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Predicting container intermodal transport arrival times: An approach based on IoT data

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ABSTRACT

The maritime container transport industry faces substantial complexity due to the involvement of numerous stakeholders and the handling of massive volumes of both container and related data. Ensuring the traceability and security of transported goods is a challenge that shipping companies and freight forwarders face every day on behalf of their end customers, the owners of the goods being transported. The use of IoT devices generates a huge amount of data about the goods, the container and its environment that needs to be processed and analysed. Therefore, to address this challenge, we conducted research on leveraging the insights offered by the IoT to gain a better understanding of the dynamics within the supply chain at the container level and all along its path through different stakeholders. We proposed an original service based on machine learning algorithms to focus on providing accurate estimates of the Expected Time of Arrival from door to door.

1. Introduction

The usage of marine standardized containers has evolved into the core of intermodal freight transportation in supply chains as globalization accelerates. Hence, the 2020 United Nations' Handbook of Statistics [1] states that "in 2019, 811 millions TEUs of containers were handled in ports worldwide. World container port throughput grew by 2 percent between 2018 and 2019". Such an intensive worldwide transportation of containers is not without flaws as routes tend to be shared by more and more carrier ships. A number of unexpected events can occur and can cause some traffic difficulties resulting sometimes in worldwide transportation delays. As a symptom, congestion can indeed be regularly observed in harbors. A very acute example is the Ever Given 400 meters-long ship that blocked the Suez Canal for 6 days in March 2021 provoking several billions of dollars loss [2]. It created disruption all along the supply chain, time delays and port congestion. As a consequence, it highlighted the need for more tracking and visibility. Solution described here intends to tackle such issue.

Intermodal supply chains are complex as they involve several stakeholders from the initial client sending products to the carrier and the shipper. To ensure a proper quality of delivery, the senders require to be able to inform their clients and make sure that containers and parcels are received on-time, or that notifications for delays could be provided. In the current state, Automatic Identification System (AIS) solutions are the most used: based on the identifier of a ship, a range of data is made available to the user, including the departure and arrival locations, the speed and draught of the vessel or the forecast of the route of the ship. However, while such tool allows a thorough analysis of unique routes of specific ships, it does not directly help to trace specific shipments at the container level. Those shipments are indeed rather identified by their senders by their initial departure and final arrival locations with no a priori information on the route and ships they will be brought on. They are also usually taken in charge by one or several other partners collaborating in the complex supply chain.

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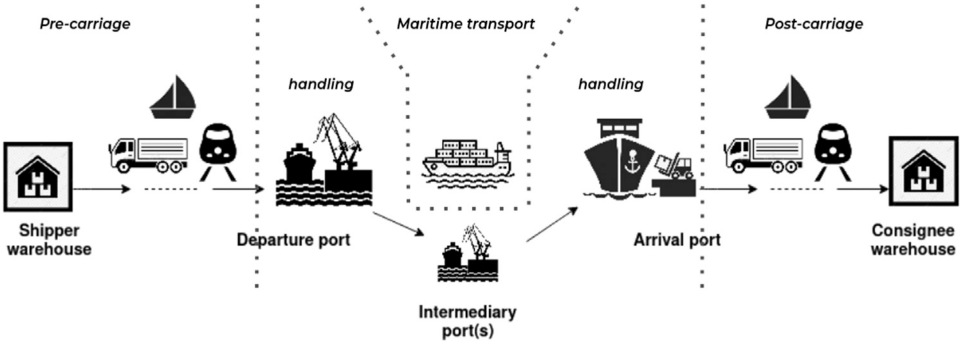

Fig. 1. Shipment schematic profile.

Therefore, Internet of Things (IoT) can help throw light on this complex route depicted here in Fig. 1: the path schema manages to expose the all as a network with edges and nodes even if it cannot capture the versatility that characterizes such a path. Indeed, by packing a range of sensors in a unique small tracker directly put on a container, it generates inherently related data.

The IoT data is independent from the various actors, culture of a complex supply chain, and closely attached to physical container. It achieves its intermodal original philosophy and raison d'être also in the numerical dimension. Taking advantage of this new opportunity, we propose here to tackle the following question: **how can IoT data from tracker devices on intermodal containers be leveraged to accurately predict their overall time to arrival ?** This paper aims at proposing an solution to estimate the arrival time of containers from door to door.

After having depicted the state of the art on container arrival time prediction, method will be detailed to collect and process trackers data in 3.1. Based on this container inherent data, a learning method that combines two different models, each focusing on distinct time horizon, to predict dynamically containers' Estimated Time of Arrival (ETA) will be detailed in 3.2. After discussing the first results in 4, several perspectives will be discussed such as ways to enrich the collected data in 5.

2. State of the art

A tremendous amount of research has been produced to deal with time of arrival estimation (ETA) as it provides relevant support to decision making in various fields: public transportation, freight logistics, resource allocation and supply chain management. It becomes especially significant as transportation processes get more digitized and consequently produce huge amount of data.

As it will be highlighted in this section, the research focus regarding maritime container is on port to port shipping although a significant part of the journey may take place in land, both for logistic manoeuvre: in warehouse, on the dock or any logistic platform and for transportation by truck, train or barge. In the following, we distinguish the different works already carried out according to the transport sections they address; maritime transportation, manoeuvres and land transportation. Indeed, that is also what is worth noting: it is segmented whereas we will argue the work presented intend to address the overall transport chain.

2.1. Maritime ETA calculation

The ships set off from a port with containers on board. This can be for long, uninterrupted journeys such as the transatlantic ones, or they could be sailing from port to port in the smaller space of the North Sea. If one follows the container and not the ship, it may change carriers several times before reaching its port of destination as shown in Fig. 1. It may be unloaded and then reloaded onto a new ship at an intermediate port. This make the all shipment hard to monitor through different information systems.

When restricted to the specific field of maritime transport, the publications are numerous but the most common data source on which solutions are built upon is AIS data as mentioned by Yang et al. [3]. A collection of data informing on the situation of a ship and issued by the ship itself and then gathered and distributed by various operators.

It is mostly about predicting trajectories and then arrival times. Alessandrini et al. [4] is the most notable example of such attempts: it exploits common algorithms borrowed to graph theory to establish optimal movement pattern for ship motion based on AIS data and long-range identification and tracking (LRIT) an international system that make ships report regularly their position to their flag administration. Its use case is bounded by the Mediterranean sea. Whereas in Tu et al. [5], several classical machine learning algorithms are benchmarked on a massive amount of AIS data to establish a model focusing on ships motion model but from which ETA is derived almost immediately. Similar examples can be listed [6–8]. Although they can differ a little with techniques used it is the same thought process. Establishing trajectory for most and then deriving an ETA from it for some using the same data resources.

