AI Based Freight Volume Forecasting

2023

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AI BASED FREIGHT VOLUME FORECASTING

2023

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

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The PLANET Project

ABOUT PLANET PROJECT

PLANET project aims at boosting the EU's leadership in global logistics flows **by effectively interconnecting infrastructure with cost considerations, geopolitical developments**, as well as **current and emerging transport modes and technological solutions**, enabling an EU-Global network that ensures equitable inclusivity of all participants, increase the prosperity of nations, preserve the environment and enhance Citizens quality of life.

The realization of this vision in PLANET is branded as the EGTN (Integrated Green EU-Global T&L Network).

Physical Internet concepts in combination with disruptive technologies such as **Internet of Things (IoT)** and **Blockchain** will be used by PLANET to move towards more optimal and efficient transport and logistics (T&L).

Accelerating the collaborative transition towards the Physical Internet in the context of the new emerging trade routes

OBJECTIVES

Project Start	01/06/2021
EU Budget	€ 7 097 670
Instrument	MG-2-9-2019
Duration	36 months
Consortium	33 partners from 14 countries

1. Generate a Simulation Capability for the assessment of the expected impact of new trade routes, national strategies and innovations on the TEN-T corridors and European logistics operations.
2. Built an Open cloud-based ICT Infrastructure facilitating the implementation of EGTNs.
3. Employ 3 Living Labs to facilitate experimentation and testbeds for project's solutions.
4. Formalize an EU Roadmap along with a Capacity Building effort purposed to accelerate EGTN realisation, closely aligned with prominent T&L blockchain initiatives and the ALICE Physical Internet working groups.
5. Ensure wide Dissemination supported by a clear Commercialisation Strategy and Policy recommendations.

Preface

The Transportation and Logistics (T&L) enterprise is in the initial phase of an exciting journey but somewhat dauting transformation to be able to cope with a more and more fast-paced world (A. Agatic). With many contextual challenges in managing optimally the transportation processes and providing the right user experiences to stakeholders, including consumers, this transformation will certainly impact T&L business and organization stakeholders striving to lower the risk of this journey toward the Physical Internet (PI) paradigm by balancing the agility and flexibility required to achieve improved transportation that is more sustainable. Such a balance is most certainly to be achieved by embracing higher levels of automation with the help of data driven technologies such as Artificial Intelligence (AI) (A. B. Anil). Equally relevant is the ability to tap into new sources of data and to acquire and share data with T&L ecosystems stakeholders, a fundamental capability of supply chain cross-industries platforms (I. Kollia) (L. Xu).

This paper looks at analysing and describing the relevance in using AI based forecasting models to predict freight volume and their usage in the transport and logistic domain towards the development of PI. Also, the paper highlights the more immediate applicability of the AI based forecasting models across different use cases within the PLANET project in predicting containers as a standalone forecast demand service. The service can also be used, within other scenarios considered in PLLANET such as, for budgeting improvement purposes, and purchasing transportation services and warehouse capacity planning.

Moreover, accurate AI based demand forecast can be used in several ways to reduce cost by minimising disruptions, such as during the last global COVID pandemic events, that continue to reshape many consumer markets (S. Gupta). For instance, the markets were re-shaped when shippers had to wait 110 days to have freight volume collected as opposed to pre-pandemic times of only 45 days.

Having accurate information on how the freight volume might change in the future is relevant to anticipate the many ways in which the transportation processes might be able to be geared to avoid getting stuck. As well as minimizing transportation disruptions, cost and satisfying delivery customer requirements and experiences when these unexpected changes in flow of freight volume arise.

For the above-described applications the demand service can be integrated and provide accurate forecasts, with the additional services developed within the PLANET project. This integration enables interoperability across services to provide higher value user information by leveraging accurate forecasts. For instance, short-medium forecasts' information could function as input parameters to trigger smart contracts to formally close agreements among stakeholders. Also, having freight volume available can improve the planning in the last mile delivery phase, to determine optimally better transport corridor routes and allocate several resources required more optimally such as number of transportation units used and drivers to routes of different levels of complexity.

The integration of the demand forecast can also take place to boost its performance in forecasting the volume itself by integrating it with a knowledge graph service. The knowledge graph service can increase the information level (A. Utku) of input signal of the demand forecast service by using data from different sources to carry out even more accurate forecasts.

Moreover, the forecasted demand can be used as an input parameter for PI simulation tools to determine future additional requirements and tailor further distribution transportation plans, for instance, regarding capacity allocation in warehouses and distribution centres.

The usage of accurate demand forecasts enables stakeholder teams to further integrate their applications and simplify processes to reduce costs across all stages of the supply chain. This by means of standardizing the information used across the services considered. The services operation includes many areas of application such as planning and collaboration within activities for booking documentation management, schedule maintenance and operations (I. Barclay).

There are four pillars that support the need of the further development of transport networks and logistics towards a more integrated framework, such as the one that the PI proposes. The first pillar supports the need for a transportation network that is robust enough to the continuous and rapidly evolving business challenges and market opportunities. The second pillar supports the need of considering these opportunities and challenges to optimise and use them as a response for future uncertainties and investments. Customer satisfaction has never been so important, therefore low-cost automation of as many steps of the freight process as possible is desirable.

