# Improving public transit demand forecasting models in case of disruptions: an integrated approach using explainable AI.

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## Short summary

Unplanned service disruptions in Public Transit (PT) systems can have major consequences on their performance and attractiveness. When such interruptions occur, PT operators must implement rapid actions to restore the service and absorb demand overflows. Among demand management strategies, short-term forecasting provides valuable information and helps to assess the levels of demand that need to be reallocated. However, short-term forecasting models struggle to take into account unexpected events such as disruptions in real-time. This work provides an integrated approach, which incorporates a Disruption Detection Module (DDM) using Random Forest together with a Demand Forecasting Module (DFM) using Long-Short Term Memory (LSTM). Results show that the integrated approach outperforms the forecasting model alone, improving prediction performance during disruption by 22%. The importance of explanatory variables is assessed with SHapley Additive exPlaination (SHAP), and the resulting analysis indicates the relevance of implementing the DDM prior to the forecasting task.

**Keywords**: public transit, disruption, demand management, resilience, machine learning, deep learning

## 1 Introduction

Public Transit (PT) systems regularly face service disruptions that substantially dissatisfy users and can ultimately lead to major dropouts in favor of other transportation modes. Most disruption management plans rely on the provision of **temporaray service alternatives**, such as bridging buses (Pender et al., 2013). However, in recent years, PT disruption management has been boosted by growing computing capabilities and increasing data availability that can help disruption detection and demand forecasting. Therefore, the disruption management paradigm has moved from service-oriented solutions to demand-oriented solutions, aiming to leverage **existing service alternatives** to handle disruption consequences and serve the impacted travel demand.

Demand-oriented solutions are designed to provide updated and reliable information information to users and therefore improve their mobility choices. To this end, short-term forecasting methods that provide reliable information directly to users, or help PT operators to build relevant information for users, are invaluable. In the recent literature, short-term forecasting is treated using Artificial Intelligence (AI) applied to Automatic Passenger Counter (APC) data (Halyal et al., 2022; Hoppe et al., 2023), Automatic Fare Collection (AFC) data (Toque et al., 2017) or Origin-Destination matrices (Zou et al., 2024).

Applications using AI are particularly adapted to disruption scenarios because they can rely not only on the regularity and the periodicity of the data but also on events that happened in the short- or long-term historical data. For this reason, AI models have been used to predict disruptions' occurrence (Maleki et al., 2021; Wang et al., 2022) and to forecast demand under unexpected events such as rainfall events (Gao et al., 2024) or subway incidents (Zou et al., 2024). However, the main drawbacks of these methods are twofold. First, short-term forecasting models need real-time operational adjustments to fully consider the effect of disruptions in the model Zou et al. (2024). Second, AI models are less interpretable than other statistical methods (Hoppe et al., 2023), which can be an issue when trying to understand the drivers of PT demand under disruption.

In this regard, this work intends to answer the following question *to what extent can short-term demand forecasting and AI-driven models be improved in case of PT service disruptions?* We propose an integrated modeling framework that includes both a Disruption Detection Module (DDM) and a Demand Forecasting Module (DFM). The DDM aims to provide the real-time adjustments identified by Zou et al. (2024). In addition, we will use SHapley Additive exPlaintaiton (SHAP) to enhance the interpretability of the proposed AI-driven model. The contribution of this methodology will be illustrated in the case of subway disruptions in Lyon, France.

## 2 Methodology

***Overview of the integrated model***

The aim of this work is to forecast subway demand at the station level each 5-minute time interval. The specificity of the proposed model is its ability to cope with service disruptions which improves its forecasting performance during such events. Figure 1 presents an overview of the integrated model. It is composed of two separated modules: DDM and DFM. To understand the methodology, we need to define the following concepts. The **service area** is the buffer zone within which PT stops are deemed accessible from a given disrupted subway station. These stops are called **alternative stops**, and are assumed to be the main alternatives used for demand reallocation in case of disruption. In the DDM, we use demand data from alternative stops to detect disruptions. The outcome of the DDM is a time series of probabilities to face a disruption for each 5-min time interval. These probabilities are then fed into the DFM, in addition to other classic explanatory variables for demand forecasting problems (i.e. historic subway demand and calendar variables). The outcome of DFM is a time series of predicted demand values at the studied subway station.