Though most often it fails to get away from proofs of concept and to establish general models. Above all, it does not reach the scale of interest here: the container scale. Indeed, for its overall trip to reach its destination, even from port to port, the container changes taxi several time, and not necessarily according to strict and omniscient schedules despite effort that gave rise to standard in maritime transportation industry [9]. Efforts on the research side have also been made around the concept of physical internet described in [10]. It pushes for a global and optimized organization of logistic networks. Though there is still a long way to go, as the incentives for different parties to share information are not manifest: it is well depicted in [11]. IoT data could take its share; once again, by nature closely attached to its physical entity make it shares its inherent intermodal characteristic.

2.2. Dock manoeuvre

For container terminal yard, literature is also prolific. Bierwirth and Meisel [12] exposes works made around berth allocation problem and quay crane scheduling dedicated to container in logistic hub. However, nothing fall close from the time of arrival topic. Nonetheless even if they do not intend to address directly ETA, it often revolves around. Time is often a variable of the objective function to minimize. Though the overall stock is considered rather than the individual container. Moorthy and Teo [13] proposes a framework to address such berth allocation problem a combinatorial one they solve with graph theory tools with constraint in space and time: solution is then evaluated, among other indicators, regarding time delays.

Legato and Mazza [14] examines this question of berth scheduling from the viewpoint of classical queuing theory and proposes simulation models enabling assessing the performance resource allocation policies or capacity changes. Where as Nishimura et al. [15] was an early bird to use genetic algorithms minimizing the total service time of incoming ships at berth considered as a whole.

Quoted paper relates here to the common berth allocation problem. Though the effort is the same regardless of the hub type;

- Rail: Boysen et al. [16] this paper reviews container processing methods in railway yards. However, this is mainly a matter of schedule optimization, and the time variable only appears in the objective function to be optimized, as in [17].
- Road with truck: Vahdani and Zandieh [18] is a prominent example among other, that compares meta-heuristics including machine learning ones in performances and efficiency for trucks scheduling in cross-dock systems. Always looking from total operation time perspective, it discusses developing multiple objective decision.
- Aircraft: for which the focus is on planes schedules [19].
- Ship that is largely discussed elsewhere in this section.

Even so, there are some slight nuances that could be declined according to the volumes involved and cross modal type.

To find the literature that addresses the problem at the container level, it is possible to turn to container stowage problem. It is about optimizing the container stowage process with factors that characterize their size, type, weight, and their purpose. Wang et al. [20] use linear programming tools to calculate the optimal loading plan for container on a ship.

2.3. On land shipping

Beyond interchange platforms for trucks and trains, here the situation is quite different: it is certainly possible to rely on certain areas of research related to general transportation like common public bus arrival time problem. Choudhary et al. [21] provides a detailed snapshot of the state of research in this area. To mention one that echoes our search for time of arrival estimation, B. Anil Kumar and Vanajakshi [22] mixes a machine learning approach, a kNN classifier with a more traditional or at least proven one; a derived Kalman filter to predict time of arrival at next stop for city bus. Sakhare and Vanajakshi [23] fits in well with the spirit of what we want to do here, since it takes advantage of data directly linked to the bus in near-real time.

There are some implementation perspectives for the rail freight industry; one can certainly mention the initiative of the association Rail Net Europe [24]. It is backed by European Union and pushing for implementing new solutions and especially ETAs for European rail freight network. It is not well covered in the literature, it can nevertheless be noted the proximity of the work intention of Prokhorchenko et al. [25] with the present paper even if its scope is smaller. Indeed its focal point is on the cargo and its future after a freight train dispatch; after analysing what characterizes trains flows it explores neural network possibilities to predict section time of arrival.

For an overall perspective on land transportation, apparently, there is not much related to container shipping that has been explored. The quantities involved the complexity and the divergent interest of different actors as already mentioned for maritime portion probably make it hard to build reliable information systems and therefore hard to access data. That being said, the efforts of Saoud and Bellabdaoui [26] can still be mentioned. It aims to develop a framework using Zachman one as fundamental structure to facilitate horizontal collaboration between the different actors in the road transport sector by accommodating disparities.

Modal shifts that are coming with Chinese infrastructure projects across Eurasia might change the game and raise the interest of collaboration. A whole section of their project “Belt and Road Initiative”, announced in 2013, aims to connect China with Western Europe by land through the development of the rail network. It is already effective for some portions and its implementation will continue in the coming decade.

2.4. Analysis and positioning

The format of this section on previous works emphasizes that everything in container shipping is segmented. It is surely conditioned by the data available. The various papers mentioned above explored in depth distinct spectrums of container transportation but the aggregation is proving difficult in practice.

Brochado et al. [27] can be cited for its attempt to aggregate and harmonize a set of logistics data from various perspectives, with IoT as the cornerstone of this ambition. The IoT allows tracking the container throughout its intermodal journey—it forms the connecting link. They place a piece of hardware on the container to gather relevant data and propose a framework to integrate

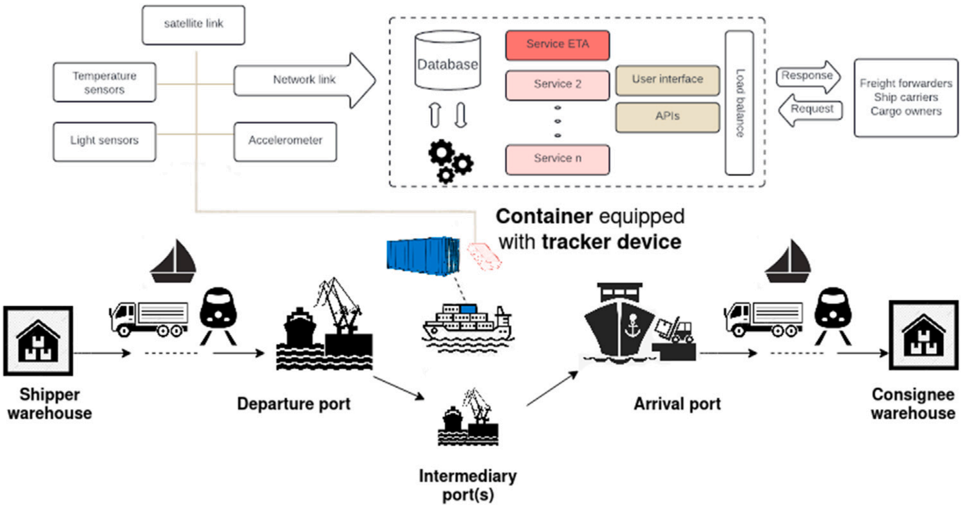

Fig. 2. Holistic overview of intermodal container tracking: physical and data-driven pathways.

information from various stakeholders. This data is then used to optimize and analyse transport routes through the deployment of operational research algorithms. The study focuses on the Port of Sines and relies on Portugal's national logistics digital platform for implementation. Another one, Lyu et al. [28] again relies on IoT to track intermodal containers and proposes a middleware approach to aggregate data from mobile cellular networks and satellite sources. However, the focus is on data sent by the IoT, which goes through different channels, with no perspective to integrate exogenous data. Muñuzuri et al. [29] describe another attempt to follow the container on its intermodal path, to associate the container to the train or vessel they are carried by and thus access to the associated data. IoT again enables that using its sensors and embedded algorithms for detecting transshipments and incidents. This worked focused on the port of Seville in Spain.