The third pillar supports the need of bringing down silos to collaborate with industry ecosystems and stakeholders. The fourth pillar supports the requirement of creating secure, resilient, and responsive business models and supportive digital infrastructure for future needs, such as for sustainability, sharing data insights and decisions across units.

Executive Summary

The services described in this white paper addresses warehouse collaboration analytics, for which AI based volume forecasting models were developed and evaluated to determine future amounts of containers arriving to a warehouse and being transported across corridors. Such models aim to help warehouse and transport operators to predict changes in the movement of freight volume and its arrival to discharge ports, warehouses, or distribution centres. This with the objective of enabling forward planning and timely readiness by reducing the risk of wasting resources, for the required management of the arriving volume. Also, with the objective to potentially reduce costs by reducing the short notice hiring and allocation of warehouse, port resources. Moreover, the service can enable a more automated, transparent, and accountable orchestration for quote-to-cash, demand, and supply planning. And finally, the service can contribute to the integration between the warehouse operations and the last-mile delivery distribution phase and determine future bottle neck congestion with the transportation journey. These capabilities can provide high value to freight forward and logistic operators including the ones in the sea and dry and inland waterway ports, freight villages and terminal. The service could help managing co-modalities and traffic flows.

Current transport and logistic technology solutions to enable IT management are often proprietary and incompatible with other transport systems. Platforms are redefining models across businesses within the T&L sector (and other industries) by empowering suppliers to interact directly with consumers without irrelevant intermediaries. Part of the intent of these platforms is to curate proprietary data diligently and securely and re-engineer workflows to use AI based cognitive capabilities.

The demand service described in this paper was designed with open-source standards and protocols in mind. This to endure the interoperability with other EGTN services developed in the PLANET project which operated with an analytics and optimisation framework that is specific to transportation systems, found at scale over local, regional, and global geographies. As the scale becomes larger so does the complexity of the transportation system, from this perspective IT can support such a scaled transportation with complex management structures by sharing information in various formats (S, Handanga) and at various times to allow a more optimal freight transportation.

The demand forecast service described in this paper addresses the use cases provided by the Living Lab (LL) partners in the project. The demand forecast service's objectives are described as follows:

- Use of forecasted output information regarding number of containers to reduce costs of the allocated required transportation resources warehouses, distribution canters and discharge ports.
- Use of forecasted information to reduce cost when allocating operational (personnel) resources at warehouses, distribution canters and discharge ports.
- Use of forecasted information of freight volume travelling from discharge ports to their destination to help plan better routes by avoiding highly congested corridors.

Beyond the applicability and performance evaluation of the service within the LLs of the PLANET project, this paper also looks at describing the technical challenges when it comes to handling the historical time series data (H. Beydoun) (N. Ponnamperuma) of freight volume available within the project to set it ready for analysis and enable higher performance in forecasting such a freight volume using machine learning (I. Paliari) based AI predictive models.

AI based forecasting services of freight volume

AI within the transportation and logistics domain

The impact of AI is expected to continue, increasing in a significant manner its usage within logistic related solutions towards enabling PI systems such as "self-driving" supply chains.

There are several areas within the transportation industry in which AI can help resolve customer problems. These include the constantly highly variable demand and capacity, availability of labour able to handle sudden increases of freight volume. Also helping in reducing high costs in operating transport vehicles and infrastructure, AI can help as well in reducing the lack of awareness into future supply chain disruptions and asset integrity, among others.

Overall, AI provides the capability of considering additional information acquired from transportation processes by means of technologies such as Internet of Things (IoT) to make more informed and appropriate decisions based on the data itself and pre-defined rules that are compliant of such processes (S. El-Gendy). In this way AI functions as a technology that can provide more sophisticated standardized interoperability amongst stakeholders to provide further reliability and resilience for transportation.

Having available future information regarding events in the transportation process provides the operator with the ability to rapidly identify and resolve issues to meet the service requirements needed. To enable this ability in responding it is required that the predictions are accurate enough and are provided when they are required. In this paper we describe the implementation and development and testing of AI based forecasting models that are able to predict freight volume in the form of containers (C. H. Yang) (Z. Guo), to enable the demand forecast service within the EGTN platform of the PLANET project.

An increase in the accuracy of the forecasting models at scale is capable of bringing considerable gains in reducing cost in transportation of unexpected excess in volume arriving to the warehouse. Also, it can reduce costs by enabling better planning in distributing capacity across the warehouse (S. Chen). For the case of forecasting freight volume in the form of containers it is possible to increase the accuracy and predictability for optimal route planning allowing drastic savings in fuel consumption and fleet management to avoid bottlenecks and disruption in the transportation process.

The flexible deployment in the PLANET EGTN of the AI services, such as the demand service, enables their usage across different datasets and services (B. Qiao). This allows the demand forecast service to add value towards different applications by interoperating with other services. This enablement creates expert systems able to allow users shorter reaction times by providing them with higher value forecasted and real-time visualisations and potential answers to their questions to make more informed decisions.

The forecast of freight volume can impact further the decision making by enabling this across logistic nodes to dynamically identify better routes based on different criteria such as transport capacity, node congestion or other timetable related parameters.