***Disruption Detection Module (DDM)***

The DDM is a Random Forest that performs a supervised binary classification task to detect disruptions. Tree-based algorithms have the ability to deal with imbalanced problems (Breiman, 2001; Ritschard et al., 2009), and Random Forest are chosen over Gradient Boosting methods because both have similar performance levels in our case, but Random Forest are less computationally demanding. Service disruptions are the target variable to explain. Explanatory variables are of two types. First, for each alternative stop, a Spatial User-Based Metric (SUBM) is built similar to the continuous user-based model introduced by Tonnelier et al. (2018). This metric aims to count the number of validations that have fewer chances (<10%) of being made at a specific stop, and therefore to identify unusual demand levels for each 5-minute interval. Second, calendar variables take into account each 5-minute time interval (from 1 to 288 for each day), days of the week (from 1 to 7), and school holidays (0 or 1). They capture the periodicity and the regularity of the demand. The outcome of this model is a time series of disruption probabilities, which are calculated as in Olson & Wyner (2018).

***Demand Forecasting Module (DFM)***

The DFM is an LSTM model (Hochreiter & Schmidhuber, 1997) that performs a supervised regression task to predict the short-term demand in the presence of a disruption. LSTM has proven to be effective for time series forecasting in many application fields, including public transportation (Toque et al., 2017; Halyal et al., 2022; Gao et al., 2024). Subway demand data are used as a target variable. Explanatory variables are of three types. First, 12 lagged time series of subway demand are used, taking into account demand value between 5 minutes and 1 hour before the observation time. Second, the probability coming from the DDM are used as lagged variables, using the same lag as for subway demand data. Third, calendar variables are taken into account as in DDM. For compatibility issues with the LSTM algorithm, cyclical variables are encoded using cosine transformation. In addition, input subway demand is log-transformed to better handle values close to zero. The outcome of this module is a time series of predicted subway demand levels.

In this work, we will compare the performance of the integrated approach (DDM + DFM) with the performance of a simple forecasting model (DFM alone). In addition, SHAP is implemented to assess the contribution of explanatory variables in each model (Lundberg & Lee, 2017).