Therefore not a lot of literature addresses the problem both at the container level and all along its route. Here is an attempt to achieve this intermodal ETA calculation thanks to IoT data. This will be conducted taking advantage of both insight provided by inherent data attached to the container thanks to IoT and surrounding heterogeneous data. It is intended, iteration by iteration, to apprehend more abstract data to refine this ETA as well as the journey conditions.

Even if they can differ a little from our goal, for papers cited earlier, it is worth noting that most of the techniques used are machine learning ones. The more recent, the more manifest. To be convinced, it is possible to refer again to Abdi and Amrit [30]. Here also our models will be borrowed from the machine learning literature.

3. Proposal: Constructing an ETA for intermodal transportation container with attached data

With predictive ETAs, stakeholders can anticipate delays or disruptions and adjust their operations accordingly. For instance, shippers can better allocate resources, freight forwarders can optimize routing, and carriers can mitigate congestion or reassign assets. This leads to more informed and timely decision-making throughout the supply chain.

Beyond that, the ETA we propose aims to demonstrate that it is possible to overcome the segmentation imposed by the intermodal nature of container transport thanks to IoT. The last can offer an unified view of the container's location and expected arrival times, which can bridge the communication gaps between different parties in the intermodal chain, who are not necessarily inclined to share their data, as noted in the literature review.

3.1. An IoT architecture producing data

A fleet of IoT devices attached to containers travelling the globe feeds data to a database. Each device checks for available mobile networks (2G, 3G, 4G) to send the accumulated data from different sensors. When a connection to the network is established — when approaching the coast with the condition electromagnetic waves can escape the ship's hold — the device offloads the buffered data to a database (as briefly depicted in Fig. 3). However, if the device cannot reach the network, such as when the container is at sea or inside the ship's hold, it conserves battery life by reducing the frequency of network checks. This ensures energy efficiency. Once the device reconnects to the telecommunication infrastructure, it resumes higher frequency checks and sends the stored data. The corresponding schematic view is shown in Fig. 2 with a simple description of the data path from the hardware attached to the container to transport stakeholders.

The backbone of this database depicted in Fig. 3 is the Event table, which is the entry point for the various sendings of the devices to the database, and that allows the shipments, outlined in Fig. 1 to be constructed. It means they punctuate a segment, section of a global shipment route, in addition to marking its beginning or end for particular events.

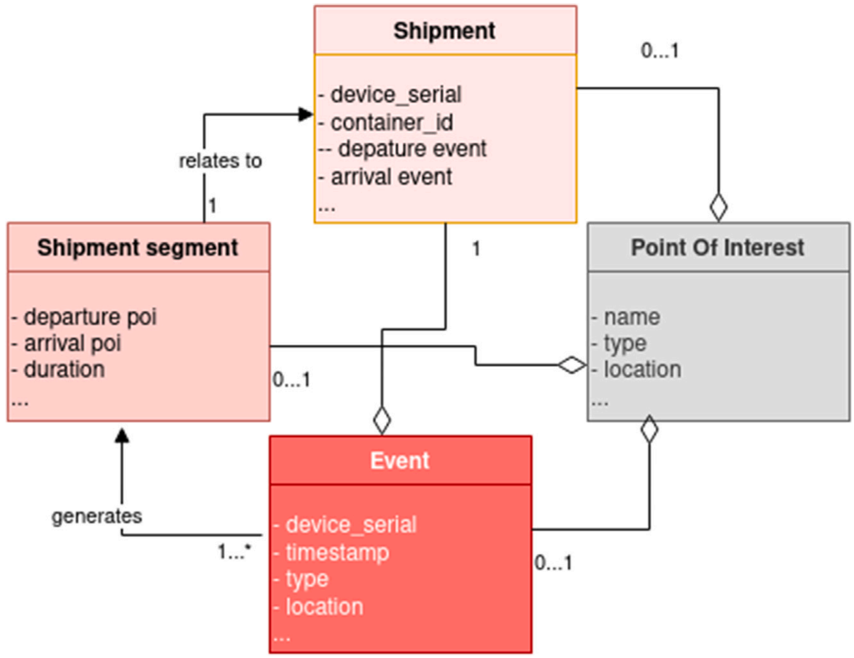

Fig. 3. Relational database schema.

Event: Punctual occurrence of special circumstances detected and communicated by the hardware. It is time-stamped and localized. Below is a non-exhaustive typology of the events that make up the database:

- 'START UP': device is turned on
- 'FASTEN': device is set down to the container
- 'UNFASTEN': device is removed from the container door
- 'OPEN': device notices a container door opening
- 'CLOSE': device notices a container door closing
- 'CRANE': device notices a container has been loaded or unloaded from a ship
- 'SHOCK': device notices a container has undergone a sudden movement, possibly a shock
- 'MOVE_BEGIN': device notices movement after a given period of inert time
- 'MOVE_END': device has not noticed movement for a given period of time after a MOVE_BEGIN
- 'PERIODIC': device has not noticed any change for a while. Time gap between two 'PERIODIC' increases to a certain limit after each occurrence until any particular event arise

Ex: A **crane** has been operated on a container tracked by device identified by **device_serial XXX** in the **port** of **Durban at 29° 53′6.197 South 31° 2′40.489 East** on **Monday the 5th of May, 2022 at 09:26:52 UTC**.

The path of a container is thus marked by points of passage (port, warehouses, ...) they correspond to the nodes of the graph describing the path followed by the container. They are designated and embodied by the table **Point of interest** (POI). Ex: A **port** named **'Durban'** delimited by a polygon on the map.

They are connected by the **Shipment segment** which act as the edge of the network. They are delimited by departure and arrival events with associated POI and timestamp. They are regularly inferred as new event populate database and they constitute the shipment segment table. Ex: A container goes through the **Antwerp** POI to join the **Montreal** POI in **9 days 2 h and 25 minutes**.

Shipment covers the entire journey of a container. The corresponding table contains overall shipment metadata. Ex: The container tracked by device identified by **device_serial YYY** starts its journey at **Event A** at **departure_poi** and should end it at **Event B** at **arrival_poi**. The ETA is **Wednesday the 21st of July, 2022 at 10:40:51 UTC**.

It is these information-rich events that will feed the models used to construct an ETA. The history of the journeys made by all the tracked containers that have travelled is used, this constitutes a base. This is the subject of the following sub-section. We will begin detailing the data and the learning model to apprehend them. Their relevance will then be judged quantitatively. Finally, we will discuss the following steps to move towards a more robust ETA.