Business Benefits

As shows *Figure 1*, AI has the potential of fulfilling a considerable number of transport and logistic customer needs and create an enhanced customer experience of reliability in the transportation process. Additionally, AI can generate by means of enhanced automation an environment of trust, higher value, and accountability.

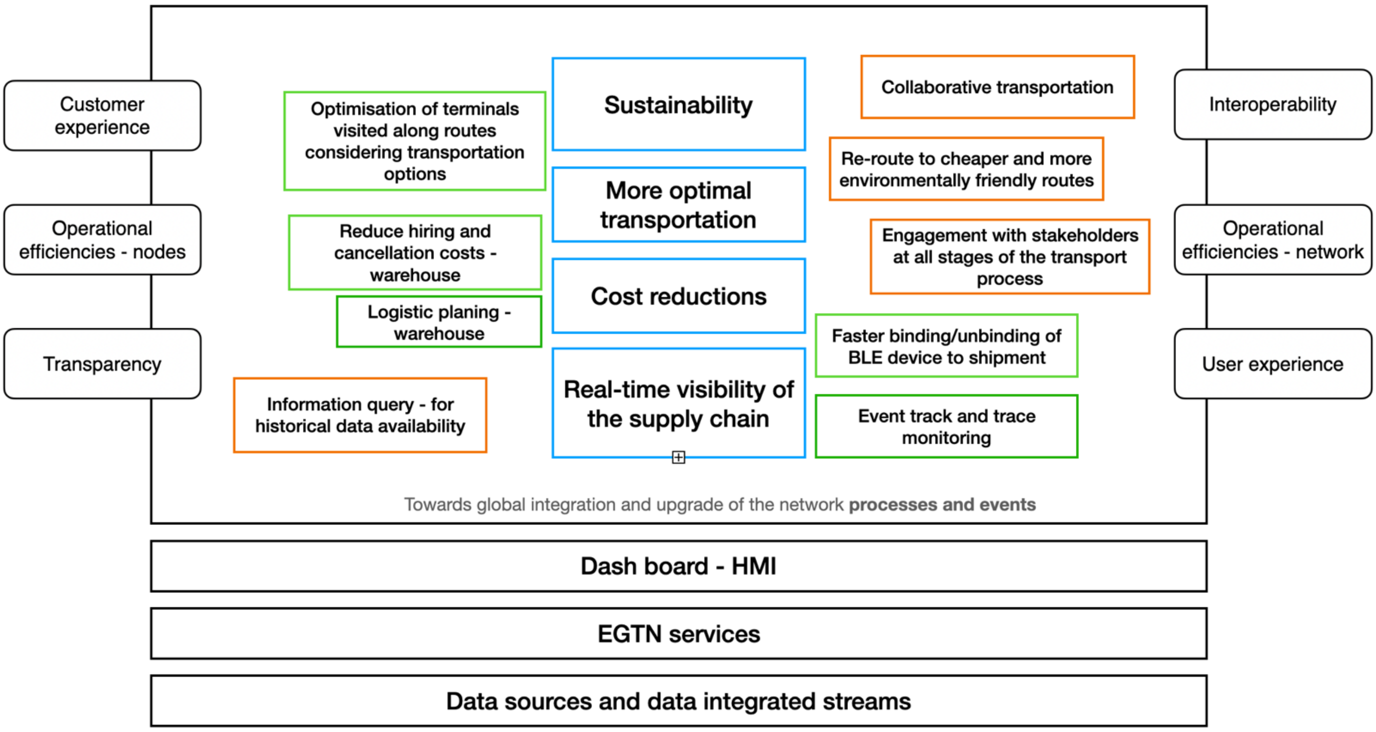

Figure 1: PLANET EGTN operational layers and business benefits of using AI when interoperating with PI services

The AI based forecasting model can effectively predict the future demand of freight volume in terms of number of containers, but also based on any other volume variable that might have a different volume unit. The forecasting models enable an increased visibility on future arrivals of cargo, which can provide enhanced capabilities of forward planning across the transportation and logistics stakeholders, and of user experience. For instance, the model can enable further the calculation and optimisation of the spare capacity in warehouses so they can be considered for routing cargo, which avoids additional potentially longer re-routing of transport units. Another core business benefit in using forecasted information regarding volume is the enablement for low-cost and timely allocated transportation and warehouse capacity resources required to optimally handle unexpected arriving quantities of freight volume.

