HYBRID MODELS FOR FORECASTING DUBLIN BUS DELAY DUE TO WEATHER CONDITIONS

MSc Research Project
MSc Data Analytics

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MSc Project Submission Sheet

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HYBRID MODELS FOR FORECASTING DUBLIN BUS DELAY DUE TO WEATHER CONDITIONS

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ABSTRACT:

Urban transport systems like Dublin's often experience delays due to weather conditions and peak hour traffic, which affects commuter satisfaction and transport planning.This research proposes a hybrid forecasting model that combines the Facebook Prophet for trend extraction with a Gated Recurrent Unit(GRU) to capture the short term dependencies and external factors.A real-time dataset was extracted via APIs, Containing historical bus delay data and then weather data. Feature engineering techniques like lagged delays, rolling averages and time based indicators were applied to enhance the dataset. Multiple models were evaluated, including GRU, Prophet with external regressors, Random Forest and a GRU+Prophet hybrid model.In the hybrid model where Prophet's trend prediction were used as additional inputs for GRU. The hybrid model achieved an MAE of 15.98s, RMSE of 22.87s, and R of 0.44, outperforming the GRU(R^2=0.2361) and performing comparably to Prophet (R^2 =0.4222), but Random forest achieved the highest accuracy (R^2=0.9963). It lacks interpretability and the model may be over fitted. Although the hybrid model was not the top performer, the model offers a balance between accuracy and interpretability. Its architecture effectively incorporates seasonality and sequential patterns, making it a robust and transparent.

Keywords:Urban transport forecasting, Bus delay prediction, Hybrid time series model, Gated Recurrent Unit (GRU), Facebook Prophet, Weather based prediction, Machine learning, Feature engineering, Public transit analytics.

INTODUCTION:

1.1Background:

There is a growing dependence on urban public transportation systems, such as in dublin. While the reliability of the bus services has improved(Sarhani et al., 2023). The public transportation system is complex as they are influenced by various external features like traffic congestion, weather changes, route specific characteristics and temporal patterns.Forecasting accurate bus delay in such a dynamic environment is a non trivial task, however, it enhances the real time decision making, passenger satisfaction and then improve operational efficiency(Jiang et al., 2022).

Traditional statistical models such as ARIMA and Holt- winters have been used for public transport forecasting due to their transparency and effectiveness in capturing the trend and seasonality(Sherly et al., 2023). However these models operate under the assumptions of stationary and linearity, which often break down during sudden weather changes etc.They also fail in capturing the temporal granularity and high dimensional interactions that are in the transport datasets(Du et al., 2022a).

In contrast, deep learning models like Gated Recurrent Units (GRU),have emerged as a alternative model capable of handling the complex temporal dynamics(Zhou et al., 2022).This model is well suited for sequential data and can learn from the lag features, weather features and time based data.Despite their advantages when this model used separately it often lacks in interpretability and requires a large amount of data.

To address these gaps, hybrid model has been developed that combines statistical model which is used to capture the trend with flexible learning power of the neural networks.In this approach the Prophet model is used to extract the trend and sent into the GRU model as an input feature to learn sequential patterns(Fahim et al., 2022).This hybrid approach aims to enhance both the accuracy and explainability of bus delay forecasting.

1.2 Problem Statment

Existing transport forecasting models, statistical or neural struggle to capture the non-linear patterns inherent in real time bus delay datasets. Time series models like Prophet and ARIMA are interpretable but they lack the ability to learn short time volatility which is caused by environment factors. Standalone models such as GRUs excel in sequential modeling but lack trend awareness and require hyperparameter tuning(Gao, 2022).

Several previous researches tried to integrate external data such as weather along with feature engineered temporal features. But they failed to evaluate the hybrid models on structured datasets derived from the real world transport systems such as Dublin's open transport API.

This research proposes a hybrid model that integrates the Prophet and GRU to forecast bus delay using historical bus data and weather data. By integrating trend extraction and sequential learning, the model tries to overcome the limitation of traditional and standalone models.

1.3 Research Question:

Can a hybrid forecasting model that integrates Prophet-based trend extraction with a deep GRU network improve the accuracy of real-time Dublin bus delay predictions compared to standalone models?