3.2. Building & updating the estimated time of arrival (ETA)

As the container journey progresses, each event input sheds light on its immediate and future situation as schematized with Fig. 4. It refines details on the circumstances of its final arrival. Consequently, it also enables adjusting an ETA that is our focus

(a) Shipment at event *i* (b) Shipment at event *i+1*

Fig. 4. Following shipment throughout its journey interspersed with events.

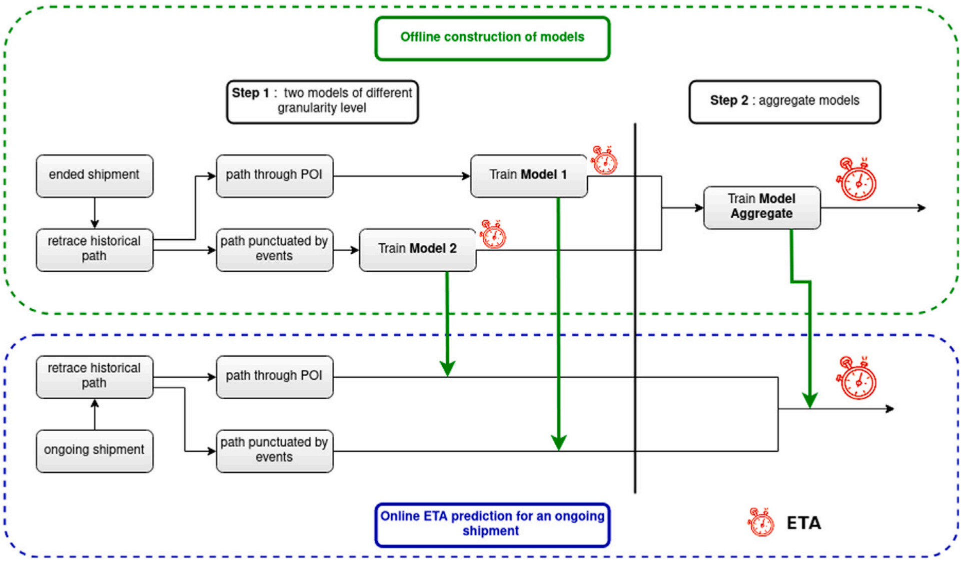

Fig. 5. Process for combining the different models.

here. The core of the current proposal is to build a first model on the data attached to the container alone. This paper consists in building this foundational blocks. It permits forming foundation on which the results of broader, forward-looking work will be added, integrating more abstract data.

This paper is dedicated to establishing these foundational blocks, providing the groundwork upon which the findings of more comprehensive, future work can be built by incorporating more abstract data

To build an ETA, milestones embodied by **POI** of the shipment constituent **shipment segments** as well as frequent irruptions of various **events** along the way and the respective associated data is used. In practice, the deployed service is called upon for each of the shipments monitored when an event *i* occurs to process in coming data. It then return an ETA. Each request at event *i+1* comes with updated data that carries updated information. Indeed an hazard might have occurred between event *i* and event *i+1*, surrounding circumstances could have changed. An example: a container at the Le Havre port is delayed due to a strike, disrupting its planned schedule. Despite this, the tracker continues to send data, updating the requested ETA service and its models. As events unfold, the current circumstances around the container become clearer, leading to a more accurate ETA at the final destination.

The concept of ensemble learning is exploited for producing an ETA. That is, several models are associated to build an output. There is early literature supporting the idea that combining multiple outcomes is better for obtaining a robust result. Indeed Sagi and Rokach [31] mentions the marquis of Condorcet (1743–1794), a French intellectual and mathematician observing that associating several voters results in higher probability of making the correct decision. More recently and before the popular breakthrough of machine learning algorithms, the benefit of combining different models has been studied. It includes, among others but an early bird, Perrone and Cooper [32] as it addresses the problem of ideal pairing. From a population of neural network based regression estimators, they build one estimator that performs better than individual one separately. Most of authors outline the key importance of diversity to enable a good generalization. The diversity here comes from the data sent to each of the models. For one, it is the data associated with the start of each **shipment segment** start that serves as its training, while for the other, it is the data associated with all the events that occur on that **shipment segment**. It will be described that diversity also comes from the technical solution chosen; the choice of XGBoost 3.3 for building an ETA estimator and whose inherent nature falls under the ensemble learning concept. While the main challenge of ensemble learning is to combine the different models in the best possible way, it will be here also left to XGBoost 3.3 to determine how to merge these two models.

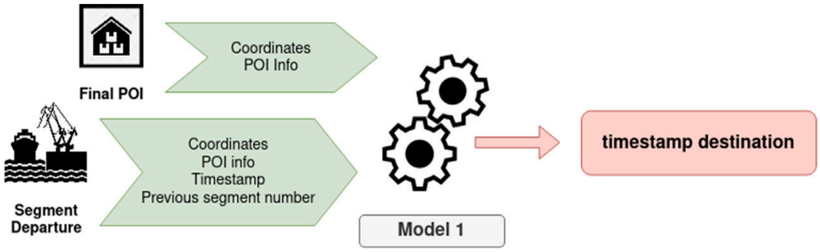

Fig. 6. Input data feeding model 1.

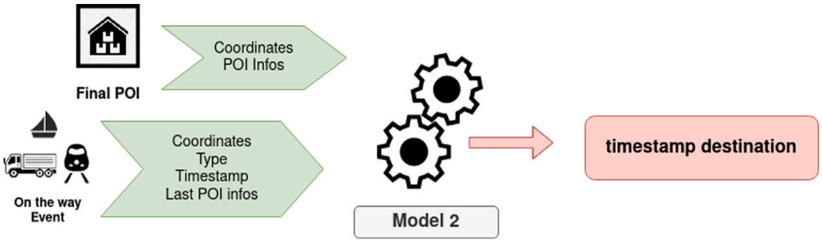

Fig. 7. Input data feeding model 2.

Fig. 5 is the schematic view of the proposition for building and exploiting an ETA model with the IoT data related to the container. Two bases of learning are constituted. They are two subsets of a more global data set with overlapping information as it is visible in Fig. 6 and Fig. 7. They feed respectively **model 1** and **model 2**. **Model 1** profits from POI **shipment segments** key point data whereas **model 2** exploits a shorter time perspective with event data inputs closer in time. Then, those two models are aggregated to produce the final ETA.

The **model 1** uses a first base built with **shipment segments** data. For each shipment, the route is retraced punctuated by distinct milestones (**POI**) already travelled with associated data as they are specified in Fig. 3. It feeds the training of **model 1**. Data characterizes containers position in time and space as well as their intended place of arrival. Their path history is also retraced. In Fig. 6 are shown some of the major features that are inputs of **model 1**: timestamp_destination being the training target.