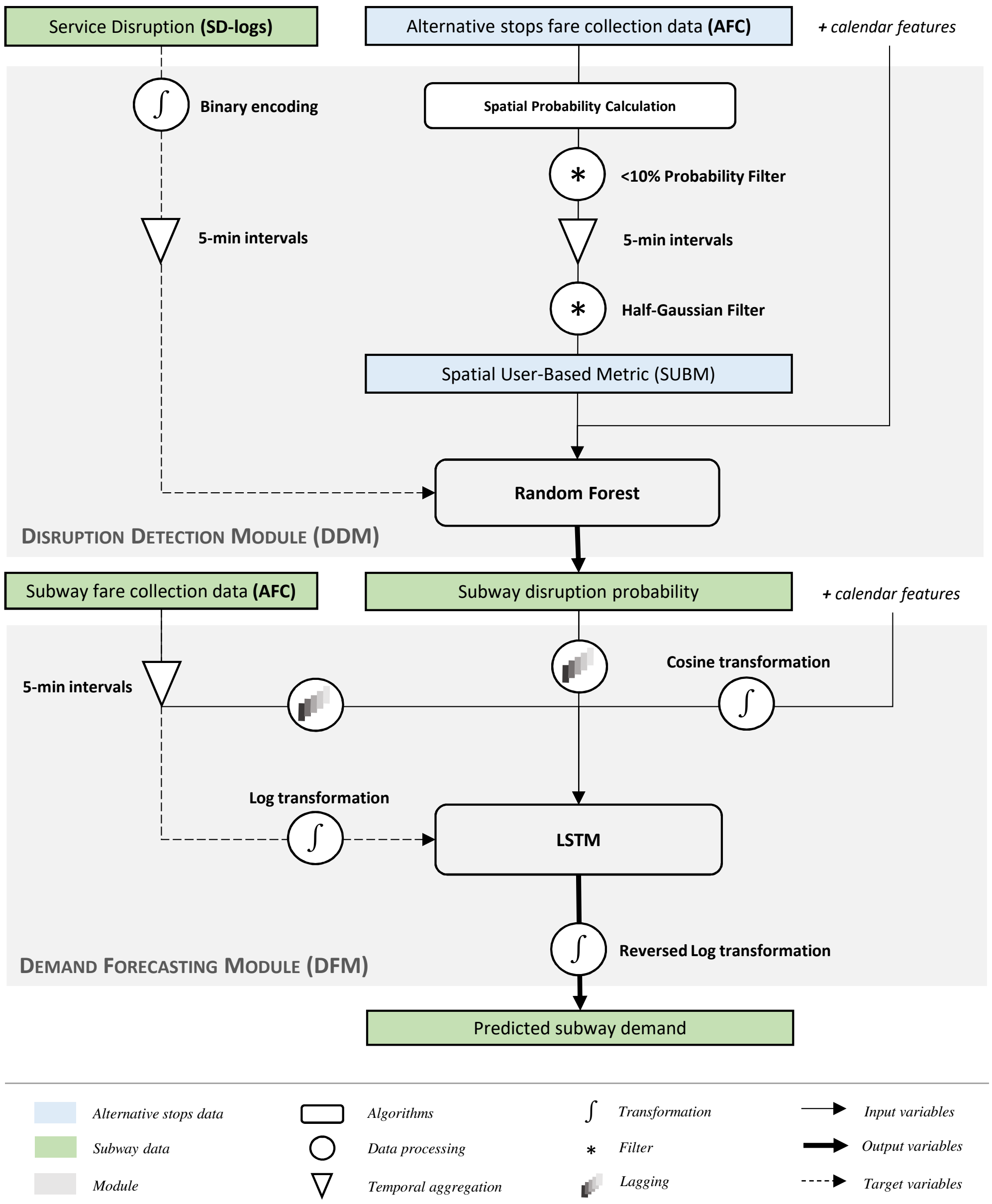



**Figure 1:** Overview the integrated model - *The model is composed of a Disruption Detection Module (DDM), followed by a Demand Forecasting Module (DFM). It uses subway Service Disruption data (SD-logs) and Automatic Fare Collection data (AFC) for subway and alternative stops. The final output of the model is a 5-minute time series of predicted subway demand values.*

## 3 Results and discussion

### *Data and model settings for the case study*

The proposed methodology is applied to the subway station that serves the city hall, between 2021 and 2023. For this station, 19 different alternative stops are identified in the dataset, using a 600-meter buffer zone (Egu & Bonnel, 2020). Service Disruption logs (SD-logs) record 137 disruptions at this station over the study period, which is the highest number observed for a subway station and the reason why we focus on it in this work. Automatic Fare Collection (AFC) data are used as a proxy for demand at the subway station, and also to calculate the SUBM for its corresponding alternative stops.

For DDM, the data are shuffled and split into a train set (80%) and a test set (20%). A grid search analysis is performed using the average precision score as a performance metric, in a 5-fold cross-validation setting. Trees in the forest are unpruned and the number of trees is fixed to 200, resulting in an average precision score of 0.91. The probabilities resulting from both the train set and the test set are considered as inputs for the DFM.

For DFM, the data are split into a train set (60%), a validation set (20%) and a test set (20%) and are embedded in batches of size 32. We count 27 disruptions in the test set. This module was implemented using a sequential architecture with an LSTM layer (128 units, ReLU activation), followed by dropout to prevent overfitting (40%), a dense layer (64 units, ReLU), another dropout (40%), and a single-unit output layer for continuous predictions. It was compiled using the ADAM optimizer and mean squared error loss. The number of epochs is fixed to 5 using loss curves. The Mean Absolute Error (MAE) is used to assess and compare model performance.