1.4 Research Objective:

The research objectives were listed below:

1. To review and analyze state-of-the-art models for Dublin bus delay prediction, focus on the GRU and prophet forecasting technique.
2. To design and implement the hybrid forecasting model that uses Prophet generated trend as an input feature to the GRU network for predicting the bus delay.

3. To train and evaluate the hybrid model using evaluation metrics like Mean Absolute Error, Root Mean Squared Error, and R^2 .These results are compared with the standalone models.

1.5 Significant of the study:

This research offers both methodological innovation and real-world utility in the domain of public transport system

Theoretical contribution :

Proposes a novel integration of an interpretable time series model (Prophet) and a deep learning Architecture(GRU) for multivariate time series forecasting.

Demonstrates the effectiveness of the hybrid model while handling nosiy, non stationary and high dimensional data.

Provides a structured evaluation framework to compare the performance of the baseline model against the hybrid model for delay

Pratical contribution

Supports public transport agencies, such as Dublin bus system in providing accurate and timely service through the delay forecasting,.

Help passengers to make travel decision based on the real time prediction system

Enables the integration of the ML pipelines into smart city infrastructure to improve the urban mobility and planing.

1.6 Structure of the paper:

The report is organized as follows:

Chapter 1: Introduction- Provides an overview of the context, motivation, research question, research objectives and key contributions.

Chapter 2: Literature Review - This section reviews the relevant studies in different algorithms and the delay prediction systems.

Chapter 3: Methodology : Describes the dataset, preprocessing steps, implementation of standalone models prediction and the hybrid model and evaluating the metrics.

Chapter 4: Results and Discussion: It provides the experimental results, Visual comparison of the results and analysis of model performance.

Chapter 5: Conclusion and Future work: summarises the key findings of the research and the direction for the future development.

Literature Review

2.1 Introduction:

There is a increasing public reliance on real time transport services, and delays caused by external factors like weather conditions and peak hour anomalies can be a significant challenge(Pragalathan & Schramm, 2023). This literature review states the limitation of traditional statistical forecasting models, the rise of deep learning approaches, and the combination of the hybrid model. This section explains the research gap the study addresses which integrating the Prophet model with GRU model.

2.2 Traditional forecasting model:

The classic time series models such as ARIMA and SARIMA have been frequently used in the transport system due to their ability to model the linear trends and seasonality. They are more efficient and interpretable, which are ideal for application which requires transparency. However these models are built with stationary and linear relationships which rarely hold in the volatile, weather features of the transport data.

Studies by sherly et al. (2023) and goa(2022) highlights the limitation of time series model like ARIMA and Prophet when faced with external weather conditions. The Prophet model was good in detecting the time-based trends but failed in capturing the short term fluctuations. Because of these disadvantages using the traditional model, especially for delay prediction which is influenced by both periodic patterns and external conditions,becomes a challenge.

2.3 Deep learning Model:

To overcome the limitations of the time series model, deep learning models like Recurrent Neural Networks (RNNs) has been widely used in traffic predictions.GRU is a simplified variant of LSTM that is less computational.Zhang and Kabuka(2017) demonstrated that GRUs model outperformed the ARIMA model in both accuracy and adaptability in Dublin bus delay forecasting. GRU models manage vanishing gradient problems more effectively than RNNs, which makes them more suitable for handling long transport sequences and time based variables like temperature or peak hour.

Even though the GRU model handles temporal patterns effectively, they require large amount of data for training and lacks the built in interpretability of models like Prophet.The review of Fahim et al.(2022) demonstrates that the GRU based model performs effectively when combined with other feature extractors like CNN’s. Hence, the full potential of the GRU model lies in the hybrid structure rather than the standalone model.

2.4 Prophet for Trend and seasonality Decomposition:

Prophet model is good at capturing the long term trends, seasonality and holidays through its additive model structure.It is robust to missing values and outliers, this makes the model more ideal for the public transport datasets which is often consist of inconsistent data.

