.6 Parameters considered to run the LSTM model

The historical data contained the date and one variable regarding the volume of container flowing for that date, we extracted other features such as week, month, quarter, weekday, year, rolling average mean for last 3 days, 5 days, 7 days and 14 days. Results using the above hyper-parameters include a test score in the order of 1.78 RMSE.

The congestion prediction model forecasts 24 hours in advance the number of containers arriving the next day at Valencia Port. Currently this model is trained on historical data based on estimated arrival times and so can be improved further if historical data on actual arrival times is available. This model is a stacked multivariate LSTM model which means it is a form of RNNs consisting of several deep layers stacked on top of each other and takes as input a range of features extracted from the historical data. The Figure 5 below shows a visual view of the results of this model when tested on 100 days, the root mean squared error is 2.11 which means the prediction is off from the actual value by approximately 2 containers on average. A comparison between the actual and the predicted arrivals against the day of arrival is shown in the Figure 5 below.

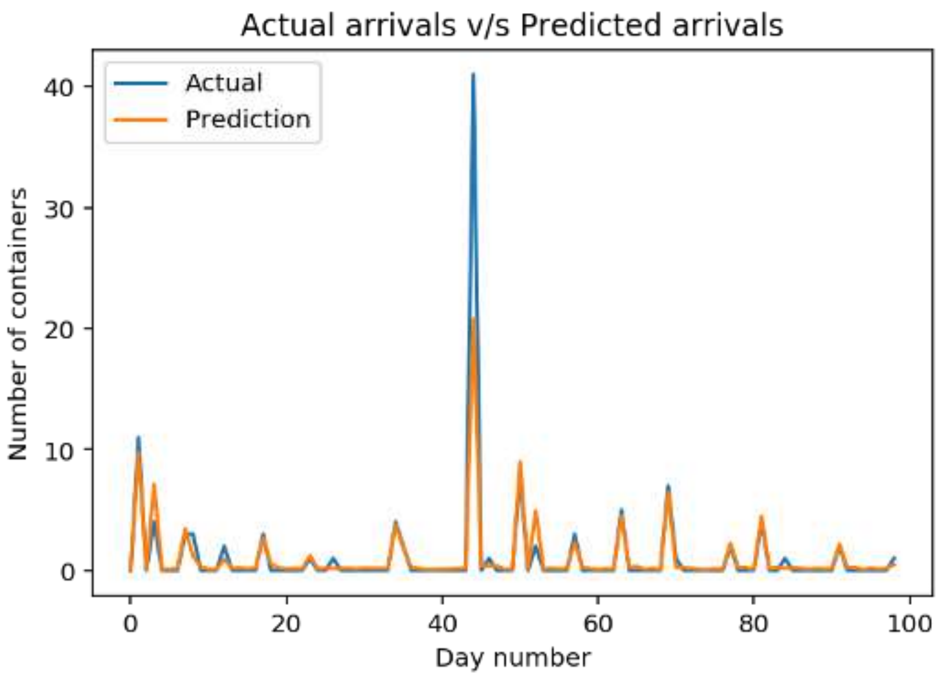

Figure 5 Visualization of results of the predicted flow of containers and the actual containers

A similar prediction model could be used for seaports forecasting application if it is trained on the historical data available from specific seaports.

3.4 Conclusions from pre-liminary forecasting results

Different measures to quantify the error in the forecasted output of the models were considered. These include measures to quantify the average error (RMSE and MAE). For the case of pallet forecasted valuers were off by figures approximately between 150 and 200 pallets. This appear to be a relatively small number of pallets forecasted mistakenly since the number of pallets flowing is in the order of thousands. For the case of forecasting containers, the mean error was in the order of one-single-digit error since the flow of container is only around 40 containers.

The MASE error was used to evaluate the forecasted performance in comparison to a naïve model. This error measure must be above 1 to indicate a poorly performer model. All the models evaluated using the MASE showed a quantity lower than 0.2, which indicates a good performance of the models. The test evaluation visualizations reported showed that all the models follow the pattern of the time series test set, which also suggest an optimal performance.

The forecasting results presented in this report are preliminary and will be expanded and reported in the next release of this deliverable D2.10. To achieve this, further experiments and implementations will be carried using extended resources of data as these are made available to project partners. Also automated approaches to evaluate larger combinations of hyper-parameters and forecasting models will be considered to expand the tests presented and increase the chances for further improvements in their performance.

3.5 Packaging process for deployment of models and services

This section describes potential approaches to enable the standardization of the AI software components into common file formats to enable their usability and interconnection as services, across users within the EGTN platform. There exists a variety of tools, including open source-based, to deploy and even optimize the development of machine learning models by improving their computational resources utilization and their performance without disrupting the overall operability of an application.

The available tools include names such as ONNX, MLflow, among others, which also have capabilities in providing registries to handle and manage better the complete cycle of the ML models development from training and testing to model versioning. Another example of these systems is the TensorFlow Serving Models that provides integration for the TensorFlow machine learning models. This service is compatible to serve other types of models developed using other tools. Another tool is the RedHat OpenShift based on containers and Kubernetes technologies which also provides a solution to rapidly deploy machine learning models-based applications.

The containerized applications, Dockers and Kubernetes, used in combination with the above tools set the basis to enable portable deployments as they can run across different cloud providers. Other applications to enhance the portability and usability of the models and services deployed include tools such as Representational State Transfer (ReST) Application Programming Interfaces (API) to allow the models' usability directly via a web server or cloud-based service. This functionality makes use of well-known standard open-source technologies available in libraries like the Flask-ReSTPlus and FastAPI which uses request methods through HTTP standard protocols (Get, post etc.) to perform the APIs actions required.

These Docker and Kubernetes applications used within the PLANET services encourage the microservices approach for a more flexible packaging of functionalities, facilitating updates and reconfiguration by promoting re-deployments and the re-usability of the ML based software components as building blocks of the services. The use of these technology applications can set the course to determine how the models and services can be deployed to exploit as much as possible the advantages of cloud computing including the optimization of computational resources (including storage), the connectivity across services and scalability.

The models and services deployed need to be agile, operable, resilient, and observable. These characteristics are useful for the software modules deployed to run as microservices, and possibly communicating to each other, in a standardized way using containers and declarative API gateways technologies which formalize, configure, and secure the models and services endpoints. Such a formalization builds, deploys and orchestrates the execution of the potential applications as cloud native, and enables them to operate horizontally across other cloud platforms, making them capable of meeting the consumer demands more seamlessly.

Other technologies to be considered to enable the above-described capabilities include Istio and Knative for the microservice mesh, facilitating further the testing, deployment, and update-in-place tasks. Other combinations of tools to enable observability of the deployments and their functionality would also be relevant in considering aspects for real-time applications, in monitoring the life cycle of the deployments and to be able to measure metrics relevant to service releases, performance and minimize time needed for problem solving and reduce operational costs and help planning additional features and expand on most used services.

4 Alignment with living labs of the prediction and optimization models

In this section it is discussed how in collaboration with project partners the IBM analytics and forecasting models could align with the real-world Transport and Logistics users and their use cases as part of the LLs in PLANET.

4.1 PI and blockchain for optimized door to door Asia – EU corridors

The LL1 will aim to evaluate how new technologies (IoT, AI and blockchain) and the concepts within the PI could improve processes, operations and efficiency along the door-to-door transport chains linking the Maritime Silk Road with EU internal corridors.

4.1.1 Use cases

The LL1 can be divided in to two main use cases which are described below.

1. The first use case will focus on import/export door-to-door transport chain of containerized cargo between China and Spain and will evaluate how the combination of IoT (for real-time monitoring of logistics assets), AI (for better forecasts and intelligent decisions based on machine learning algorithms) and blockchain (for paperless transactions and the register of transport events), can contribute to a better management of the transport chain. The development of the PI paradigm will be investigated, where intelligent logistic nodes or hubs play a key role in transport decisions and are optimized based on real time events/information and historical data.
2. The second use case will focus on warehouse operations and will explore how new IoT, AI, AR and automation technologies can contribute to the development of intelligent automated logistics nodes of the EGTN/PI network. This use case will complement the use Case 1, particularly on how to integrate smart Warehouse Nodes for EGTN routing decisions, ultimately creating PI Warehousing Nodes. The extended level of potential automation will be represented through simulation (T1.1, T1.4).

IBM has been in discussions with LL 1 regarding both their use cases and has provided insight into how analytics services can be implemented to benefit the business cases presented in this LL.

4.1.2 Data provided to build forecasting models

The analytics services developed by IBM are trained on real world data provided by DHL and COSCO Spain. COSCO provided data on the estimated time of arrivals of containers coming into Valencia Port from May 2019 to December 2020. This data has been useful in training the Container flow forecasting model which was discussed in detail in Section 3.3.2. The format of the data was as in the following figure with Estimated Berth Arrival and Container Size type being the most relevant features for our machine learning based predictive model.

The data provided so far include datasets relevant for building models forecasting the numbers of incoming containers to ports. The data variables provided within this data set includes a total of 10. The variables provided for these datasets are enlisted in the annex II. The number of records available within this data set is 633. The data describe transportations taking place between Valencia and Madrid, Spain. This data is currently a resource that is relevant within the use case 1 of the LL1 which overall aim to improve the container operations regarding cargo between China and the Spanish hinterland through the ports of Valencia, Algeciras and Barcelona with the aim of developing intelligent services and algorithms in applications for vehicle routing, in collaboration with the PLANET project partners.

Another dataset provided by DHL was the warehouse package/pallet flow data for a period of 3 years. The most relevant features from this data for our models were Date, Process and Quantity. This data was used to train our warehouse flow prediction model. The total amount of variables provided for this dataset is enlisted in the annex II. This dataset is currently considered at least relevant for the use case 2 for the optimization of warehouse operations and their further automation. This includes the smart contracts application for the further automation of payments. The pipeline model implementations that ingest this dataset could be expanded to applications for maritime transportation and seaports related datasets should they be required and made available within the PLANET project.