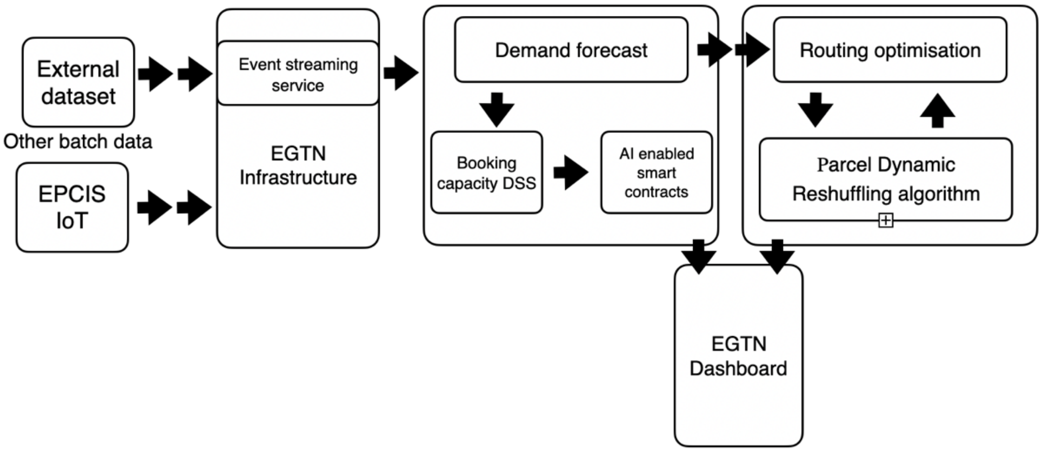

Figure 2: Example of interoperability of demand forecast service

The major business benefits of AI arguably appear when enabling interoperability capabilities in our case between the demand service and the other services that could leverage the forecasted information as an input parameter within the EGTN platform. *Figure 2* shows an example of interoperability of demand forecast service.

These services include the smart contracts to further automate warehouse operations including digital documentation sharing. Also, further integration of operations between warehouse and the last-mile delivery by enabling more optimal planning of low-cost schedules. The low-cost schedules planned in the last mile delivery can improve performance in the operations across different aspects and reduce considerably costs since this is considered the most expensive phase of the transportation phase. The aspects that could be better optimised in the last mile delivery phase include, higher performance across a higher number of delivery nodes. A more fine-tuned planning can also impact in reducing the distance travelled and time used to deliver the packages to its final destination. The fined-tuned planning can also help reduce the overall number of (particularly petrol-based) vehicles used. These improvements in the delivery operations have not only a direct impact in reducing the cost of drivers and fuel, but also have an impact in reducing the CO_2 emissions.

The reduction of the CO_2 emissions goes even further when thanks to the forecasted demand and further fine-tunned planning the overall user experience is improved reducing the number of complaints and re-shipments, and re-delivery of products.

The benefits of forecasting freight volume effectively have additional advantages impacting a range of business outcomes such as when the irregular activities can be determined based on outliers contained (unexpected sharp increase or decrease) in the level of forecasted volume.

The detection of sudden and unexpected changes in freight volume can also help predict freight congestion at ports avoiding or at least minimizing bottle necks. This enables new ways of generating value from the continuous and fast-growing data in volume and enables new ways of making business by opening different channels of interaction with users and customers.

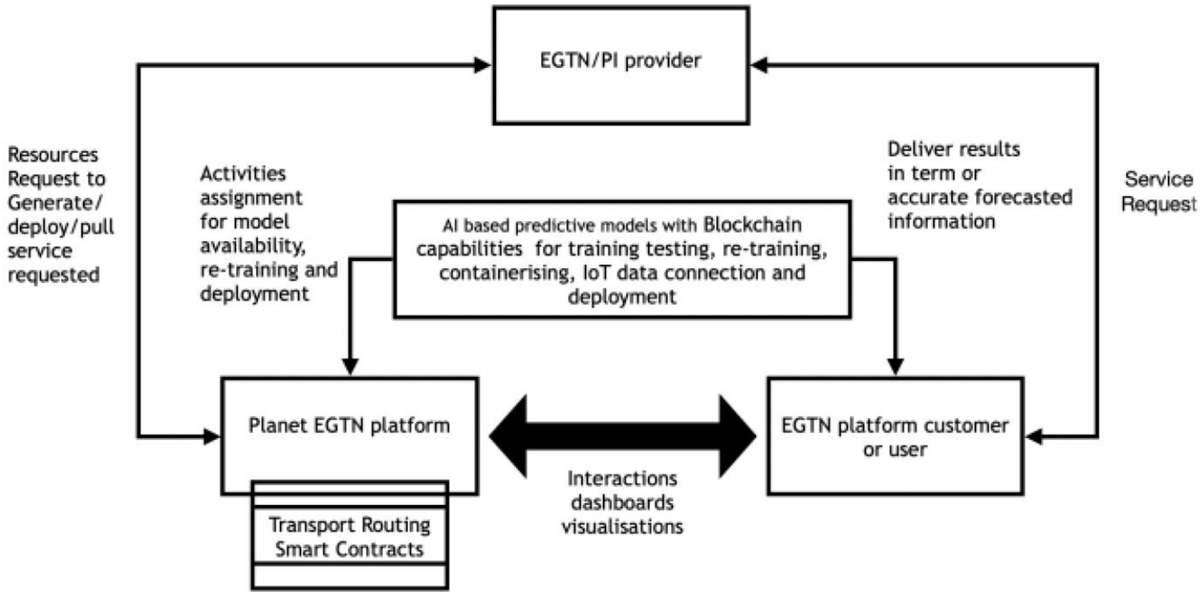

Figure 3: Value provided to business users and industry.