The **model 2** uses a second base that exploits occurrences of events that punctuate these **shipment segments** frequently. They carry data that feeds the base of training for the same model. It is possible to refer to type of event typology defined above for details. Here in Fig. 7 some of the major features that are inputs of **model 2**: timestamp_destination still being the training target.

Those two models have been trained separately to perform the best on their own. They are then associated to produce an expected more solid ETA, it is aggregation phase of **model 1** and **model 2**. For that purpose, to add context and infer the interdependence between the segment beginning circumstances and event occurring on this segment: it adds some of the inputs of both preceding models as its own input. The proceeds of this aggregation is another model, **model A**. Therefore an ETA is calculated with the existing information at the last departure of a segment: **Model 1** does it. Another ETA is produced at each new event that occurs between this new departure of shipment and the next: performed by **model 2**.

Both for training of separate parts and then the aggregation part, gradient boosting method is used to build models. This will be detailed in the coming subsection. The aggregation phase includes some inputs in addition to the output of these two distinct models.

The learning phase relies on various bases with overlapping information. While their individual performance varies, they are designed to differentiate based on specific situations, addressing distinct granularity levels. Think of them as two complementary models that may underperform individually but do better in generalization. The main goal is robustness, given the diversity of the real world and the current specialization of the training data.

3.3. XGBoost for training model 1 and model 2 and combining them

Benchmarking different learning algorithms resulted in choosing eventually XGBoost for its ease of deployment in exploitation environment, its scalability and for its performance as reported by Bentéjac et al. [33]. It is a popular library that exploits tree boosting methods to achieve state of the art performance.

As it implements the principles of ensemble learning; there are two main concepts that support XGBoost.

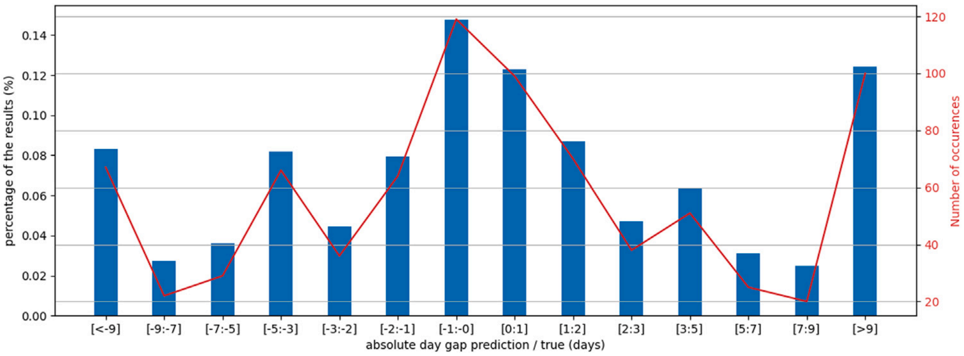

Fig. 8. Indicator **I1**. Learning phase. Actual prediction day difference.

3.3.1. *Random forest*

Random forest is a machine learning approach used for both classification and regression. It is about constructing a pool of decision trees randomly built. Each element is first trained on a bootstrap sample out of different parts of the same training set and just a given proportion of input features. The final output consists in aggregating the ensemble outputs. Here for regression, aggregating means averaging the different outputs.

Another slight difference for the regression lies in the node best split selection for a tree, it is not a question of minimizing the Shannon entropy as in the case of classification but rather minimizing the mean square error prediction of each potential node split.

Such method has proven good results. Though, in order to step up in terms of efficiency, a heuristic for the selection of trees must be added. Especially as renowned [34] has shown that generalization error of a forest of tree classifiers tends to a limit as the number of tree in the forest grow and that this error depends on the correlation between trees. This selection is the subject of the following section.

3.3.2. *Gradient boosting*

Boosting method consists in associating weak learners to build up a strong one. Here this is tree estimators that are iteratively added and the addition process aims to minimize a loss function. Reference to Chen and Guestrin [35] is needed for further details and write down the core equation that shape the boosting process :

$$L^{(t)} = \sum_{i=0}^{n} l(y_i, \hat{y}_i^{t-1} + f_t(x_i)) + \Omega(f_t)$$

Where $\hat{y}_i^t$ the global model prediction at t-th tree addition for the ith instance, y_i the corresponding true value, f_t the new model to add and $\Omega(f_t)$a regularization term to penalize the complexity of the models

Obviously it involves other concepts that are not developed here for the sake of readability.

4. Experimental results

Having the opportunity to utilize real data for training models and subsequently deploying them in a production environment is advantageous. Deployed models feed a log from which data is retrieved to build up the following exploitation phase indicators.

Data volume: ∼400 shipments, yielding ∼15,000 examples for model presentation. Path profiles are highly diverse. Training samples, occurring at different times and with distinct shipment profiles, differ from those used for testing in the operational phase. Notably, training data covers a different part of the world than the operational testing samples, with a time gap of approximately 2 months coinciding with production deployment.

To judge the relevance of the models, three indicators (I1, I2, I3) have been constructed and applied to both the training and operational data. Operational data being the one deployed service put in logs when requested. These indicators are described below. Figs. 8 9 10 for training and Fig. 11 Figs. 12 13 for testing can be found in appendix.

The indicator **I1** depicts the differences between predicted times of arrival and actual ones distributed. But this difference is of greater importance the shorter the journey, which is not reflected here. That is the spirit of next indicators. **I2** includes the distance parameter.

Indeed, the indicator **I2** describes differences between predicted and actual shipment remaining duration for each distance. Put into perspective with the number of occurrences. This metric aims to highlight the intuitive assumption that the longer the distance left to travel, the more things can happen that can impact on the ETA. It takes into account the particular geodesic of the Earth. Although short journeys are over-represented.

The indicator **I3** is strongly linked to the previous indicator, though maybe the number of remaining segments have more concrete meaning, at least different than the sole distance. It details differences between predicted and actual shipment remaining number of segments. Also put into perspective with the number of occurrences.

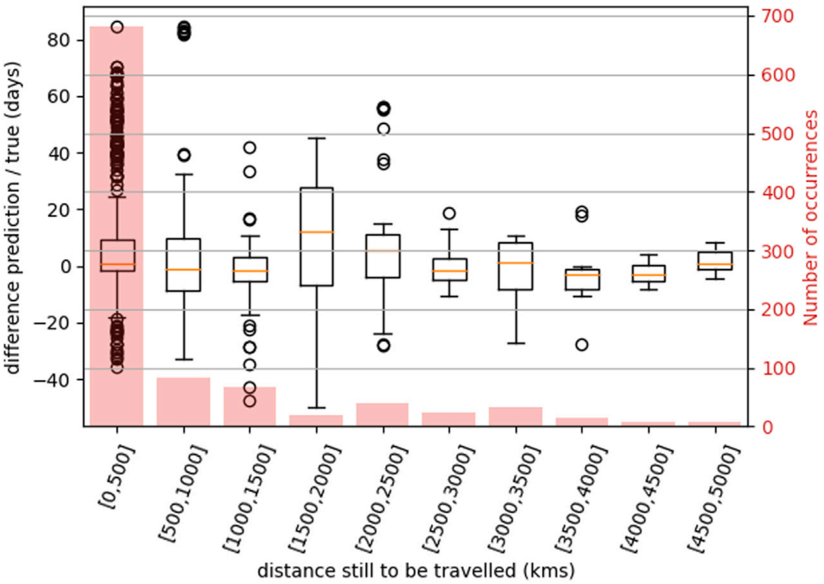

Fig. 9. Indicator **I2**. Learning phase. Actual prediction day difference for remaining distance bins.