Studies by Burity et Al. (2025) and Arslan(2023) demonstrated that while using the Prophet trend component(yhat) as an input feature for the neural networks enhances the stability and long term generalization.Prophet models limitation is that it cannot dynamical adjust to the evolving short term changes which is required in predicting the bus delay.Through this study Prophet is not used as the standalone model but it is used as a component that provides smoothed temporal signals to the GRU model.

2.5 Hybrid Architectures: Combining Interpretability and Learning Power

Hybrid models have created a possible solution to check and analyse both statistical and deep learning methods. The topics consist of reducing the forecasting task into some components like trends, seasonality, residual and providing them to models best suited for each of them. Say for example, ARIMA ,GRU or Prophet–LSTM architectures can model global trends with statistical tools with deep learners.

Du et al. in 2022 and Zeng et al. in 2023 developed multimodal deep learning architectures that combines spatial, temporal, and contextual data to address complex transport behaviors. Still, few studies have shown that Prophet’s decomposed trend outputs can be used directly as input features to a GRU model - a gap this research addresses.By integrating Prophet’s trend values into the GRU model as additional input variables, this approach retains interpretability by improving response to actual variations. It balances between transparency and adaptability, which was lacking in previous models.

2.6 Role of Weather and Temporal Features in Delay Prediction

Natural calamities , weather and time-of-day significantly impact bus delays. Research by Nuli et al. in 2022 and Pragalathan & Schramm in 2023 analysed the effect of humidity, rainfall, wind speed, and temperature on traffic dynamics. And also, Trinh et al. in 2022 concluded the importance of time-based features for capturing latent temporal dependencies.

The model’s use of features like cosine-hour encoding, peak-hour flags, and precipitation are the best practices . Altogether, these are Prophet’s trend and GRU’s non-linear learning, the architecture supports both macro-level planning and micro-level operational forecasting.

Author(s)	Year	Approach	Model(s) Used	Advantages	Drawbacks
Zhang & Kabuka	2017	Weather-integrated traffic flow prediction	GRU	Captures weather-influenced traffic trends with sequential learning	May overfit without regularization
Fahim et al.	2022	Ensemble for traffic	CNN-GRU-LSTM	Strong spatiotemporal	High complexity,

		flow		learning capacity	longer training time
Gao	2022	Combined trend + sequence model	Prophet-LSTM	Handles seasonality and short-term dependencies	Dependent on tuning and sequence length
Sherly et al.	2023	Time series hybridization	ARIMA + Prophet	Improved accuracy by merging linear and seasonal insights	Lacks ability to handle nonlinearities
Trinh et al.	2022	Multivariate + distributed forecasting	Deep learning (unspecified)	Scalable across systems with parallelization	Needs significant infrastructure
Burity et al.	2025	Delay forecasting with LLM & attention	Prophet + Attention + LLM	Enhances forecast precision using advanced LLM support	May not be feasible in low-resource settings
Du et al.	2022	Multimodal hybrid for traffic flow	Multimodal Deep Learning	Handles diverse inputs: sensor, traffic, and external data	Higher complexity, input synchronization needed
Shoman et al.	2020	Bus delay across multiple routes	Deep Learning Framework	Works on multiple route profiles simultaneously	Dataset heterogeneity may reduce model focus
Arslan	2023	LSTM + Prophet for hybrid energy forecasting	LSTM + Prophet	Decomposes data into learnable components	Prophet depends on clean, stationary trends
Zeng et al.	2023	Missing data traffic flow prediction	Hybrid DL Models	Deals well with noisy and incomplete data	Higher resource requirements

Table 1: Comparative Analysis

2.7.Summary and Gap Identification

Several conclusions can be derived from the literature:

- Statistical models like ARIMA and Prophet are used for detecting long-term patterns, but they fail to react to sudden increases in variability in public transport systems.

- Hybrid models, that combine trend-based and deep learning approaches,give good results compared to the individual models .

- There is no major study has attempted implementation of a Prophet-GRU hybrid architecture for the real-time forecasting of public bus delays based on open urban datasets combined with weather data.

In addressing this gap, the research proposes a hybrid model that uses the Prophet trend decomposition as an addition input to a GRU model, with the goal of attaining better forecasting performance and robustness in Dublin's public transport system, where weather, time, and historical delay patterns all interact in complex ways.