The above *Figure 3* depicts different interaction channels amongst stakeholder across the T&L industry. This figure helps describe an example of how a future scenario could operate by providing increased visibility on future arrivals of freight volume to provide enhanced capabilities of forward planning.

In order to achieve this, a set of core stakeholders must be considered, such as the EGTN/PI provider which effectively would be responsible for providing other stakeholders access to a PI platform and to its services. The EGTN/PI provider could be a governmental body or other type of transport authority that is accountable for the flow of cargo across regions. The RGTN/PI provider is allocated between the EGTN platform (such as the one developed in PLANET) and the customer/user of the services that such a platform provides. Once the EGTN/PI provider grants access to the customer (or user) this has direct access to the EGTN platform and services which include visualisations from historical and most updated IoT data for monitoring assets as well as higher value processed information such as future levels of freight volume. Having forecasted information on freight volume arriving to a particular port could minimize costs in the moving excess of volume from such a port. This by means of planning a syncrhomodal more effective approach of transportation. A more fine-tuned planning could also allow choosing users for more optimal transport modalities but also more optimal routes to take towards inland distribution centres. Once the volume has been transported further towards the inland and has arrived at distribution centres or warehouses that are closer to the urban area further planning can be carried out. This planning includes schedule and route optimisation which is integrated to the last mile delivery phase operations by means of the forecasted information on freight volume available. Also in this way, the user would have access to the latest real-time updated relevant information that also can contribute to reduce costs in the transportation process.

Challenges

There are still several relevant challenges to consider for enabling AI within the transport and logistics domain in a cost-effective manner. For instance, the AI systems usually require expansive bandwidth to enable the predictive models or specialised fog hardware to take advantage of all the AI capabilities in terms of performance, this usually requires in many cases determining the initial amount of computational resources to allow scalability, needing a considerable investment for several T&L stakeholders.

The cost and time of training the models is also a considerable monetary investment. This is particularly so when an initial deployment of a training solution is to be done and requires considerable work for integration purposes which could impact the business efficiency while such an integration finalises. Other operational challenges include the maintenance of infrastructure which includes continuously re-training the predictive models to keep them running within acceptable performance thresholds.

A key challenge is to manage cost to keep such a performance within acceptable ranges in order to fulfil the organizations' original expectations in terms of costs and return on investment when using AI based forecasting models to acquire the value in information that stakeholders in transport and logistics require. With this aim it is key that the EGTN platform enables ease in the deployment of AI to minimise cost and ensure investment. Moreover, the EGTN platform must ensure to take full advantage of the data sources available across all the transportation phases, from IoT and other external sources, so the AI usage is effective and provides an increased value that is expected to help address business problems.

Another key challenge is to try to balance the level computing resources required to for instance, in our case, enable the recurrent neural network (RNN) applications, particularly when this is done at scale. The AI based applications need to be carefully designed to avoid costs becoming prohibitive in the pursuit of high forecasting performance that is so needed and which would prevent AI investment from being translated into benefits. But a fine-tuned balance needs to be determined to also avoid significant errors in the forecast which would certainly incur significant and perhaps highly cost errors for organizations when making less-informed decisions.

From this perspective the PLANET EGTN platform can reduce cost when offering cloud and data resources to minimize the total cost of using AI based forecasting models. The platform considers the cost of labour and infrastructure required to gather the data and make it available to train and re-train models.

There are various other technological approaches that can possibly contribute to overcoming the challenge associated with high costs, these include the usage of transfer learning and foundation models. The foundation models can help in a number of ways to save resources such as when these are pre-trained and used on unlabelled datasets, including for timeseries data that is used for forecasting purposes. More and more foundation models are becoming an essential ingredient and emerging point of control within AI workflows, establishing a new paradigm for AI based models, including for forecasting development.

Deep learning is considered already to be one of the fundamental technologies underpinning the fourth industrial revolution.

This new paradigm of development can reduce the AI development cycle by half, saving time in model training, hyper-parameter optimisation testing and deployment, but might still require considerable specific domain knowledge depending on the task of data available to further optimally fine tune them. There is still work to do, when using foundation models to save cost with regards to resources required for deployment, this includes storage costs, governance, explainability and running the applications within acceptable performance thresholds. For this reason as a next step in developing AI further for it to deliver even faster business value, it is required to continue the conversation regarding ideas, client use cases and research.

In this paper the use of machine learning Long Short-Term Memory (LSTM) models is used to enable forecasting models core for the enablement of the demand forecast service that is capable of accurately enough forecasting freight volume. The model can be trained and re-train rapidly in the order of minutes, not requiring large amounts of computational resources such as dedicated graphic processor units (GPUs). The forecasting models were built using datasets provided by PLANET project partners across living labs and their performance evaluated across standard measurements.

Implementation Methodology

The core component for this application is the AI based model for the forecasting of containers for which an implementation and deployment as a service was carried out as one of the outputs of the PLANET project.

The forecasting of containers was carried out using historical data provided by project partners regarding containers being transported from a discharge port in Valencia to the city of Madrid. A main characteristic of this data provided is its sparsity, which is the result of a significant number of dates for which containers did not travel throughout the Valencia-Madrid corridor. The number of containers is the only data variable considered which makes it challenging to carry out a forecast, since there are not additional variables to consider that could help compensate for the high levels of sparsity and help in boosting the performance of the models.