Another potential impact of this dataset is with regards its usability to determe related services for the last mile delivery route optimization, which includes sustainability aspects for carbon footprint calculations to become an eco-friendlier transportation network system.

Other data provided include a series of datasets regarding the actual time of arrival of shipments. These datasets are currently being explored and analyzed in terms of their usability for building forecasting models to determine data processes needed to predict the actual time arrival from Asia Europe Maritime (AEM) routes. This data was provided by COSCO and could be relevant for the scenarios and use cases of LL3, including the carbon footprint models. Other data provided include a small sample data file containing the format for the Electronic Product Code Information Services (EPICS). This type of data is usually gathered using IoT technology, stored in repositories for the purposes of informing service providers about the arrivals of shipments. This type of data can be used for tasks regarding loading packages onto a truck and monitoring the packages movements and trajectories by using tracking sensors. This tracking can provide speed and location information that are relevant for a carbon footprint estimation for the duration of the truck journey.

There are additional data files provided by consortium partners containing sample data that could be relevant for the enablement of predictive models-based services. This includes data related train services, last mile data, shipping related data and other that are yet needed to be assessed in the future more in detailed to identify potential variables required for aggregation with existing or future datasets accessed or to be accessed.

4.1.3 Models considered and developed

IBM implemented two machine learning models that align well with LL1 use cases: Warehouse flow prediction model and Container flow prediction model. The warehouse flow prediction model can predict 24 hrs in advance the volume of pallets that will be flowing into the warehouse and can also be easily trained to show volume of pallets flowing out of the warehouse. The model can benefit warehouse management by allowing to plan their operations thus saving time and cost each day. IBM has explored with other project partners ways to integrate these models with other services provided on EGTN to execute intelligent decision making, this led to the development of 2 innovative collaborative models: PLANET Integrated modelling capability and AI enabled smart contracts. Both models demonstrate the idea of how machine learning can be combined with other types of models to make complex decision making more informed and efficient. These models will be discussed in further detail in section 5.

The below sections and subsections briefly describe the use cases and models considered and developed so far across LLs. Also, it is envisaged how these models fit within the currently defined use cases and scenarios of the living labs.

4.2 IoT for Silk Road route

LL3 design is currently focused on streamlining logistic processes in flows from China to Europe by implementation of IoT technologies and Electronic Code Information Services (EPCIS) platform as well as other GS1 standards that facilitate transmission of data between the partners involved in the logistics operations along the Silk Road Route. LL3 goals include the following.

- **Increased visibility of goods along the silk road facilitated by IoT technology**

Development of IoT solutions based on standard alliance communication protocols DASH7, RFID (EPC global class 1sensor network protocol), Low power Wide Area Network (LPWAN)[30] and sensors systems that help control resource parameters in real time and identify them while moving in the transport process, examining potential positive results in terms of broad implementation.

- **Standardized information flow**

Creation of a digital connection between actors in the transport network, enabling standardized data flow and access to information about cargoes coming from China to Poland in the whole supply chain in real time (implementation of the SSCC number and EPCIS test).

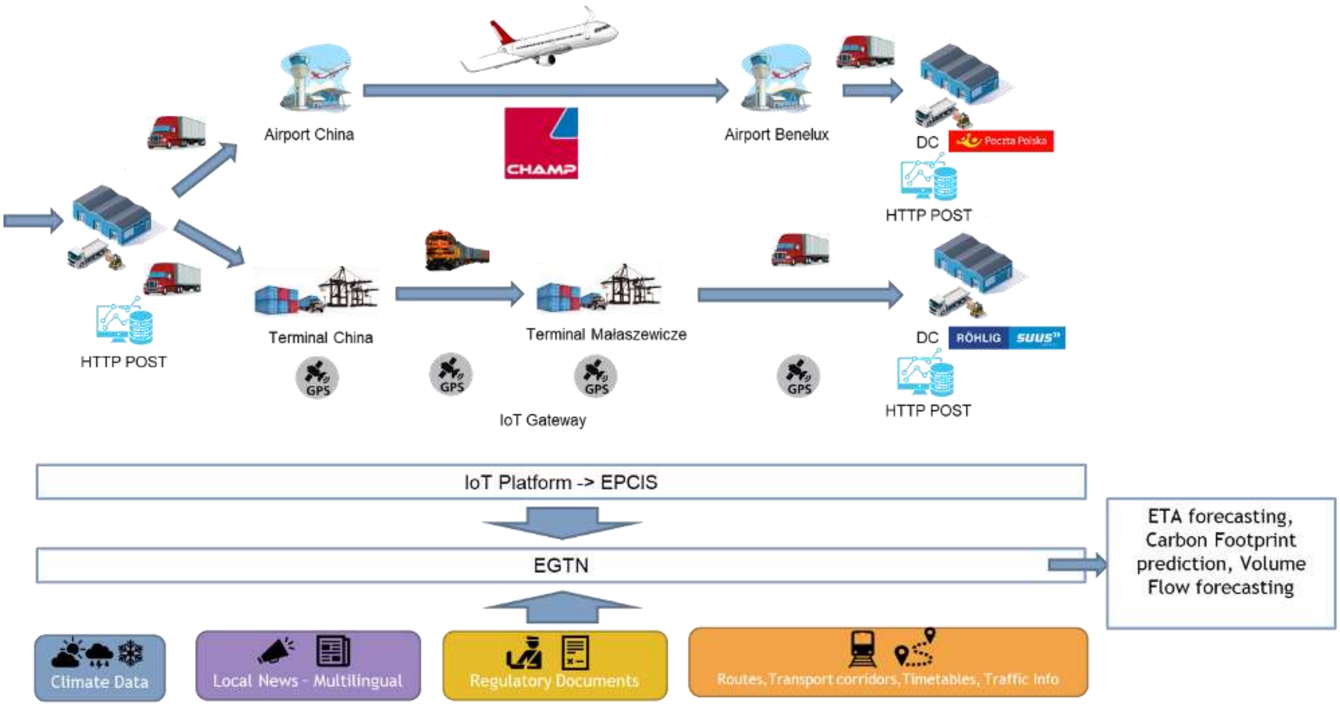

Figure 6 *A general diagram on the LL3 scenario*

The identified business needs of our partners were the starting point for developing the LL3 use cases (see Figure 6). Looking at both the business needs of the partners as well as the capabilities of testing solutions in the LL3, two primary scopes were identified to be tested for this LLs.

- Container transport monitoring on the New Silk Road including rail transport (Rohlig Suus - RS),
- E-commerce parcel distribution monitoring on the New Silk Road including air transport (Polish Post - PP).

This subdivision of use cases results from the specific business characteristics of the partners in the LL3 and the used solutions. Therefore, each use case includes the following activities.

- Use case 1 monitoring and optimization of container flow along the New Silk Road:
    - Activity 1: Development and installation of sensor network mobile base stations and beacons on containers and selected logistic units. Implementation of sensor network technology to collect data on container transport conditions and selected logistic units during transport.
    - Activity 2: Integration of operational data in the supply chain - Use of EPCIS for event data collection based on IoT sources and integration with EGTN and IT systems of business partners.
    - Activity 3: Use of EGTN for estimation and prediction of selected logistic KPI's including:
    1. Volume Flow forecasting,
    2. Carbon Footprint Prediction
    3. ETA forecasting. Comparison of different ETA calculation models on the bases of ETA forecasting accuracy.
- Use case 2 optimization of e-commerce flows in global supply chains:
    - Activity 1: Information flow standardization in supply chains through application of GS1 standards (mainly SSCC) for monitoring e-commerce parcel shipments from China to Poland.

- o Activity 2: Integration of operational data in the supply chain - Use of EPCIS for event data collection and integration with EGTN and IT systems of business partners.
- o Activity 3: Use of EGTN for estimation and prediction of selected logistic KPI's including:

1. Volume flow forecasting,
2. Carbon footprint prediction
3. ETA forecasting comparison of different ETA calculation models on the bases of ETA forecasting accuracy.

In both use cases the EGTN platform will integrate with EPCIS, and in use case 1 also with IoT sensors. The integration logic of the solutions used in LL3 is shown in the Figure 7 below.

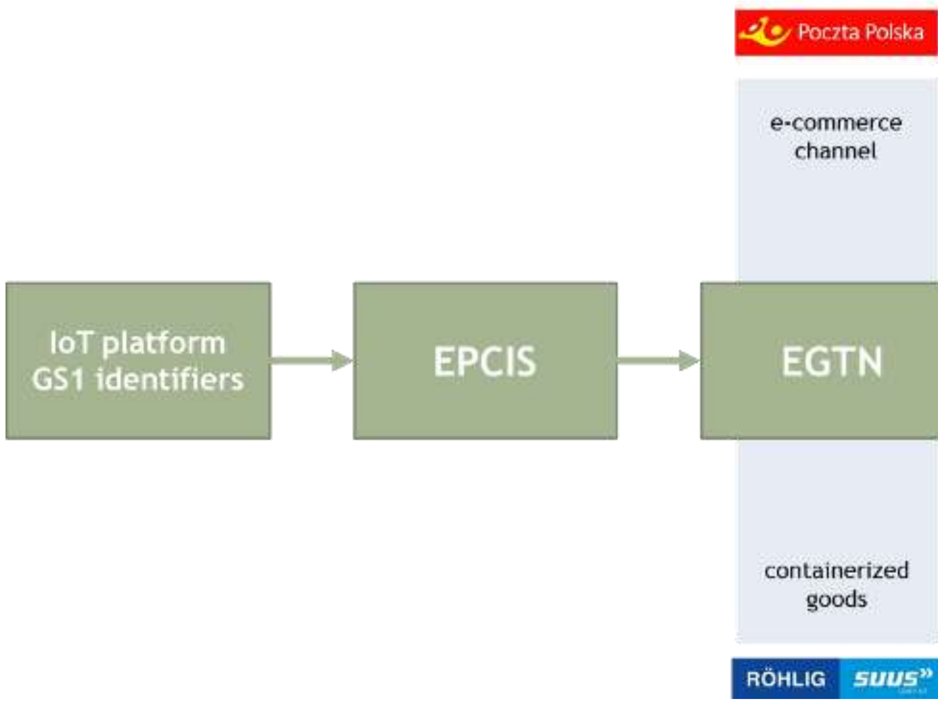

Figure 7 *Integration of solutions used in LL3*

This scheme contains the following logic:

- IoT collects some of the data based on use of wireless sensor networks (DASH7 – LPWSN – Low Power Wireless Sensor Network) that corresponds to parameters identified by business partners during the execution of logistics processes - the collected data feeds the EPCIS system.
- EPCIS is a GS1 standard that enables trading partners to share information about the physical movement and status of products as they travel throughout the supply chain, from business to business and ultimately to consumers. It helps answer the "what, where when and why" questions to meet consumer and regulatory demands for accurate and detailed product information. The goal of EPCIS is to enable disparate applications to create and share visibility event data, both within and across enterprises. This sharing is aimed at enabling users to gain a shared view of physical or digital objects within a relevant business context. In LL3 EPCIS receives some data from IoT, but also independently collects some of the data/parameters identified by business partners during the execution of logistics processes. Storage and exchange of data is based on EPCIS and API 's by HTTP POST requests and information capture interfaces. The collected data (from both IoT platform and EPCIS) feeds the EGTN system,
- EGTN (Integrated Green EU-Global T&L Network) is an open infrastructure enabling integrated digital communication between actors in the transport network, access to various data in the supply chain and additional analytics. The EGTN receives data from the EPCIS (and IoT platform via EPCIS), but also independently collects some of the data/parameters identified by the business partners - the set of

necessary data (separately for Polish Post and Rohlig Suus) is transferred to business partners' IT systems (system integration is necessary).

The potential benefits that could be enabled by analytics services across the use cases are highlighted below.

Use case 1: Monitoring and optimization of container flow along the New Silk Road (Rohlig Suus) to decrease the costs of transportation.

1. Percentage of containers filled (LCL service).
2. Percentage of timely collected containers from the TM in Małaszewicze.
3. Costs of storage and detention of shipments.

Predictive analytics can increase the accuracy of estimated transportation time and the transparency of rail transport.

1. Percentage of transport with accurate ETA.
2. Percentage of transports with documents prepared on time for customs clearance. And considering exceeding the permissible temperature / humidity and shock levels.
3. Percentage of the transports with interference with the goods during transport.

Use case 2: Optimization of e-commerce flows in global supply chains (Polish Post) to improve the container filling, and the overall container occupancy. This would impact the overall loading strategy and structure for improving the task of scalability of each container.

IBM plans to explore how the train loading optimisation service derived from ICONET can be applied in the LL3 to improve the filling of containers thus optimizing the container flows from China to Poland. IBM also intends to experiment with machine learning models that can improve prediction of ETA and carbon footprint provided with the suitable data resources that the project partners would made available within the project PLANET. These models once tested on the LL3 use cases could perhaps be integrated further as services within the EGTN platform.

4.2.1 Data resources for predictive analytics with the project

As part of the analytical functions of the EGTN platform for the needs of pilot implementation scenarios, three parameters were identified for which predictive mechanisms will be implemented. The same data sets were selected for both implementation scenarios: volume flow forecasting, carbon footprint prediction and ETA forecasting.

Each of the parameters has clear requirements for the input data necessary to obtain. The project assumes that input data will come from a variety of sources and will be provided in two ways. In a first phase, as historical data for the needs of training the predictive model will be provided, and on a second phase data generated on an online for its integration in the form of newly data instances for the purpose of predicting the required variables.

For the purposes of volume flow forecasting, the following data inputs were identified: Packaging lists and DC inflow and outflow cargo quantities. In the case of a pilot implementation carried out with Rohlig SUUS, the source of these data will be the internal transport management system, while in the case of a project implemented with Poczta Polska, the data will come from various communication systems including the Zone Sonography Technology (ZST) system.

The situation is similar with carbon footprint prediction. This indicator is much more complex and demanding both at the stage of machine learning and in operational conditions of a much larger number of different types of input data. During the conceptual work, the following types of input data necessary for carbon footprint prediction were identified: weight of packages, transport mode with information about train / plane (technical information), origin and destination and quantity of packages/pallets.

The sources of these data were identified in both pilot projects. In the case of rail transport, this will be Rohlig SUUS in-house TMS, the platform of the location service provider Vayasens, and data from train registers and information from cargo consolidators in China. In the case of air transport, an additional source of data can be the Champ or FlightRadar system.

The last parameter to be implemented and predicted under the EGTN platform will be estimated time of arrival (ETA). The accuracy of ETA prediction is directly dependent on the amount of various data included in the learning process. Many different models in the field of AI can be used for this scenario for example the following predictive models: Decision Tree Based Models, ANNs such as RNN and Support Vector Machine (SVM).

The learning process itself will be carried out considering the following data types: origin & destination, GPS data, traffic density & intensity, weather conditions along route, train / plain parameters i.e. (length, weight, speed, schedule etc.), route information (distance, intermediate stops / nodes) and holidays such as Chinese New Year which is usually a major event that creates considerable spikes in consumption of products.

The indicated data types will be obtained from various sources, including the above-mentioned TMS systems by Rohlig SUUS, EN and ZST solutions from Poczta Polska or the GPS from Vayasens platform or Champ / FlightRadar solutions.

One of the most difficult categories of collected data will be information on traffic density and intensity in the case of rail transport. It should be noted that the transport process itself will be carried out by different routes through different countries. As a result, the data is scattered and heterogenous and often have different formats and types. Basically, it is assumed that these will be internet official portals indicated in each country, informing about the current railway traffic, delays, planned repairs, and others.

5 Collaboration with PLANET partners

This section contains an updated description of the collaborative work (see Table 5.1) that the IBM team has been conducting in collaboration with the other project partners from WP1, WP2 and WP3 where necessary. We will be describing the integration experiments that have been conducted to date as a way of demonstrating the innovation in having different services working together in a pipeline to make intelligent transport and logistics decisions.

Work Stream	Collaboration relationship with Partners
Use of a cloud based EGTN infrastructure to effectively operate within the PI paradigm.	IBM has collaborated with project partners with regards the EGTN infrastructure, setting how to connect the analytics services to other services in the platform, how the data will be input and stored and establishing the requirements for the technical architecture of the predictive analytics components to work effectively as services. This service includes an AI based smart contracts service for the further automaton of payments across multiple blockchains.
Flow monitoring, and data connectivity for T&L planning and route optimization.	IBM also collaborates with regards the use of knowledge graphs as components that can facilitate the access to time series data of events that are relevant for the predictive model to ingest to carry out useful forecasts. Also, how the forecasted information could be feedback to the knowledge graph to issue alerts, estimations visualization and recommendations to carry out logistics within the transportation network for route optimization services.
Decision support software based on smart nodes.	Collaboration has been also carried out on using AI based predictive models, as part of the enablement of smart nodes, jointly with the multi-criteria and multi-actor analyses to support discissions (in simulated environments) to improve the transportation across networks.
Smart contracts applications.	IBM collaborates to jointly develop an AI based smart contract interoperable service. This service will make use of the IBM forecasting models output information to help evaluate the need to execute smart contracts and payments across member of the supply chain.
Unified user interfaces	Collaboration has also taken place towards setting elements of information to be displayed

	in dashboards for the users of the EGTN platform.
Modelling and simulation capabilities.	IBM has participated providing contributions for deliverables and workshops, and various partner discussions and workshops to jointly develop a PLANET Integrated modelling capability within the EGTN platform, to capture and characterize the dynamics of transportation networks using data driven tools.
LLs use cases and scenarios	IBM has collaborated within workshops, and encourage other project partners, to continue determine further the value in using data driven solutions within various LL scenarios and where the PLANET predictive models can effectively be set as services, such as routing, smart contracts, carbon footprint. Collaboration has also taken place to identify sources and the relevant data required to enable the predictive models.

Table 5.1 Overview of the collaborative work within the WP2

5.1 The PLANET integrated modelling capability

In this section, we define the prototype of the PLANET integrated modelling capability. The development of a prototype was decided with the aim of quickly providing a combination of quantitative models that could be showcased to other task leaders across LLs within the project. This allowed for a joint development of the prototype which was enriched with several perspectives. The prototype took the shape of a pipeline, i.e., a combination of models where data are exchanged in an Input/Output sequence. In this section, we will refer to the pipeline as this was found to be a descriptive and accepted concept. Moreover, we elaborate on the modelling requirements for a joint application of data analytics forecasting and synchromodality adapted to the EGTN platform.

In what follows, we first describe the approach followed for defining the prototype as it provides the guide to a proven path for enriching the model further. We then define the modelling use case and show the details of the various models used. Finally, we describe the synchromodality enhancement for EGTN.

5.1.1 Workflow towards a pipeline definition

The pipeline that was developed was the result of several workshops between all partners involved in this task. The approach follows the below steps, some of which are depicted in Figure 8.

1. The selection of a modelling use case based on LL from D1.2.
2. The selection of the relevant models for the modelling use case and context considered.
3. The modelling use case has been formalized aiming at a secure and well-motivated interface between the models
4. Relevant modelling scenarios have been selected, tuned to the modelling possibilities while tuning the modelling towards the modelling scenarios.
5. The first pipeline concept has been elaborated (cf. Figure 8).
6. The pipeline has been tested on artificial data.

Figure 8 also shows the planned workflow and the relation to previous deliverables and WPs.