3.METHODOLOGY

3.1 Introduction:

This chapter outlines the methodology used to develop and evaluate the hybrid forecasting model that predicts bus arrival delays in Dublin using historical bus data and weather data.The methodology follows a step by step pipeline. Starting with real time data extraction through the public APIs, followed by data preprocessing, feature engineering, exploratory analysis, and model development (both standalone model and hybrid model). Finally, the models are evaluated and performances compared.Prophet, GRU, Random Forest, and a hybrid GRU + Prophet model were implemented to assess the effectiveness of all the approach under the same features and evaluation conditions.The evaluation metrics such as Mean Absolute Error(MAE), Root Mean Square Error(RMSE), and R^2 score were used for the model comparison.

The main goal of this methodological framework is to not only improve accuracy of delay prediction but also to ensure the transparency, robustness and the real world applicability in the transport forecasting with varying weather conditions.

3.2 Data Collection and Preparation:

The datasets used in the research was extracted from two key APIs:

- **The National Transport Authority(NTA) GTFS** - realtime API for live bus updates and vehicle positions,
- The **OpenWeatherMap API** for real-time weather data in Dublin.

The bus data includes attributes such as trip ID, stop sequence, latitude , longitude arrival and departure delays, timestamp, and weather variables like temperature, humidity, wind speed, and precipitation. These datasets were fetched from the APIs , and merged. The combined data was stored in the SQL. The entire process was automated using the Dagster orchestration framework.

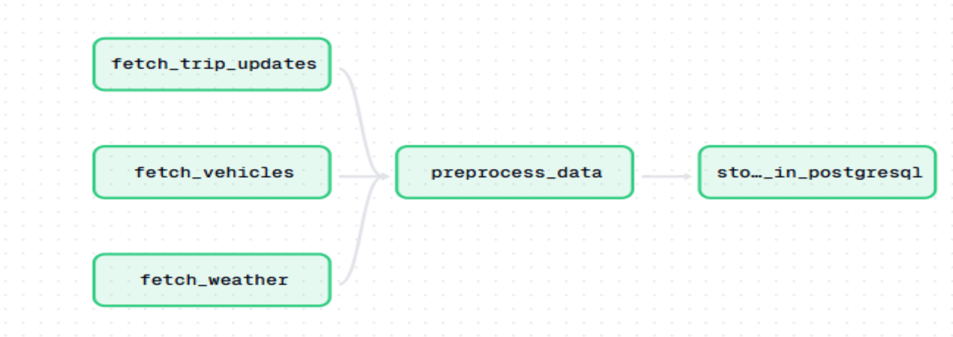

Fig 3.1: The data pipeline

After storing the data in the SQL,The dataset was download as transport csv file and the data preprocessing was preformed in Jupyter Notebook.Invalid or missing entries were removed the inconsistent timestamp were handled. To capture environmental patterns, time-based features such as hour_of_day, day_of_week, and is_weekend were extracted from the available data.

After preprocessing the final dataset was enhanced by doing some feature engineering such as lagged delays(arrival_delay_lag1, lag2), rolling averages and some binary indicators like is_peak_hour and is_morning. This comprehensive preparation ensured that both trend and the external influencing factors were encoded, makeing the dataset available for the time series forecasting.

Feature	**Type**	**Description**
trip_id	Categorical	Unique identifier for each bus trip
start_time	Timestamp	Scheduled start time of the trip
route_id	Categorical	Bus route identifier
stop_sequence	Numerical	Order of the stop in the route
arrival_delay	Numerical	Arrival delay in seconds
departure_delay	Numerical	Departure delay in seconds
stop_id	Categorical	Unique identifier of the stop
GPS coordinates(latitude,longitude)	Numerical	Geographical position of the bus
timestamp	Timestamp	Time when the vehicle location was recorded
vehicle_id	Categorical	Unique ID of the bus vehicle
hour_of_day	Numerical	Hour (0–23) extracted from start time
day_of_week	Numerical	Day of the week (0 = Monday, 6 = Sunday)
time_of_day	Categorical	Time bucket: Morning, Afternoon, Evening, Night
is_weekend	Boolean	1 if Saturday or Sunday; 0 otherwise
temperature	Numerical	Measured and perceived temperature in °C
humidity	Numerical	Relative humidity (%)
pressure	Numerical	Atmospheric pressure (hPa)
Wind (speed, direction)	Numerical	Wind speed and direction
cloudiness	Numerical	Cloud cover percentage
Rainfall details	Numerical	Rainfall amount in the last hour