Therefore, the implementation of the IBM forecasting demand service within PLANET was carried out with the aim of it being able to handle sparse data, which in any case is a common scenario when forecasting containers, at least within the data provided within the project. The containers forecasting models were built in a univariate way, this is that only the historical data variable of transported volume was used to carry out the forecasting. Univariate predictive modelling has its advantages as it facilitates the deployment, re-trainability, usage, and overall maintenance of the forecasting model.

The methodology of implementation of the model included pre-processing steps of the data available. The pre-processing steps are key transformations of the data that enable further improvement in performance of the forecasting models. The steps are described below.

The first step in the process was to select only the variable that represented the number of containers transported across the different years considered within the dataset. This variable corresponding to the historical number of containers transported is partitioned in training and testing sets across different time spans considered and shown in *Table 1* below. For the building and evaluation of the LSTM models considered for the forecasts. After a process of feature extraction was carried out for both, the training and testing sets separately. The features were extracted from the time stamp by using the indexes for week, month, quarter, and day of the week number. More features were extracted by calculating the rolling means from windows of size 3, 5, 7.

After, the additional features were extracted from the training and testing sets, separately. These were scaled to constrain their values within a range of 0 to 1. For the purposes of boosting the performance of the forecasts the training of the LSTM models was carried out in the following way.

The following step consisted in generating a set of the independent variables (predictors) and dependent variables (target) for both the training set and testing set. This step in the process was carried out separately for the training and testing partitions. The set of independent variables was constructed using batches of two multidimensional data instances that had a time stamp immediately before their corresponding target variable (container quantity to predict). As a result, 3-dimensional vectors that consisted of two multidimensional data instances per target were generated.

For the case of the training set, the time stamp of the target variable in question could be shifted backwards in the timestamp to guide the learning of the predictive model across different data patterns. The shifting of the timestamp of the target variable led to different training performances (A. Botchkarev). It was found through experiments that the shifting of the time stamp of the target variable led to a forecasted signal that had a considerable closer shape-pattern to the one of the actual (ground truth) number of containers, as is shown in the below ***¡Error! No se encuentra el origen de la referencia.***. It is important to highlight that this shifting of the timestamps can only be done within the training set and not within the testing set. For the case of the testing set the predictors or independent variables must remain with a time stamp of one day before the time stamp of their corresponding target or dependent variable. This is because, for the test set, there is no point in evaluating the forecasting performance for containers that have already arrived at their set destination, in this case the city of Madrid. In this configuration the model receives input data for the same day that is predicting for, so this is only possible for the training phase.

In the *Figure 4* below it is shown the training and testing sets plotted in colour blue and orange respectively. The time spans of these training and testing sets corresponds to the time ranges enlisted in the first row of *Table 1* below. The model built and evaluated using these training and test sets provided a performance quantification of 0.5443 using the MASE performance measure, and when using the shifting label approach during the training phase of the model. For the training of this model, it was used the maximum of data instances for the training set that would allow to have a testing set with one hundred data instances. This model built with the maximum of data instances for training available, provides the best performance in comparison to other models that were trained and tested using smaller training sets. But primarily the models show a considerable improved performance when the model is trained using the shifting label approach.

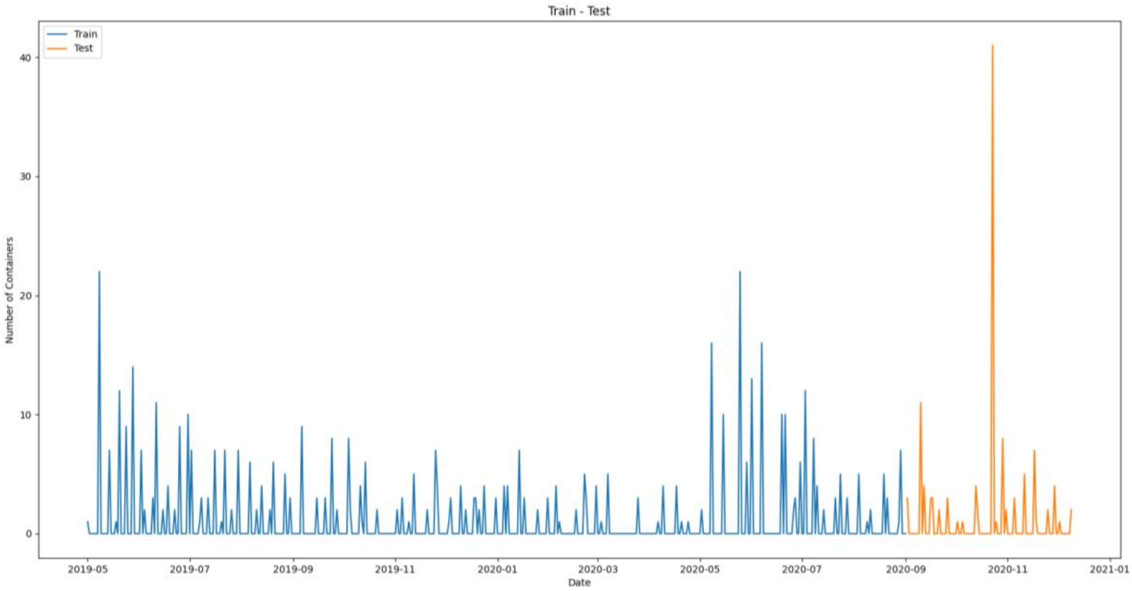

Figure 4: Train - Test

The below *Figure 5* shows a visual comparison of the performance of the forecasting models when the timestamp shifting step is not used during the training phase. As it can be seen, the forecasting model performance is rather low as the forecasted signal generated does not match the original signal of the test set that represents the actual number of containers arriving to the city of Madrid.