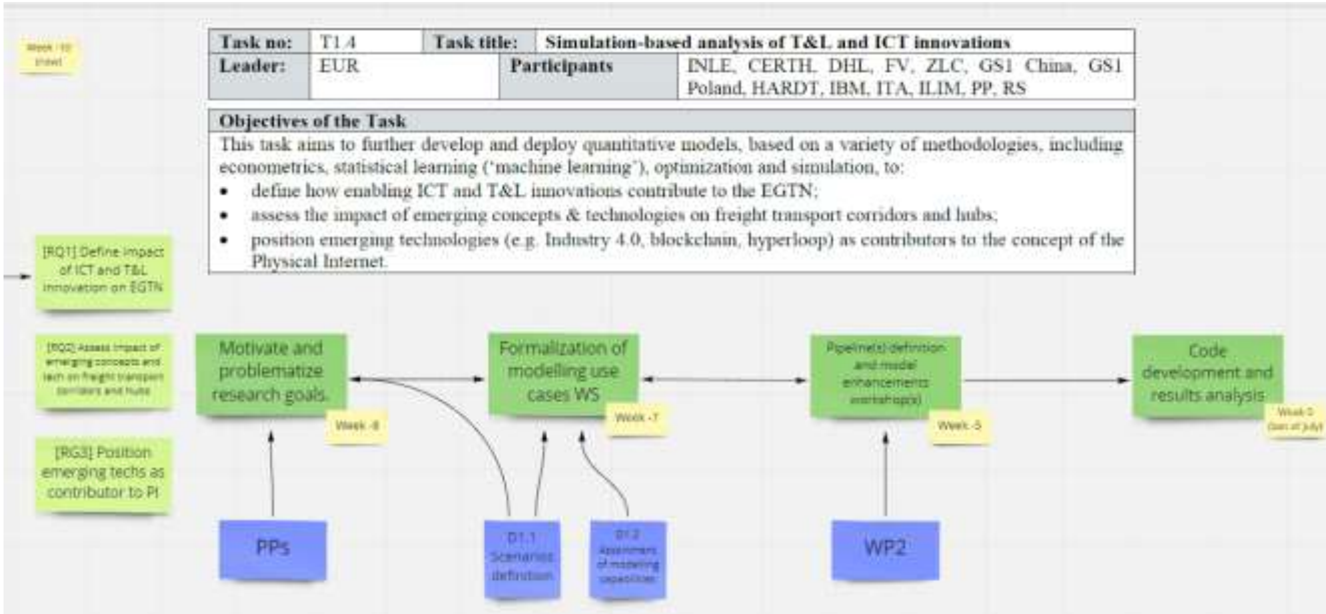

Figure 8 Planned workflow to define the pipeline.

Figure 9 provides a high-level description of the pipeline. It shows how, starting from a simple instance, two separate scenarios have been considered for modelling. On the two scenarios a combination of models (still to be defined at this stage) is executed outputting values related to the KPIs defined in Section 4.2. This output is then processed and presented to a macroscopic model (in our case the terminal model). The pre-processing pipe step was required to transform the output of the model execution into valid, and meaningful, input for the macroscopic model.

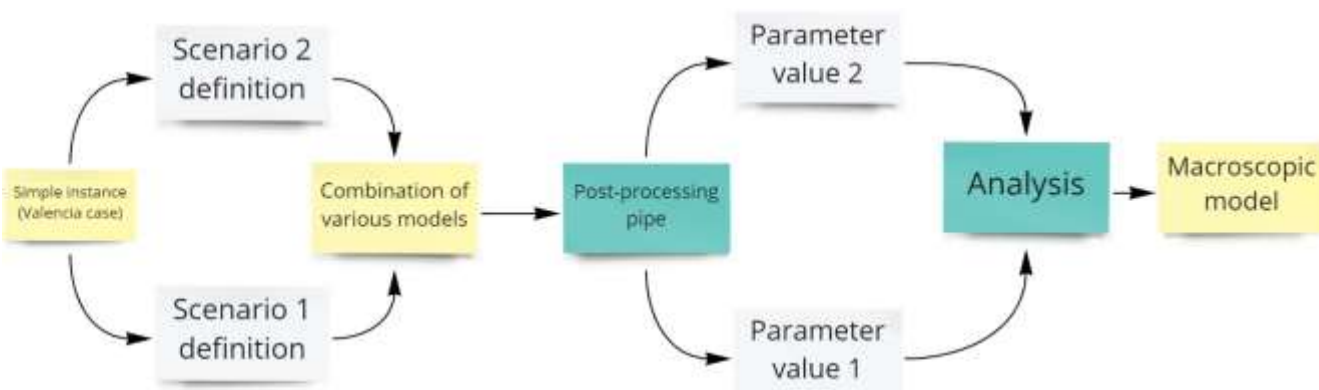

Figure 9 Pipeline high-level definition

5.1.2 Modelling use cases

A modelling use case is a specific situation in which a model could potentially be used. For our purposes, it provides main user (stakeholder interested in the analysis), context of application (logistic setting of interest), research question (declination of the D1.4 RQs to the context) and evaluation scenarios of interest.

The modelling use case is related to a specific pipeline. The term pipeline refers to a sequence of models that run-in sequence in such a way that the output of one will be the input of another. For our use here, a pipeline should substantiate a modelling use case. In other words, for each modelling use case, we devise a pipeline. A pipeline is written in a certain programming language.

In Table 5.2, we formalize a template for a generic modelling use case which is composed of several features that are explained in the Table itself. We provide an example answer for each of these features which describe the pipeline developed in this deliverable. The answers provided are a summary of the content of Section 3, which explained the context in more detail.

Feature	Explanation	Answer (for the developed pipeline)
Modelling use case title:	A title for the modelling use case	Prototypical PLANET integrated modelling capability
Narrative presentation:	Explain what the problems are being modelled and how this is being done.	Containerized cargo from China to inland Spain can enter the Mediterranean coasts of Spain via several ports. Congestion at the ports impacts the decision of the ocean liner shipping company which results in different hinterland connections being used. In this setting, several technologies impact decision-making. Having as a base a multi-agent simulation, AI and Optimization models are integrated to evaluate the impact of emerging technologies on T&L processes. Finally, a macroscopic model analyses long-term changes in flows deriving from the operational results.
PLANET partners involved:	List of the partners involved in the modelling use case	WP1 collaborators
Model stakeholders:	List the main stakeholders considered in the model	Ocean liner, port authorities, port terminal operators, trucking companies, rail operator, hub operators.
Involved models (reference to D1.2):	List the models involved (as defined in D1.2 or additional ones)	PI simulation, Forecasting model, Port call selection model

Focal technologies and innovations:	List the technologies considered in the modelling use case	Physical Internet, Artificial Intelligence, Optimization, Blockchain
Modelling scenarios:	Describe the scenarios at a high-level	As is situation vs PI deployment

Table 5.2 Modelling Use Case template and information for PLANET integrated modeling capability

5.1.3 PLANET integrated modelling capability as a pipeline

The modelling use case summarized in the above table, has been translated in the pipeline depicted in Figure 10 below and descriptions of the pipeline are provided which explain how the models interact and relate to the EGTN concept envisaged for the PLANET project.

In the Figure 11 a graph is shown with yellow boxes representing data and azure-coloured boxes representing models that are connected by several arrows. An arrow from a data box to a model box means that data is used as an input to the model, while an arrow from a model box to a data box means that output from the model is stored in a dataset. Each model box is also accompanied by a logo to represent the main capability of that model. Snapshots of data and red arrows show precisely where each model interacts and proves the positive result of the dry run of the prototype. Maps show the output of the Terminal model. As a final remark, the red lock icon next to the "COSCO data" box shows that some real (and confidential) data have been used in the pipeline.

After this presentation of the elements of F, we can describe the flow of information. Starting from the COSCO data, the congestion prediction model forecasts by means of AI the number of containers predicted at each port. As for now simple calculations of the congestion at the port based on an estimated port capacity

F

level, and the congestion level is provided to the Simulation Input “Excel” spreadsheet. This document contains all specifications of transport means, technologies and demand information required to execute the multi-agent simulation. Before starting the simulation, it is the turn of the port call decision model that, using the predicted congestion, computes the optimal port call for the ocean liners. The decision is then stored back in the simulation input “Excel” and serves as input for the PI multi-agent simulation.