### *Model performance*

Results shows that the MAE of the integrated model (DDM+DFM) and the forecasting module alone (DFM) is 8.57 and 8.98, respectively. More specifically, the MAE during disruptions is 7.15 and 9.16, respectively. Therefore, **the integrated model performs better than the forecasting module alone (5% reduction in MAE), especially during disruptions (22% reduction in MAE)**. To visualize why the integrated approach performs better, Figure 2 provides an excerpt of the data that includes a disruption that occurred on October $20^{th}$, 2023 between 14:05 and 15:10. Two insights can be drawn from this figure. First, at the beginning of the disruption, a delay between the true demand and its corresponding prediction is often observed when only DFM is used. The integrated approach addresses this problem by reacting more swiftly to the disruption event. Second, at the end of the disruption, demand levels are often overestimated with DFM alone. The integrated approach keeps predicted demand levels closer to the true demand levels.

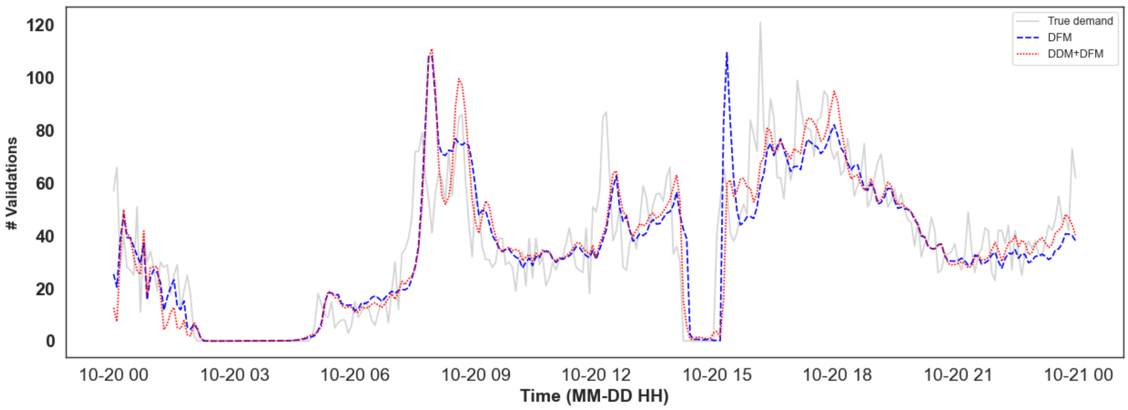



**Figure 2:** Demand forecasting for subway station *Hôtel de Ville - Louis Pradel* on October $20^{th}$, 2023. *The grey curve is a 5-minute time series of true demand levels. The blue curve shows forecasting results for DFM alone, and the red curve shows the results of the integrated model.*

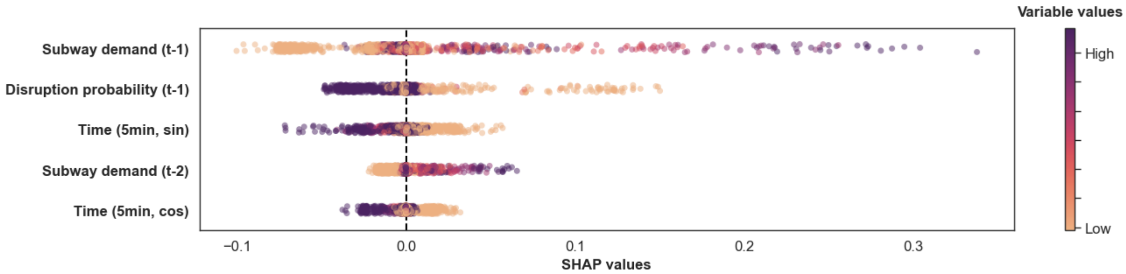
### *Variable importance using SHAP*

Figure 3 shows the SHAP values for the five main explanatory variables for disrupted data points, ranked according to their SHAP importance score. SHAP importance score can be interpreted as the weight of the variable in the model. They are mentioned in parentheses in the following.