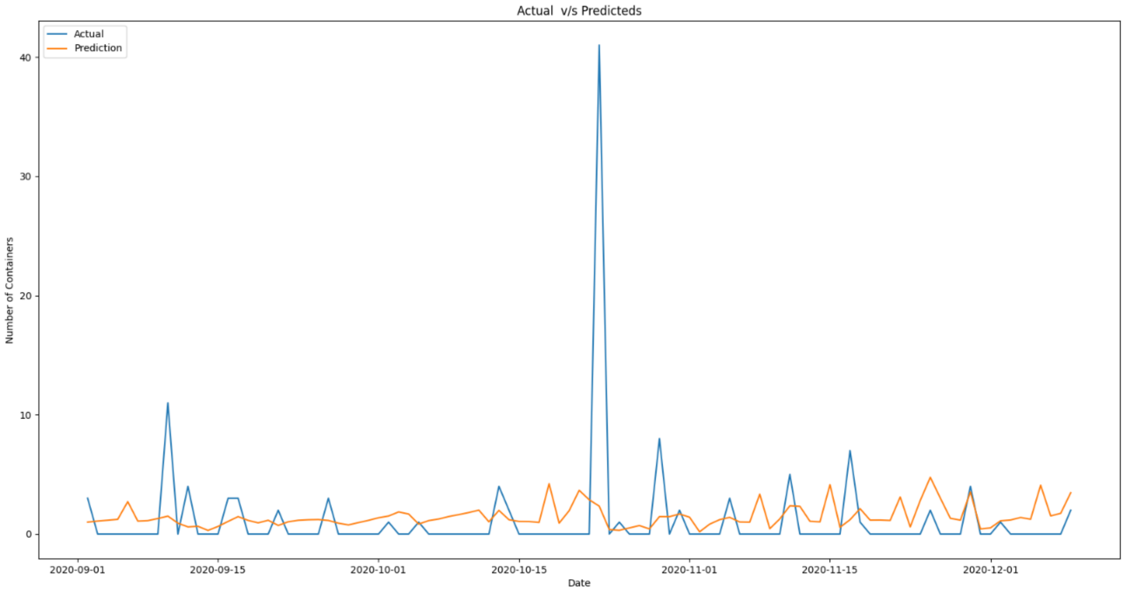

Figure 5: Actual vs Predicteds

In the below *Figure 6* shows the forecasted output of the forecasting model when the timestamp shifting step is carried out during the training phase. As it can be clearly seen from this Figure 6 the performance of the LSTM forecasting model is considerably improved when the timestamp shifting proposed approach described above in this section.

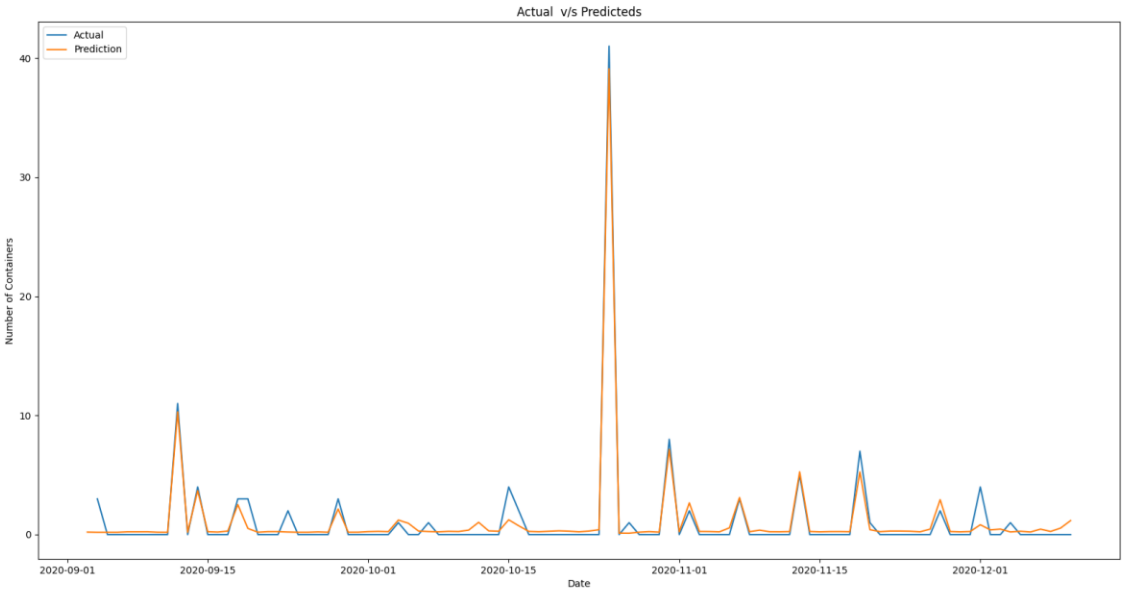

Figure 6: Actual vs Predicteds: Results for additional time spans

The *Table 1* shows the additional couple of time spans considered for two additional experiments in forecasting containers. These two additional time spans (B-C) in both cases are shorter than the one used in the above-described example and that corresponds to the first in the below table (A). For these two smaller training sets and then not using the shifting time stamp approach MASE performances of 1.0493 and 1.3181 were obtained.