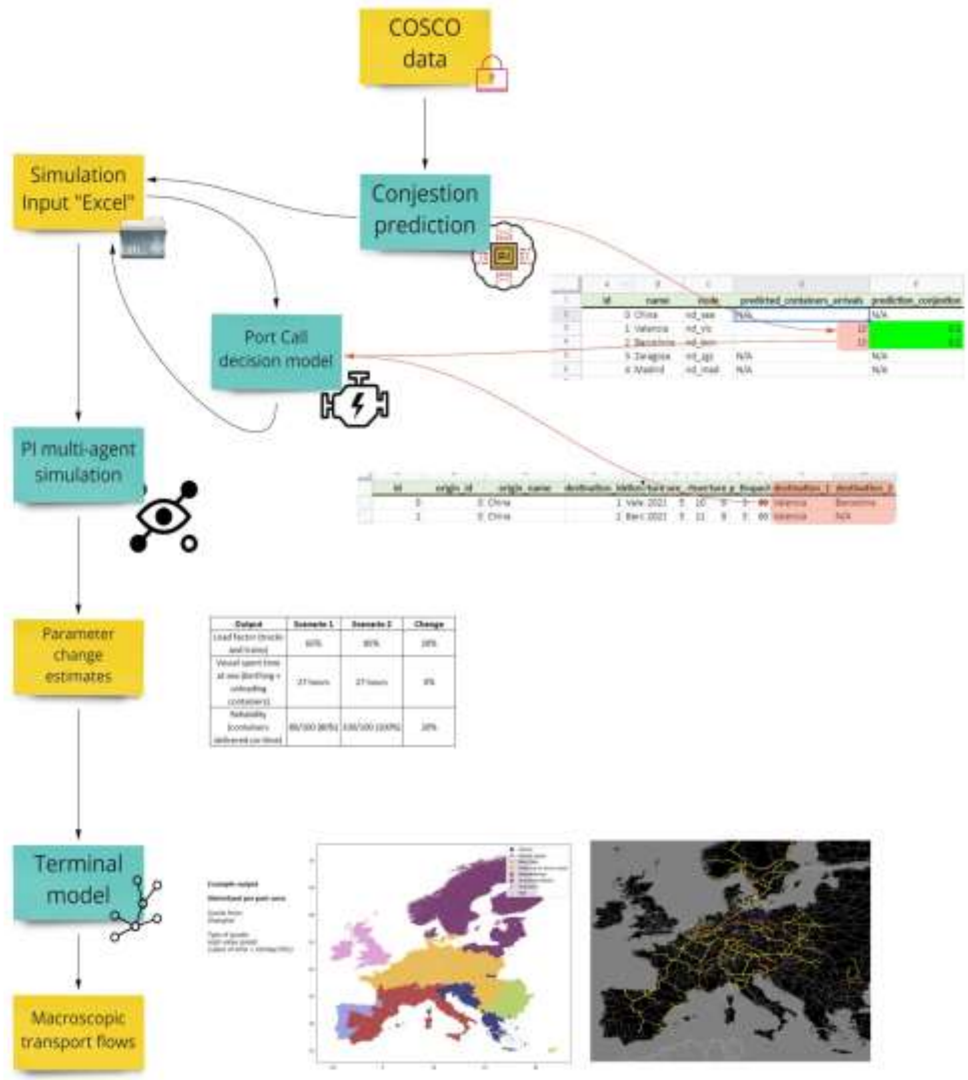

Figure 10 The prototype pipeline – The PLANET integrated modelling capability

This model generates an instance of the maritime network in LL1 and executes a multi-agent simulation where a prespecified scenario is executed by simulating all transport and transshipment operations. By comparing two scenarios run, the parameter changes relevant for the terminal model are computed. Finally, an execution of the Terminal model allows for an estimation of the macroscopic effect of technology.

After the presentation of the prototype PLANET integrated modelling capability, the pipeline just presented, we show how this is related to EGTN concept. First, the containerized cargo flow that is considered crosses the EU border with a decision on which points of entry to use. This is a fundamental feature to qualify this modelling effort for the EGTN concept within the PLANETproject. Indeed, this allows for an understanding of the impact of PLANETary/global decisions at the local level. Second, several emerging technologies are considered in a concerted deployment and their effect at the macroscopic level is computed. This relates to the Innovation and Impact attributes of the EGTN concept as it allows for the evaluation of the impact of innovation at the EGTN level. Moreover, the integration of the different processes within the different technologies considered relates to the Integration attributes envisaged for the PLANET EGTN. This prototype PLANET integrated modelling capability also shows that the several attributes of the EGTN concept interact with each other and is an important consideration. The following sections provide a detailed description of each of the models considered in the pipeline.

5.1.4 PI multi-agent simulation

The Figure 11 below shows an overview of the main view of the PI multi-agent simulation. The model is composed of 5 main nodes: deep sea, Valencia, Barcelona, Zaragoza and Madrid. The blue nodes correspond to seaports and the yellow nodes to dry ports.

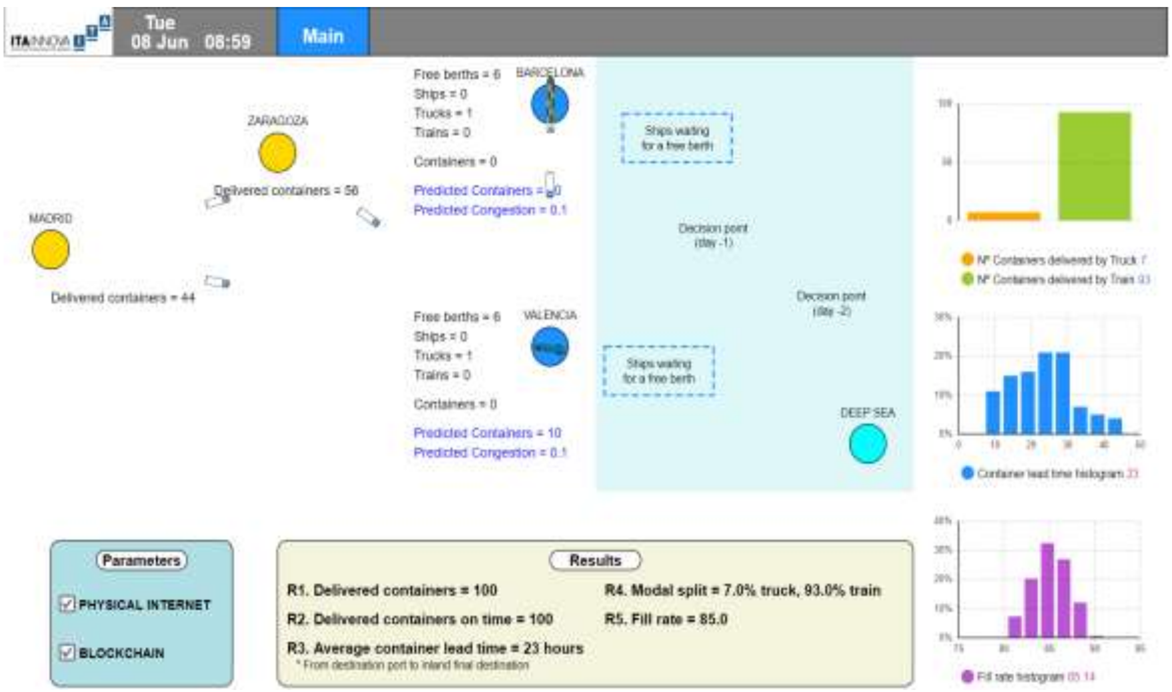

Figure 11 Multi-Agent Simulation overview

At a given time, vessels carrying containers depart from the deep sea. They have two decision points (day -2, day -1) as they approach the seaports, and can choose which one (Valencia and/or Barcelona) to go. Once the containers arrive at the port, they are unloaded.

On the other hand, there is a fleet of transports (trucks and trains) that run circular routes with a given schedule. When they arrive at one of the seaports, they load containers and transport them to their final destination (dry port).

Each agent in the model (nodes, vessels, transports, containers) is modelled by state charts that capture the actual process sequence of that agent. Communication between agents is done by messages, which allows

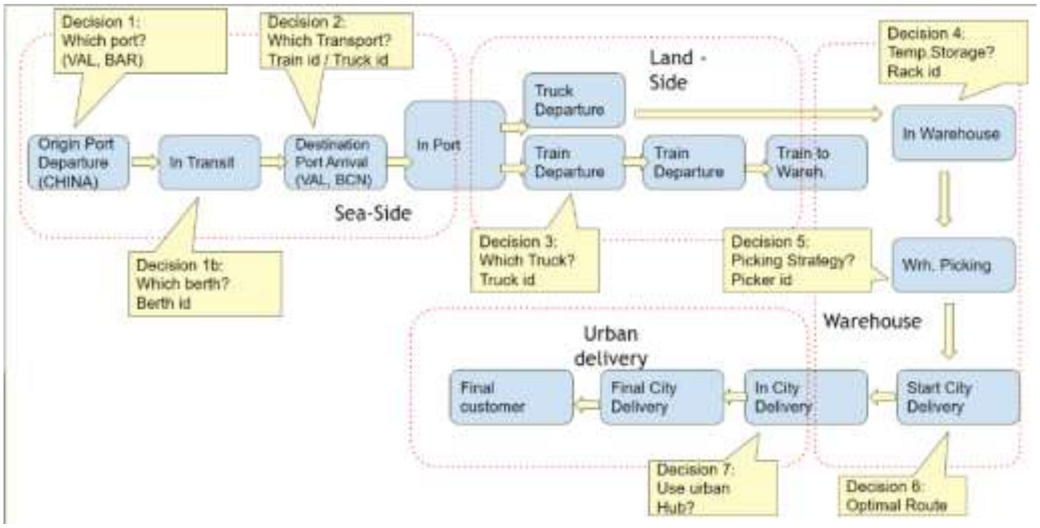

Figure 12 Detailed process flow modelled by the multi-agent simulation

triggering transitions that make an agent take a decision or move from one state to another.

During the simulation, the model allows the collection of statistics (numerical indicators, graphs, histograms) such as the number of containers delivered, how many containers have been delivered on time, the containers lead time, the fill rate of the transports or the modal split, among others. In addition, the model allows different scenarios to be parameterized, evaluating for example the impact of applying or not applying technologies such as blockchain in certain processes or considering the adoption of PI.

The Figure 12 depicts an overview of the process flow of the Physical Internet enabled supply chain considered within the PLANET Project. The operations depicted show a generic set of processes, from an infrastructure and connectivity perspective, at different operational levels that could be instantiated to specific scenarios with the LLs regarding the TEN-T network and global trade corridors. The Figure 12 shows diagrams with block elements representative of processes in which technologies such as IoT, AI and blockchain are considered for operational improvements. These include the synchro-modal nodes for the container auto route adaptation using variables for their capacity, cost, and level of service. The use of blockchain at ports (Valencia) and hinterlands for the use of real-time and forecasted information for the allocation of resources and execution of processes in a more pro-actively way.