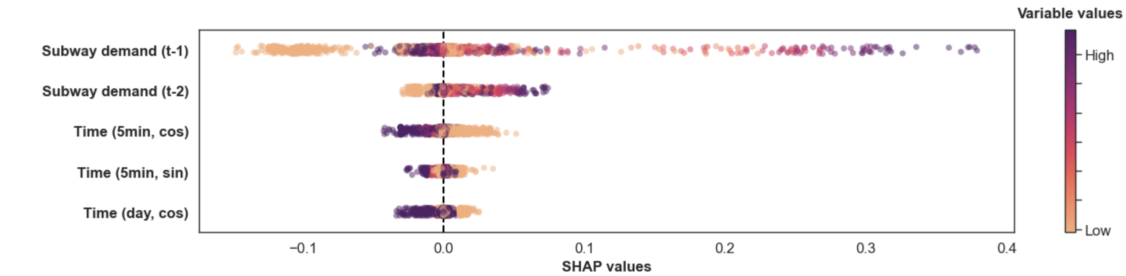
Figure 3(a) indicates that the prediction made by the integrated model at time $t$ is mainly driven by the value of subway demand at $t-1$ (SHAP $=$ 46), then by the probability of disruption at time $t-1$ (SHAP $=$ 20). The subway demand at time $t-2$ is also highly involved in the model output (SHAP $=$ 10). Finally, the cosine-transformed variables of the 5-minute time intervals play an important role in the prediction (respectively, 14 for the cosine component and 8 for the sine component).

In addition, Figure 3(b) indicates that the prediction made by DFM alone at time $t$ is also driven by the values of subway demand at time $t-1$ (SHAP $=$ 68) and $t-2$ (SHAP $=$ 15). As the information provided by disruption probability is not available, these two variables have more explanatory power in this model compared to the integrated approach (respectively, +22 and +5 in terms of importance score). The variables representing the 5-minute time interval stay in the same range for both approaches (SHAP = 11 for the cosine component and 9 for the sine component, using DFM alone). Finally, the day variable is the fifth most important variable in the DFM model (SHAP = 7).

SHAP also provides the direction of the effect for each variable and each data point. As expected, the previous values of subway demand positively affect the predicted value, while the probability of disruption negatively affects the predicted value. Dynamics for time variables reveal the periodicity of the subway demand, which is mainly driven by peak hours / off-peak hours at the day level and working days / week-ends at the week level.




**(a)** Integrated model (DDM + DFM)




**(b)** Forecasting only (DFM)

**Figure 3:** SHAP values for the five most important variables - *Only disrupted data points are selected to compute SHAP values. Results notably shows that disruption probability provided in the integrated approach significantly influence the output of the model.*

## 4 Conclusions

The paper addressed the following question: *to what extent can short-term demand forecasting and AI-driven models be improved in case of public transit service disruptions?* Using Automated Fare Collection (AFC) data and Service Disruption logs (SD-logs), this work proposed an integrated approach, which incorporates a Disruption Detection Module (DDM) together with a Demand Forecasting Module (DFM). For a given subway station, the DDM aims to target unusual fare transactions at surrounding stops (i.e. alternative stops) to identify disruptions using Random Forest algorithm. For every 5-minute interval, it produces a probability that the chosen subway station experiences a disruption. Then, the DFM uses the output probabilities from the DDM as an explanatory variable for the demand prediction task, using Long-Short Term Memory (LSTM) algorithm. Finally, the integrated approach is compared to the DFM alone and the explanatory power of the model is interpreted using SHapley Additive exPlanation (SHAP).

Results show that the integrated model outperforms the DFM alone, enhancing demand forecasting during disruptions. More precisely, it improves the ability of the model to forecast demand more swiftly when the disruption starts, and to avoid the overestimation of demand when the service recovers from the disruption. The analysis of explanatory variables shows that short-term historical data have an important role in the model output. It is noteworthy that the disruption probability introduced by the DDM significantly improves the prediction.

This work is a valuable contribution to tactical demand management. It could help PT operators and authorities implement faster actions in case of disruptions, by continuously tracking the probability to face disruptions and rigorously forecasting the demand levels that need to be reallocated in real-time. In this work, we simulate a real-time data inflow, but some adaptations need to be made to build a proper online model that would allow real-time applications. Further studies could investigate the possibility of switching from offline to online models. In addition, different machine learning or deep learning models could be tested to improve detection and forecasting tasks. The model is transferable to any subway station and could be generalized to an entire subway network, which would require individual tuning procedures for each station.

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