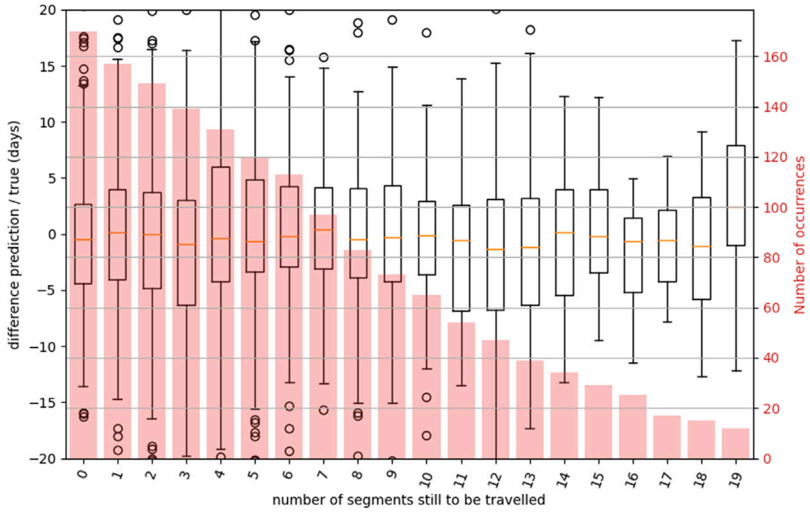

Fig. 10. Indicator **I3**. Learning phase. Actual prediction difference for number of remaining segments.

The key information for ETA is the remaining route data, which intuitively and practically influences the prediction. Hence, factors such as remaining distance, segments, and time to destination explicitly appear as variables in performance indicators, with the latter two known only after the fact.

4.1. Training phase

A classical supervised learning approach has been pursued. Randomized grid Search 10-fold cross-validation has been performed for tuning XGBoost hyperparameters: maximum number of levels in tree, forest population, minimum number of samples required to split a node, using bootstrap sample or not for training a tree. A common Mean Squared Error as loss function to minimize has been adopted but many other could be bench-marked. The indicators are plotted on test data that were not used for training but have the same distribution.

It is assumed that the selected features as entries described earlier in 3.2 Figs. 6 7 for our model are explanatory and have an influence on the target variable—ETA. In other words, the model assumes these features provide relevant information for predicting arrival times and that changes in these features will lead to corresponding changes in the predicted ETA. It is also assumed a certain degree of stationarity—that the patterns in historical data are relevant to future predictions.

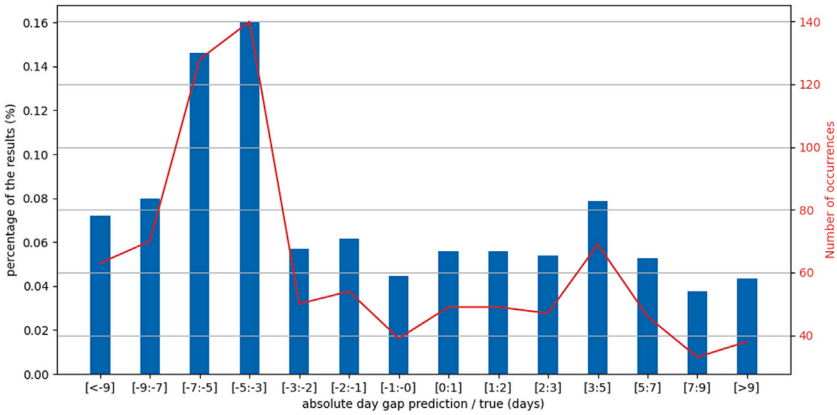

Fig. 11. Indicator **I1**. Exploitation phase. Actual prediction day difference.

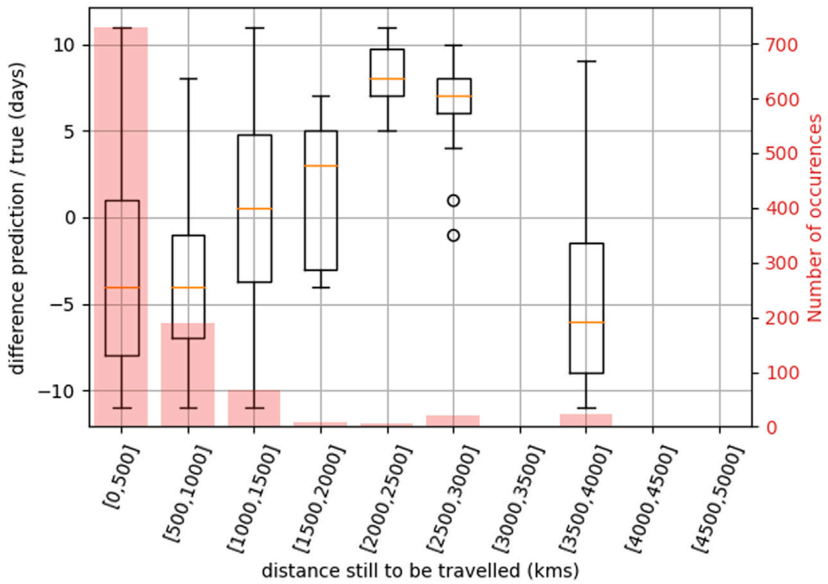

Fig. 12. Indicator **I2**. Exploitation phase. Actual prediction day difference for remaining distance bins.

The indicator **I1**, illustrated in Fig. 8, highlights that most prediction fall close from actual ones with less than 4 day differences. This threshold fits the business part requirements. It means it is an acceptable error margin. Only this has to be put in perspective with the path still to be travelled. This is with the indicator**I2** (Fig. 9) that a slight trend emerges. It confirms the following intuition: the longer the remaining journey, the bigger the uncertainties are. Therefore, how far the target destination has an impact on the quality of the prediction. It is also worth noting that most shipment remaining distance are less than 500 kms. It could justify that the results are better for more represented data. Although with the indicator **I3** (Fig. 10) there is not clearly the same trend. Intuition would have pleaded for raising error along with number of remaining section, difference along with growing remaining number of sections. Here again, it can be noticed that short journeys (regarding remaining segments) are over-represented. It can though be noticed that for very long trip the distribution is tightening and accuracy improving. In order to clarify this observation, the figure Fig. 14 shows the number of sections in relation to the distances. Long distance with not so many sections indicates long uninterrupted sea routes. They are relatively unaffected by hazards. It can explain those better ETA results on very long distance.