5.1.5 Port call decision model

For a given liner shipping route, which ultimately can be seen as a sequence of port calls for a container ship a goal is to decide whether to call at all ports within a subset of the route ports or not. The hinterland transport can forward some to the containers to their hinterland destinations, the program minimizes the cost of the maritime, and hinterland transport as well as port handling and accounting for delays. In the LLs context, the question concerns COSCO's AEM1 route that is designed to call both Valencia and Barcelona ports. Figure 13 depicts this situation: a decision between two alternatives must be taken considering both port and hinterland congestion on the route to the customer. The decision variables capture if a specific cargo shipment (container) is discharged in Valencia or Barcelona. For example, x_{pc} where p resembles the port of discharge and c the container identification, which is further tied to a specific destination. Therefore, for any container c, $x_{bc}+x_{vc}=1$. Then a binary variable indicating whether a port will be called can be defined as y_p, that will be equal to 1 if at least one container is discharged there. The point of having a y parameter is to allow for port handling and vessel queueing costs of calling an additional port to be represented.

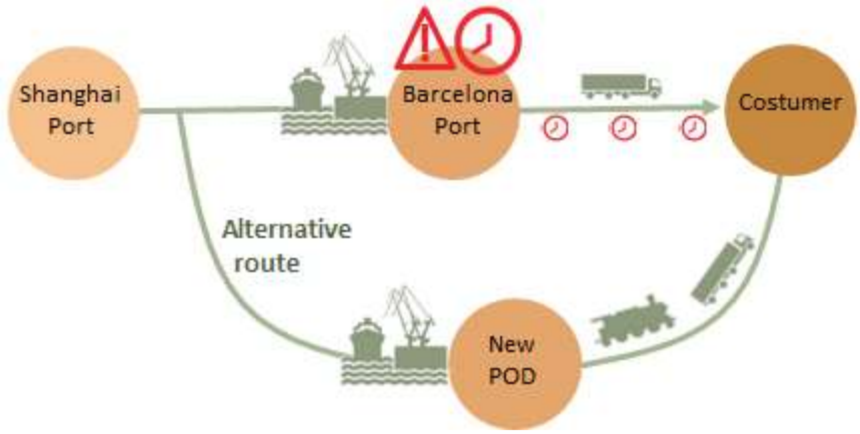

Figure 13 The real case motivating the port call decision customer model

In the below Figure 14, a simple implementation of the port call decision model is illustrated. The left column (light green) names the destination of each container. The y variable (first line below the colored section) reflects the main decision variable of the model, which captures which of the two ports the vessel should call. When equal to 1 the port is called, and when equal to zero the port is not called. Both colored columns on the top right capture the x decision variable, which indicates where each container is discharged (1 resembles the discharge location). The figure below captures how the solution of the program changes for different port call costs. On the left, the port call cost is low for both Barcelona and Valencia, and the algorithm decides to call both, also indicating where to discharge each container. In the instance in the middle, the call cost increases substantially, representing a large queue for both ports. In this instance the algorithm chooses to call only at the port of Valencia, as the hinterland connections are closer. The third instance (right) illustrated that the decision changes if the level of congestion at the two ports is not even, and a longer queue is observed at Valencia. The program then, decides to only visit the port of Barcelona.

	discharge port, x	
final destination	Barcelona	Valencia
Zaragoza	1	0
Madrid	0	1
Albacete	0	1
Zaragoza	1	0
Zaragoza	1	0
Madrid	0	1
Madrid	0	1
Valencia	0	1
Murcia	0	1
Barcelona	1	0
Call port, y	1	1
Call, LHS	100	100
Call, RHS	4	6
M	100	100
Call cost	0	0

	discharge port, x	
final destination	Barcelona	Valencia
Zaragoza	0	1
Madrid	0	1
Albacete	0	1
Zaragoza	0	1
Zaragoza	0	1
Madrid	0	1
Madrid	0	1
Valencia	0	1
Murcia	0	1
Barcelona	0	1
Call port, y	0	1
Call, LHS	0	100
Call, RHS	0	10
M	100	100
Call cost	2000	2000

	discharge port, x	
final destination	Barcelona	Valencia
Zaragoza	1	0
Madrid	1	0
Albacete	1	0
Zaragoza	1	0
Zaragoza	1	0
Madrid	1	0
Madrid	1	0
Valencia	1	0
Murcia	1	0
Barcelona	1	0
Call port, y	1	0
Call, LHS	100	0
Call, RHS	10	0
M	100	100
Call cost	100	5000

Figure 14 Port Call decision model - Comparison of different parameter settings

The congestion prediction models forecast 24 hours in advance the number of containers arriving the next day at Valencia Port. This model has been described in further detail in 3.3.2 as container flow prediction model.

5.2 AI enabled smart contract capability

The smart contract application was initially introduced in Ethereum which extended Bitcoin's baseline technology, creating the first programmable Blockchain and a featured scripting language that could automate tasks and allow apps to be built on top. Custom business rules could be enforced by a special kind of software program called smart contract and executed by a distributed computing environment, thus extending the reach of the system well beyond finance.

A Smart Contract can contain values, just like a program, that are stored in the blockchain, and the Smart Contract is the way to interact with these values (add, delete, or change any value). The actors of the blockchain network should agree on:

- How transactions and their data are represented on the blockchain
- The "if/when…then…" rules that govern those transactions

Finally, they should also explore all possible exceptions and define a framework for resolving disputes.

5.2.1 The AI enablement of smart contracts

The smart contracts bring trust in a network of untrusted participants and enable the integrity and transparency of the data stored in the blockchain, however, the liability of the data entering the system remains an issue. AI comes into play for enhancing the trustworthiness of the data.

AI-enabled smart contracts are proposed in PLANET for predicting the load of incoming pallets in a warehouse for the next days and automatically renting extra trucks or hiring personnel to manage the work. Warehouse operators can take advantage of the service to decrease time and costs and increase their efficiency by automating the procedures.

Part of the aim of this section is to determine a preliminary potential back-end implementation and integration of the predictive models with the blockchain, for potential future deployments of smart contracts, and their enablement within the EGTN PLANET platform. The smart contract applications aim to impact and bring further a technology integration value to the transport and logistics software components considered and outputted within the PLANET project. This integration at its core currently includes the capability to forecast warehouse pallets flow integrated with the blockchain, as depicted in the below Figure 15, in order to provide an enhanced transparency and therefore integrity to the data shared through the blockchain ledger to enable smart contracts.

The pallet flow forecasting models have been preliminary evaluated in this deliverable 2.9 to determine the load of pallet in a warehouse for the incoming days. The forecasted information provided, by the predictive models, within a suitable timeframe in advance could enable warehouse operators or decision makers to take more timely and accurate decisions to optimise resources regarding the allocation of trucks or additional personnel to handle the pallets more effectively. Such an improved allocation of resources in hiring additional trucks or personnel can impact the services in several aspects, for instance by decreasing time and costs, and by increasing efficiency when automating further procedures such as the signing of contracts required for the allocation of such resources.

The work presented in this section regarding smart contract is a work in progress in terms of identifying in a more specific way the required and available data resources and software components mainly for the AI based predictive models and blockchain, and their suitable integration. Other requirements that would be required to be specified in more detail include the required forecasted time frames. This and other unforeseen considerations from the project partners, based on their expertise, will be determined when the scenarios of the LLs are fully defined.

A first approach considered for the development of the smart contract application includes the below figure in which the forecasting module output functions as the input of the Hyperledger Fabric Blockchain application. To implement such a connection REST API would be required to be accessed within a client application. Within the client application an analysis of the forecasting algorithm will be carried out either in a manual way or perhaps in a more automated way. The analyses of the predicted information with the client application would depend directly on the specifics of the forecasted time series data provided and how ready this is for a user to be interpreted. It could be the case that additional statistics or additional time resolution adjustments might be required, for instance to adjust different levels of information abstractions and granularity. These additional analyses could vary for the different use cases scenarios.

The information gathered and interpreted further within the client application is outputted in a quantified form in a compatible format to initiate the smart contract application. Although the data that is used within a smart contract application is usually obtained from within the blockchain where the contract is deployed, in this project it is proposed to consider additional external data, as required, from the big data analytics forecasting models and related support services, provided in a secure and trusted form.

From this perspective the smart contract application is activated based on the data from the client application as depicted in the below Figure 15. The data would most likely be provided in the form of data instances in such a way that enables the evaluation of each of the *if-then* based rules that a smart contract is comprised, which could vary depending on the use cases or scenarios considered.

Depending on the complexity or the amount of the *if-then* based rules to be considered in the smart contracts further rule or tree-based machine learning models could be enabled. These types of models would be able to comprise and summarize the rules considered for a particular contract aiming to acquire additional resources required. The *if-then rule* based models would particularly be useful in the case further automation is required for scalability purposes of the smart contract applications, and for handling a possible increase of the needed data to evaluate the *if-then rules*. Also, in in the case the rules to consider within a contract or a set of contracts for a particular application grow exponentially. In this case a self-adaptive approach such as using a *rule-based* (or tree based) model could synthetize and prune off automatically the number of rules in case these are redundant and not relevant. In this way a mechanism for the contracts to automatically react and accommodate information variations within particular use case would be enabled.