Training period	Forecasting Horizon (days)	MAE	MSE	RMSE	MASE
A - [2019/05/01, 2020/09/01]	100	2.0665	38.6007	6.2129	0.5443
B - [2019/05/01, 2019/10/01]	100	1.0277	3.5512	1.8844	1.0493
C - [2019/05/01, 2020/01/01]	100	0.9219	3.446	1.8563	1.3181

Table 1. Results for additional training time spans

The current results obtained suggests that the more data used from the dataset provided the more accurate the forecasting models tend to be. Moreover, the usage of the sifting time stamp boost considerably the MASE performance of the forecasting models. In all the experiment carried out a time horizon of 100 days was considered.

Conclusions

The IBM forecasting demand services developed in planet were inspired and guided by the PI and EGTN concepts. The forecasting demand services developed within the PLANET project were customized to the unique challenges and requirements associated with the T&L industry and their associated supply chains. This was particularly achieved by considering the requirements of the LLs project partners that were provided within the project. The forecasting demand service was prototyped to advance and develop re-usable services for the EGTN in the real-world. Also following the guiding principles of the EGTN platform architecture blueprint built within the PLANET project.

This paper described and presented a shifting timestamp approach to improve the forecast performance of the number of containers transported from China to Spain. The approach controls the input data fed to the model, during its training process, by shifting the timestamp of the data instances that is used as a dependent variable. With this shift-control approach proposed it is possible to train the models more effectively, in the presence of sparse data, by correlating different historical levels of volume patterns to future ones that are non-sparse and have “higher-quality” information, allowing the model to forecast the volumes with higher performance and overcome the severe sparsity (“lower-quality” information) present in the dataset used. The models built forecast the freight volume in a univariate way; only one single data variable is used which corresponds to historical data regarding the number of containers transported to Madrid.

The proposed training approach is used in conjunction with LSTM artificial neural networks (V. Gosasang) whose training is enabled in a univariate way to be carried out rapidly, and not requiring large additional cloud computational resources such as GPUs. These characteristics facilitated the deployment, usage, and maintenance of the forecasting models built as transport and logistic services within the EGTN platform developed as part of the Planet project for the further integration and development of the future global PI (M. Fazili).

The forecast services with the above-mentioned characteristics can enable an increased visibility on the future arrival of cargo and further equip the transportation and logistics stakeholders with capabilities of forward planning and timely readiness in the allocation of capacity and transportation resources required to handle unexpected arriving volume at lower costs.

Four standard measures for the quantification of error of the forecasting models were evaluated. These include the MAE which indicates the average error in the number of containers forecasted, and which remains overall low for the time spans considered from *Table 1*. The MASE error was a measurement used to quantify the performance of the model’s forecasts in comparison to the naïve model. This error measure must be above 1 to indicate a poor performance of the forecasting model. In order to increase the performance of the model an approach to pre-process the data by shifting the timestamp was carried out during the training process. This shifting timestamp approach was able to boost the performance of the forecasting models particularly for the cases in which more data instances were used.

The higher performance of the forecasts enabled by the training approach proposed can reduce costs by allowing a more automated orchestration of warehouse operations and their integration when planning the scheduling of transportation units within the last-mile delivery distribution phase.

Machine learning and deep learning-based AI holds the key to unleashing the full potential of data. AI enhances data exploration capabilities of users equipping them with better decision-making skills and helping groups of stakeholders find answers to questions they didn’t even consider before asking in order to address better the problems at hand. AI is a competitive advantage and any stakeholder that does not adopt it will get left behind.

A transformation of the T&L sector towards the PI is supported by exponential technologies such as AI, automation, blockchain and IoT by enabling stakeholders and organizations to re-engineer workflows, leverage vast amounts of data and create platform-centric business models and maybe emerge as an incumbent disruptor in the T&L and supply chain industries.

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About PLANET

PLANET addresses the challenges of assessing the impact of emerging global trade corridors on the TEN-T network and ensuring effective integration of the European to the Global Network by focusing in two key R&D pillars:

- A Geo-economics approach, modelling and specifying the dynamics of new trade routes and their impacts on logistics infrastructure & operations, with specific reference to TEN-T;
- An EU-Global network enablement through disruptive concepts and technologies (IoT, Blockchain and PI, 5G, 3D printing, autonomous vehicles /automation, hyperloop) which can shape its future and address its shortcomings, aligned to the DTLF concept of a federated network of T&L platforms.

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