4.2. Exploitation phase

Deployed models provide real-time ETA for active containers. Simultaneously, they log input data and generated ETA at each request. Utilizing past indicators allows assessing model relevance and observing operational differences.

During the exploitation phase with data from operations the distribution of predictions, the indicator **I1** (Fig. 11) indicates that the results are more disparate but 46% still fits into a 5 days difference. For the indicator **I2** (Fig. 12), the same trend as for learning

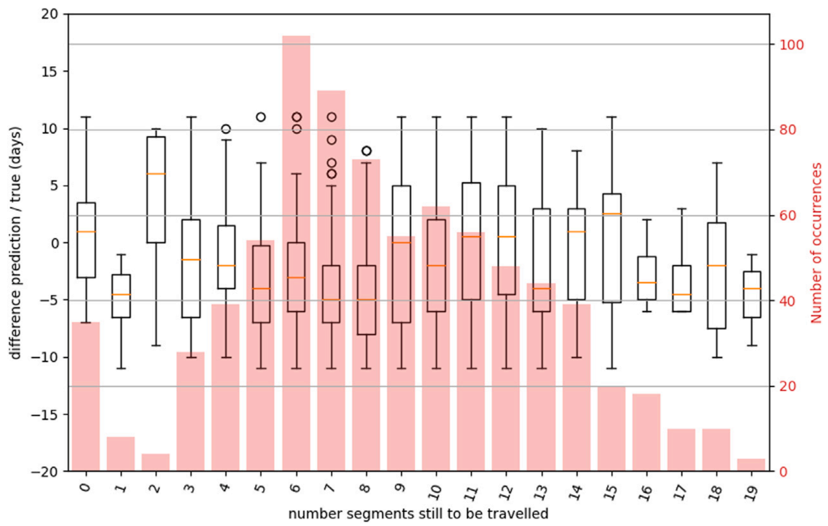

Fig. 13. Indicator **I3**. Exploitation phase. Actual prediction day difference for number of remaining segments.

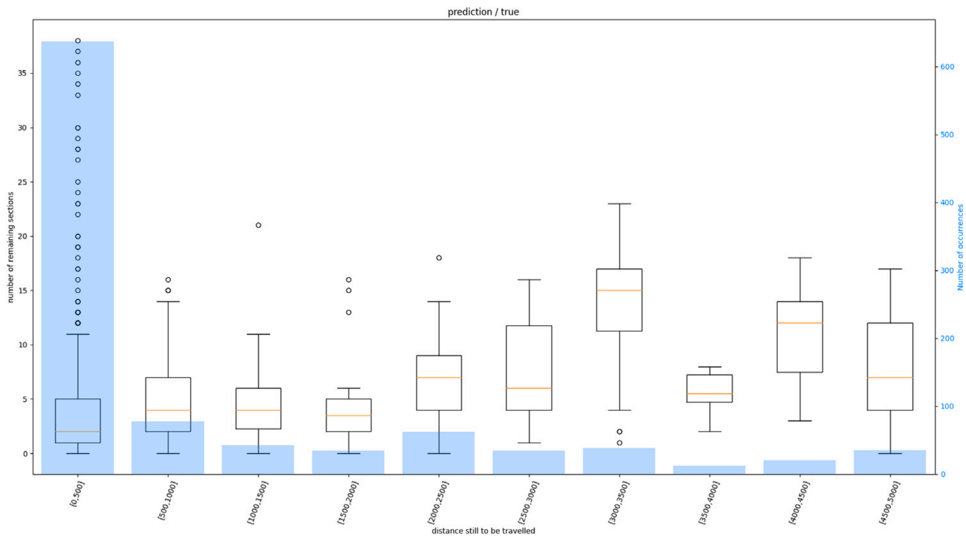

Fig. 14. Training data. Distribution of number of remaining segments for remaining distance to destination.

dataset is observed, only it is more pronounced here. This logic disappears when the results are no longer significant with very few occurrences. There are some remarkable values for intermediate distances without clear explanations except that the range of the number of sections transcribed in the figure Fig. 15 is quite large. This pleads for shipments of various natures. More over standard deviation is bigger than for learning phase. Same comment as for learning for Fig. 13, nothing special comes out of it. Though here again standard deviation is much bigger.

To summarize, to explain the discrepancy between training and exploitation phase we mentioned the problem of evolving data patterns; The model is trained on historical data, and sudden changes in logistical operations or new trends can create discrepancies if the model has not yet adapted to these evolving patterns. Continuous retraining with fresh data will mitigate this issue. Generally speaking, to explain why the models do not perform better, we allude to the limited data set available. To this can be added unaccounted external factors; unforeseen events like weather conditions, port congestion, or unexpected delays in transit are not always captured in the model's training data. These external factors can cause the actual arrival times to deviate from predictions. There is also, almost inevitably th model limitations in capturing complex intermodal dynamics. Indeed, while the model generalizes well across a variety of scenarios, certain complex patterns — such as specific delays at intermodal transfer points (e.g., switching from ship to rail) — may not always be fully captured in the current version of the model.

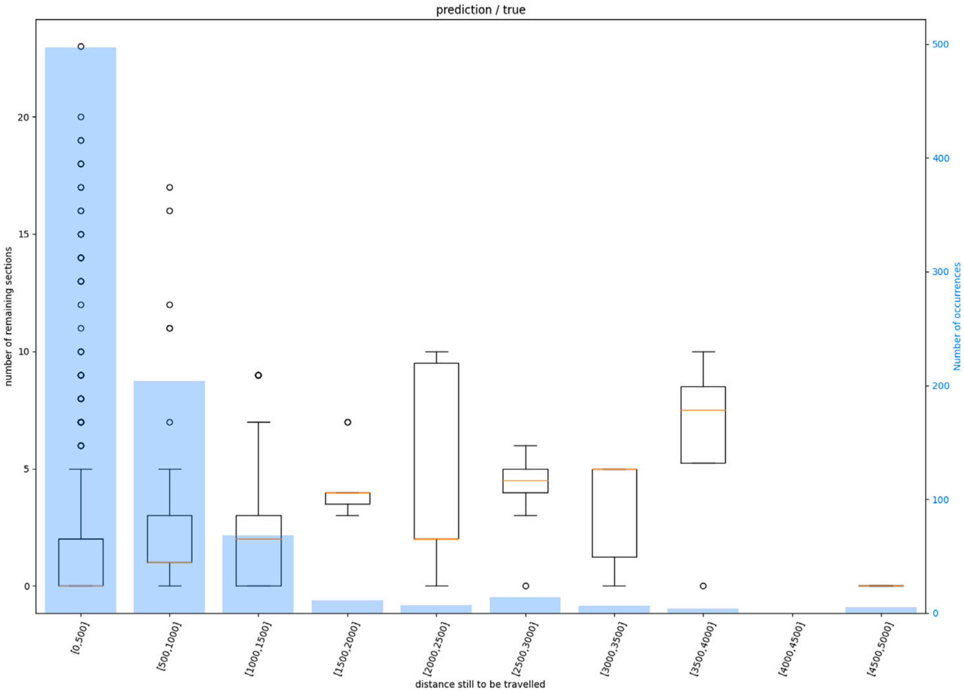

Fig. 15. Exploitation data. Distribution of number of remaining segments for remaining distance to destination.