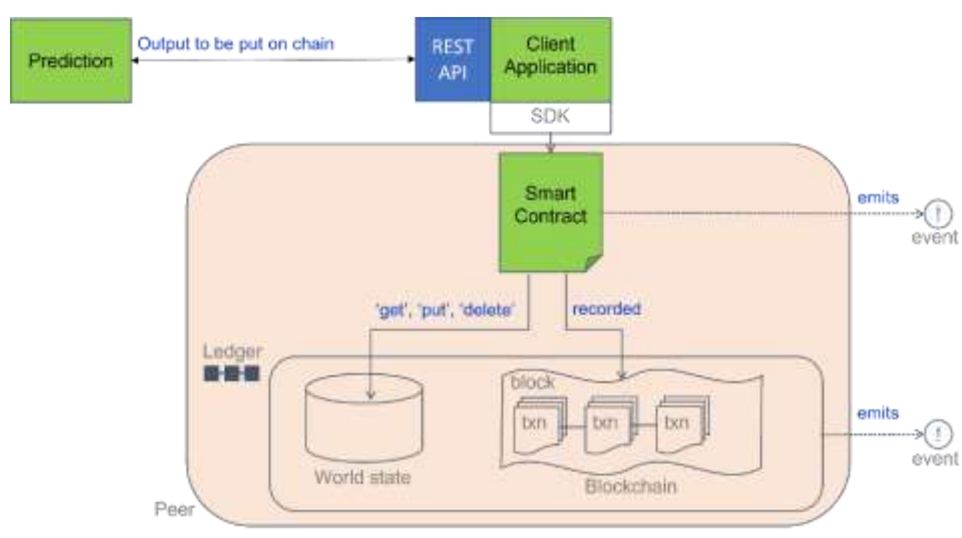

Figure 15 General pre-liminary implementation diagram of a smart contract application

After the *if-then* based rules are evaluated within the smart contracts, the application would output a state type output regarding the contract itself. These outputs or set of outputs are recorded in the blockchain ledger and database as depicted in the above Figure 15. The Blockchain technologies are a straightforward fit to handle the smart contracts information since it provides transparency and non-tampering of it, which is required by the stakeholder's collaboration, specially to provide decentralised services over the shared data.

The generation of the smart contracts and their execution when tested will aim to quantify usability of the specific solutions within the LLs, considering one of the main characteristics of smart contracts which is that they should be easy to use. Evaluations will aim also to include testing novel approaches in using machine learning based models, and their predictive outputs to handle information more effectively, focusing also on trust and privacy preservation and encoding the functionality needed accordingly to provide higher automated services on the EGTN PLANET platform.

5.3 Proposed interoperability of the PLANET predictive models

To overcome the challenges that an overloaded transportation network presents in terms of multiple bottlenecks within its nodes, it is required to determine further approaches for automation to allow information reach users and operators to change routes and allocate resources in a more proactively and timely manner. The previous section of this report it has been described the different identified uses of forecasting models for different applications such as the warehouse operations management. The forecasting model providing future arriving information regarding pallets or containers enables their better organization and allocation. Also enables ways to assign resources in more proactively ways to manage the warehouses more effectively. Provided with the various relevant data resources and cloud deployments for their accessibility, the predictive models in the PLANET project will be interconnected and tested as services for other applications such as the dynamic routing for the last mile delivery.

The predictive models need to be interconnected to enable more automated interoperability capabilities. A main interconnection of the models is to the IoT sensor-based streams of data, which is needed for the models' validation and subsequently to their continue usage by means of predicting future information on events, trends, or other relevant information. Other interconnections include software components, such as knowledge graphs, able to post process the forecasted information to output alerts, visualisations, recommendation, or other estimations that a user might need.

In a general way the future information issued by the models needs to be inputted to software components able to further process and integrate such an information, this by means of expert domain knowledge integrated in functions and relationships capable summarizing and comprising several relevant data streams of information. Several data sources and data types are considered across the LLs, for instance a data source includes GPS data which can enable delivery and carbon footprint estimations by aggregating it with other sources of data such as routes, railways, stations, and ports.

Once the AI models for prediction are validated and connected to more continuous data sources, they will require further connectivity to enable additional interactions as services within the PLANET EGTN platform from external requests. In the below Figure 16 it is depicted the general architecture connectivity proposed for the task 2.3 which aim to place the AI based predictive models as an element of a broader information system that enhances its capabilities to handle disruptions, traffic congestions and other unforeseen events that could impact its operability.

The interactions depicted in Figure 16 aims to overcome deficits of traditional and centralized supply chain and transportation networks, reducing risks in facing disruptions or bottlenecks, enabling more automated and transparent applications through AI and blockchain. These digital technologies can create various interconnections by using IoT [31] to gather and share real-time transportation operational information. A key challenge from the below diagram is their enablement of an AI based multidimensional and multi-data source, for the aggregation of information streams to build a more informative training set for the forecasting models. Such an aggregation of the data could also be applied to the outputs of the models to merge forecasted outputs and summarize the information in ways that is readable and meaningful for the user. This is an important capability to break down data silos within the transportation network, since data sources of information are held by more than one organization participant of the network, or member of the supply chain.

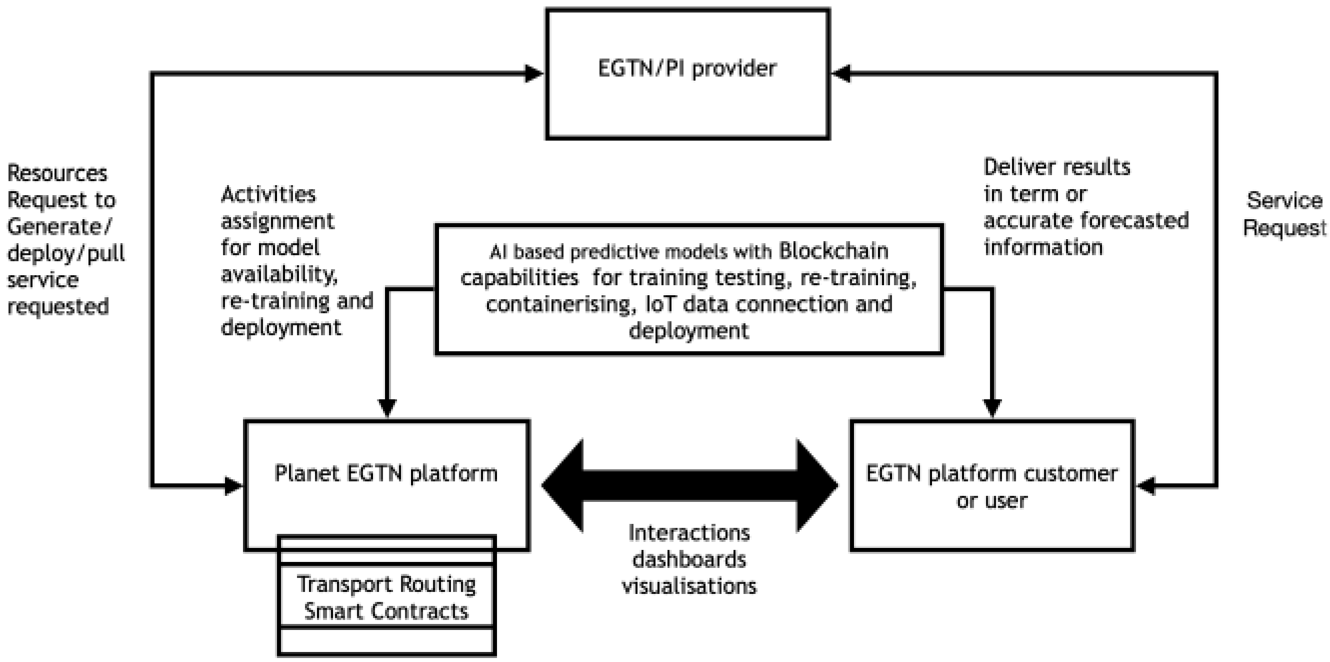

Figure 16 AI based forecasting models as services, actors, and interactions

Another capability to consider in the re-trainability of the models on the face of an environment that is constantly changing, and therefore updates and fine tuning of the models is not a rare event for them to remain in levels of accepted non-bias performance. Other approaches such as transfer learning remain as an option to consider for building based models that could be re-trained or fine-tunned as needed as the have the capability of predicting or forecasting two or more similar variables.

Tracing systems for supply chain applications using blockchain have been applied across driven information systems that are complex and integrated with other systems, such as in the transportation network and supply chain [32] [33][34], where the real-world social and economic challenges of existing systems are described [35]. This includes the geo-locations of resources and synchronizations of the steps required, and keeping up-to-date the information minimizing the human intervention that in many applications currently consumes a great deal of human effort[36].

5.4 Future work

There are several interdependencies across the PLANET project and within the WP2 required to continue the work described in this deliverable report. Part of this work includes the development of additional models and their further validation. Additional IoT data is also needed to finetune the parameters required for the current models to be deployed, and for which preliminary test and evaluations have been presented in this deliverable report. The models further developed will directly depend on the requirements of the LLs.

Moreover, the development and performance in testing and validation of the models will be dependant primarily on the data available and the measures chosen or required to quantify such a performance. This is in case additional performance measures are needed besides the ones used in this deliverable.

To develop and evaluate further the models and enable additional services additional data sources, ideally in the form of real-time series, will be required from the IoT sensors and devices. Such IoT sources of data ideally deployed across the LLs will provide close to real applications' samples of relevant events from the scenarios, once they are fully defined and the IoT infrastructure is put in place.

There are additional interdependencies in the form of expert domain knowledge across project partners, part of the living labs, that are required. This knowledge is needed to help define alignments of the predictive models' outputs in the right format and direct them in such a way that are effectively made available to the user. To reach the availability a set of criteria and information from additional analyses such as the multi-actor and multi-criteria applied within the LLs and use cases are required. These analyses are also relevant for the predictive models continuous and further calibrations and fine tunings.

Regarding the corridor route optimization, the implementations of the use cases described in section 3.1 will be considered and adapted as required in collaboration with project partner collaborators. The validation of such implementation will also depend on the availability of the real-time IoT data made accessible by the relevant project partners and LLs business collaborators. This is since the IoT real-time data is particularly relevant for the route optimisation service implementation.

The implementations regarding warehouse applications described in section 3.2 and 5.2 will be considered for further development with project partners/ particularly the smart contracts application which could be extended depending on the resources available which includes data and expert domain knowledge, to confirm and validate their suitability for the LLs future use cases and scenarios or future additional deployments in the EGTN platform.

The transportation models application in subtask ST2.3.3 will be based on the development of software applications and components such as forecasting models and IoT timeseries data analysis modules. This subtask will be implemented in the next deliverable D2.10. One of the main elements to determine in order to take steps forward on these applications is considering the definitions of the macro and micro data models, as well as the actual trip lengths and distribution/topology of the nodes. Future work regarding a containerization of the above applications and their deployment within the EGTN platform will be carried out across several iteration as described in the section 3.4.

6 Conclusions

In collaboration with PLANET project partners, the benefits that AI technologies can provide to enhancing the logistics network decision making processes and further improving the transportation of goods has been conveyed. This representation of improved transportation emphasises the value of employing AI based machine learning approaches to streamline and automate processes and facilitate a more decentralised data driven approach. This is achieved by using predictive models that are compatible with multivariate and interoperability analyses and mechanisms. The multivariate analyses enable a more robust forecasted information by using two or more variables. The interoperability mechanism effectively interconnects data streams for applications such as the optimisation routing and smart contract services. The multivariate interoperability can contribute to further advance the Physical Internet by introducing collaborative aspects for re-routing and shareability of information across blockchains.

The models developed and presented in this deliverable demonstrate the feasibility of the LSTM network model to accurately predict the time series variables from the data provided regarding the volume flows of containers at a seaport and pallets in a warehouse. A core characteristic for the predictive models is their level of accuracy, such as reported for the LSTM model in respect of the standard econometric approach, showing the enablement of machine learning based AI solutions to handle big data. These models when validated further using IoT data could be packaged and integrated with the EGTN platform in a standardized way to enable their usage within other services on the platform or as a stand-alone model.

Despite describing how the AI based data solutions built in this deliverable could bring value beyond the state-of-the-art within the current LLs descriptions, this remains a work in progress until such an LLs description is finalised. The PLANET forecasting models of containers and pallets can be used as a congestion predictor at seaports and warehouses. These models work on solving the real-world problems and challenges presented by the Living Labs. The AI enabled smart contract service will also use our warehouse flow forecast model as one of its key forecasting components and it aligns directly with the objectives presented for the need for more efficient warehouse operations.

In LLs IBM has been in regular communication to solidify their use cases and help them understand the importance of exploring analytics services to enhance future operations. Together we have agreed on working towards forecasting of ETA, carbon footprint and volume flow. Currently we are working with LLs partners to identify additional data sources that would enable us to better train our models on real world data.

The content presented in this deliverable re-affirms that the creation of an EGTN community of operators is key to allow effective data driven advanced solutions. Application of AI will enable a PI environment that can exploit decentralised data sources for making automated and timely decisions that would allow dynamic adaptation in transportation modes, facilitate dynamic resource allocation, and overall increase automation in decision making in key logistic network processes. In the next deliverable D2.10 ,and final release in this work stream, beyond the cloud deployment of the generated logistics services, it will also further move forward the current state of the art under investigation.

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Annex I: Overview of LSTM (long short-term memory)

In this annex, we seek to aid the understanding of the machine learning model used in this deliverable, by leveraging an excellent informative blog by Christopher Olah for LSTM.

Long short-term memory (LSTM) networks are a special kind of recurrent neural networks (RNNs).

Recurrent neural networks address the issue of making prediction according to a sequence of inputs rather than only by looking at a single one. They are networks with loops in them, allowing information to persist.

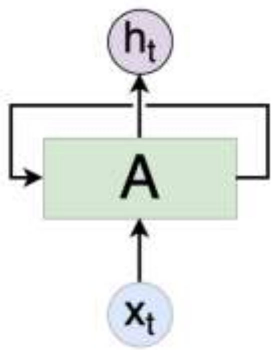

Figure 17 - Neural Network section

In Figure 17, a section of a neural network, A, looks at some input and outputs at value h_t. A loop allows information to be passed from one step of the network to the next. These loops make recurrent neural networks seem quite complex. However, upon further analysis, it turns out that they are not very different from an ordinary feedforward neural network. A recurrent neural network can be thought of as xmultiple copies of the same network, each passing a message to a successor. Consider what happens in Figure 18 when a loop is unrolled:

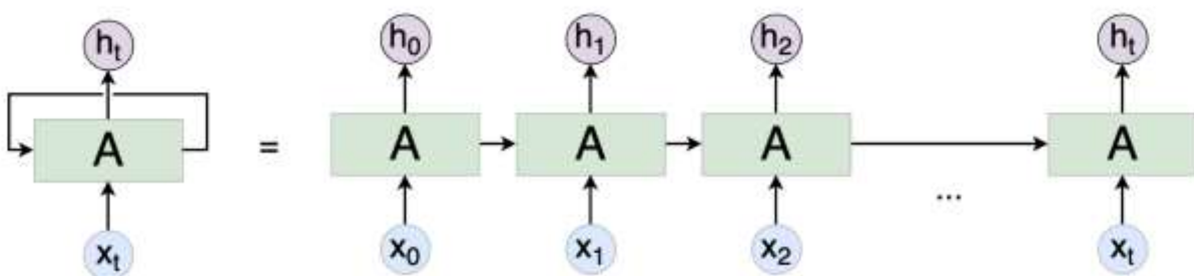

Figure 18 - Neural Network Loop

Long Short-Term Memory networks are capable of learning long-term dependencies and are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is inherent to their design. All recurrent neural networks have the form of a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer Figure 19.

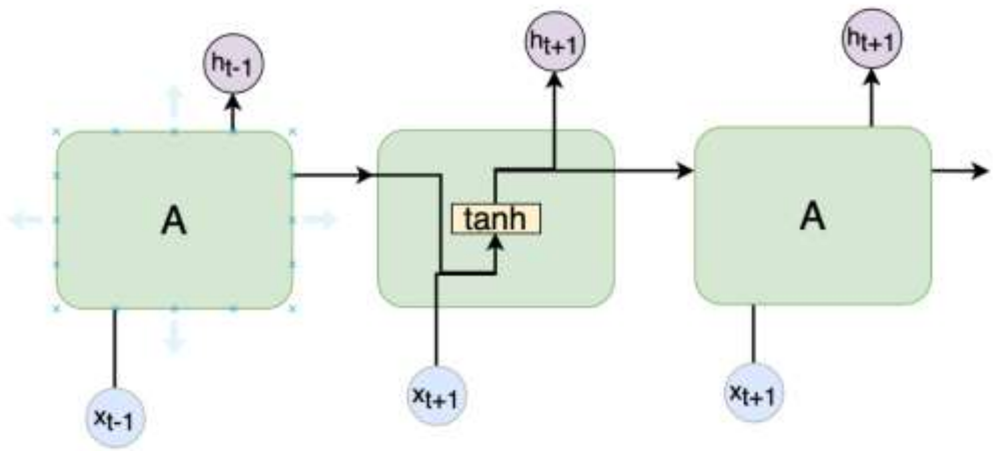

Figure 19 - Tanh Layer

LSTMs also have this chain-like structure, but the repeating module has a different structure. Instead of having a single neural network layer, there are four interacting layers.

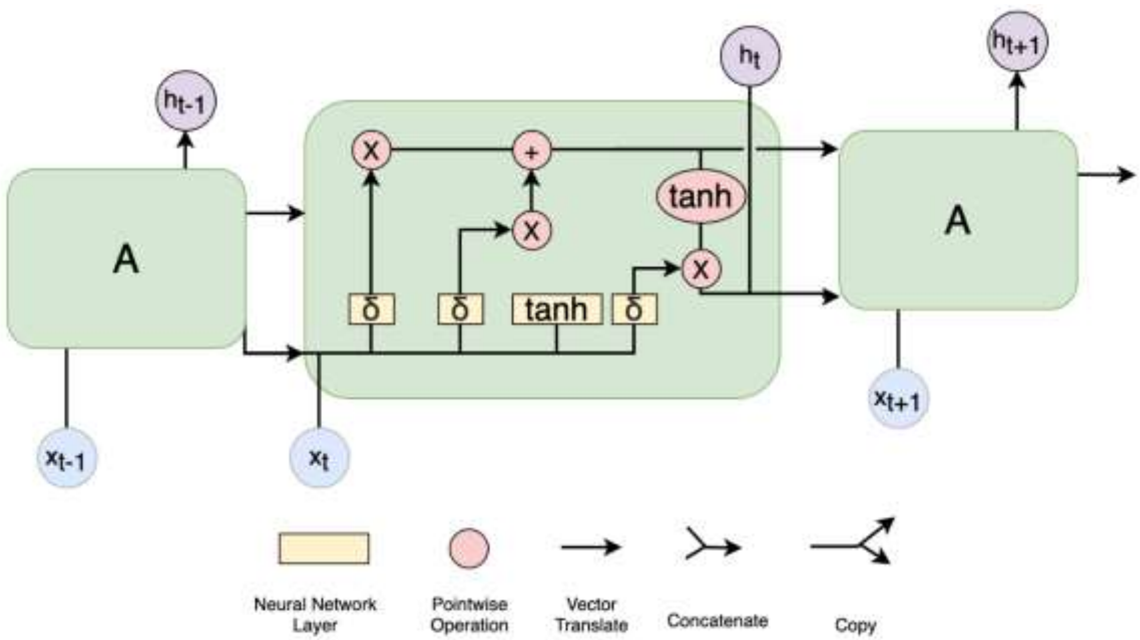

Figure 20 - Detailed LSTM

In Figure 20, each line carries an entire vector, from the output of one node to the inputs of others. The pink circles represent pointwise operations, like vector addition, while the yellow boxes are learned neural network layers. Lines merging denote concatenation, while a line forking denotes its content being copied and the copies going to different locations.

Annex II: Data provided and used to build preliminary predictive forecasting models of incoming flow of container and pallets

Variable name
Container Number
Container Size Type
Cargo Nature Code
Estimated Berth Arrival
Container Last Discharge Voyage Code
BL POL Port English Name
Container Last POD Port Code
Container Last Hub Code
FND City Local Name
Container Empty Return Location

Annex Table 0.1 Variables provided within the data for container flow prediction

Variable
DATE
CUSTOMER
PROCESS
SUBPROCESS
QUANTITY

Annex Table 0.2 Variables provided within the data for pallet forecasting