5. Discussion & perspective

Despite regular updates, models drift with renewed shipments and changing path profiles. User profiles ordering tracker devices in batches for specific routes or areas introduce deviations from the models' validity domain, challenging their generalization. Although data volume starts modest, the proposed solution's strength lies in continuous growth, allowing training and predictions on expanding actual data.

Model trainings rely solely on ad hoc tracker data, limiting their scope. This serves as a foundational starting point with room for improvement, particularly in designing loss functions. The results advocate for integrating broader data beyond the container level, although merging proves challenging, as elaborated in the following sections.

5.1. More consistency with data related to logistic networks

To link the work to more explored research topics and arm the embryonic ETA calculation proposed here with different data. It is a matter of changing scale, from the container to the vessel, train or truck that carries it. It is a fight against noise at a granularity level where it swarms. It would achieve consistency with the scale above and thus connect corresponding logistic networks. Leveraging data across all levels of the supply chain (vertically) and from multiple stakeholders (horizontally) could make the ETA more robust.

As it has already been mentioned, different stakeholders are reluctant to open even a part of their information system and because strict schedules are in practice difficult to follow or simply do not exist, an agnostic approach must be preferred. It means here reducing intermediaries to get the data.

5.1.1. Bridging the gap from container to vessel, from IoT to AIS

Crossing some particular and opportune event GPS pings with third party API enables identifying on which ship the container is loaded without relying on any shipping lines schedules API and operator manual information collection. It could be a breakthrough leading to a lot of unexplored possibilities backed by already explored but distinct research areas as highlighted in the literature review. As a consequence, it enables access to a large range of data associated with the vessel, the AIS data. That is crucial to go beyond mere a posteriori traceability. Ship almost live position would be available rather than relying on punctual frame of data.

It implies a sub-requirement consisting in correctly detecting pivotal events it is necessary to pursue continuous improvement, gathering hardware data for then:

- Building models on top of them to discriminate these pivotal events: conducting a classic approach to build and train these models.
- Consider embedding light machine learning algorithm into the firmware. Energy and computation constraints then arise.

This last point is interesting to follow as machine learning algorithms can adapt more dynamically to a wider range of unforeseen scenarios than expert systems, making them more robust for handling the complexity and variability in intermodal logistics. In addition, embedded algorithms could specialize, learning along the container's path.

Different approaches could be examined, A non-exhaustive list of possible methods can be found in numerous publications. To mention only those dealing with neural networks, several quantization methods could be compared and the advantages could be detailed with regard to the various constraints that must be overcome. Roth et al. [36] provides good overview of path to explore for that matter.

A certain amount of development effort is still required to hope to deploy such algorithms, but it is in progress. In particular for assessing computational efficiency and still guarantee a certain quality for the prediction.

5.1.2. Closing in with the rail tracks.

Same reasoning as for AIS and ship related data can be applied for identifying which train the container embark on and then link to specialized rail freight data. The initiative led by association Rail Net Europe [24] and backed by European Union provide these data and pursue continuous progress to develop related new services including Estimation of Time of Arrival for rail freight.

Such work seems opportune as rail freight is gathering momentum at a time of energy efficiency and low carbon emissions necessity awareness. A proof of concept has already been delivered.

5.2. Enriching with exogenous data

As containers enable intermodal transportation, the scope of time of arrival prediction (ETA) goes beyond the maritime transport portion and there are higher level circumstances that could reshape its global route, such informations lies into exogenous data. Therefore sticking to convenient AIS data or other inherent insights is not enough. That is why collecting data from different media allows to look at socio-economic movements, weather events. By mobilizing research in text processing, work could be done to more finely distil events of interest such as port or road congestion, social movement, weather specific conditions... Anything that is likely to have an impact on the considered supply chains. Initial work has been carried out by Ouedraogo et al. [37] to establish a risk map to guide this undertaking. Data has been collected and first analysis performed. The results are still in the preliminary stage.

As the IoT-enabled container fleet grows, the resulting increase in data provides opportunities to improve the accuracy of predictive models with broader training dataset. Thus it enables better generalization and reduce the risk of overfitting allowing it to perform well under different environmental and logistical contexts. By leveraging near real-time IoT data to continuously learn and adjust to fluctuating operational conditions, the models remain relevant and avoid drifting. It echoes the modal shift to come mentioned in the introduction. However, for this to work, the supporting infrastructure — including data storage, processing power, and security measures — must scale accordingly.

Additionally, as the solution must integrate seamlessly with the diverse information systems of various stakeholders, interoperability is key. There is also concern about data ownership, with larger transportation companies potentially controlling the development of this business and the data being reluctant to share it, which could hinder the growth of open, collaborative ecosystems.

From a commercial perspective, predictive ETA services have a strong business case, especially in industries dealing with perishable goods and pharmaceuticals, where accurate ETAs are essential. However, the service must also prove its economic viability, showing that the benefits justify the energy and financial costs of implementation.

6. Conclusion

We have laid the first bricks of our tool and we have tackled an emblematic topic: the prediction of ETA in container logistics, utilizing IoT data attached to the containers.

We provided a method to predict this ETA leveraging IoT data attached to the container and exposed the results of the service deployed in operation.

We have also paved the way for the following steps to move towards more finesse in container tracking. We emphasized that achieving consistency between different granularity level is of great importance. Indeed it would connect them as the container would achieve its intermodal purpose also in the numerical dimension. Therefore it would enables leveraging distinct research areas as highlighted in the literature review. We now intend iteration after iteration to refine our models notably with exogenous data on a path that [37] has traced.

CRediT authorship contribution statement

Rodolphe Barlogis: Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Aurélie Montarnal:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Cheik Ouedraogo:** Conceptualization. **Didier Gourc:** Writing – review & editing, Supervision, Project administration, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the first author used ChatGPT in order to make certain corrections during the revision process more idiomatic in English, as the author is not native speakers. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Figs. 1–15.

Data availability

The data supporting the conclusions of this study involve real-world information that may compromise the anonymity of entities involved. Due to ethical and legal considerations, we are unable to make the raw data openly available.

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