visibility	Numerical	Visibility in meters
Weather conditions	Categorical	General and Detailed weather condition description (e.g., light rain, drizzle)
Sunrise/sunset	Time	Sunrise and sunset time on the observation day

Table 2: features of the dataset

3.3 Exploratory Data Analysis (EDA)

Several Exploratory data analysis was done to better understand the dataset and the delay patterns.

Shows the distribution of arrival delays by day of the week. The average delay remain consistent across the weekdays, but Saturdays have slightly higher variation. While sunday show lower variance.

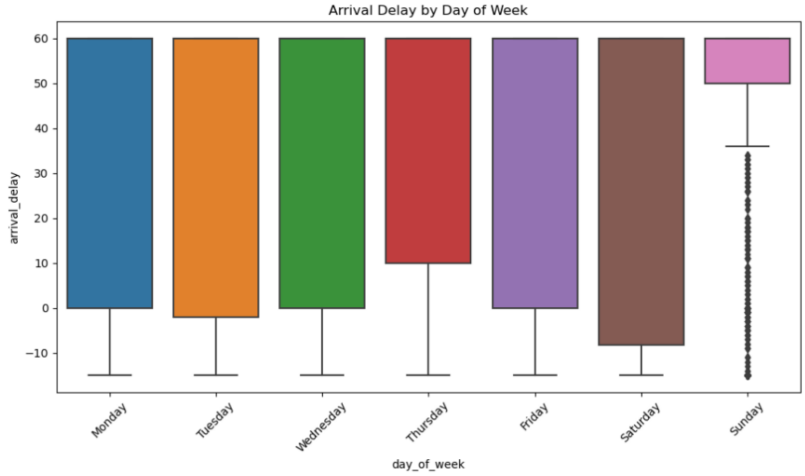

Fig 3.2Arrival Delay by Day of Week

The relationship between arrival delays and precipitation. While most delays occcur during the low precipitation levels, several outliers indicates the extreme delay during the heavy rain.

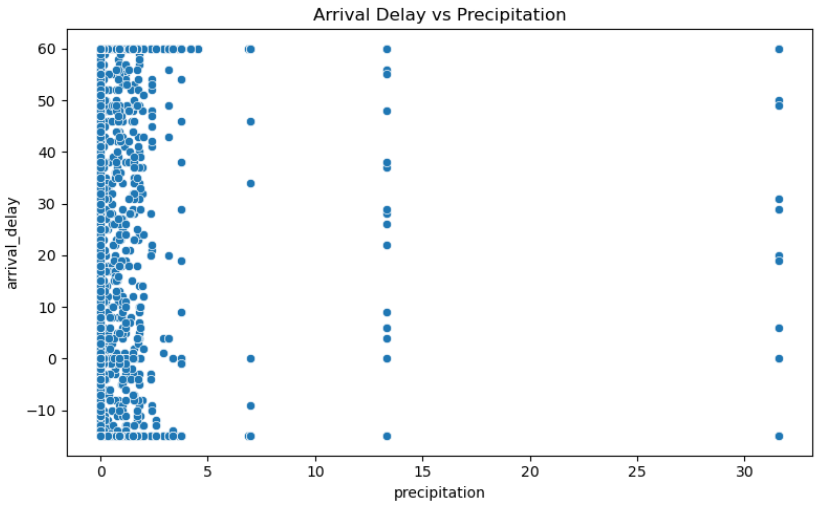

Fig 3.3 : Arrival Delay vs Precipitation

The autocorrelational of arrival delays, revealing the short time dependencies up to approximately 8 to 10 lags, after which the autocorrelation drops. This supports the inclusion of lag features in the model.

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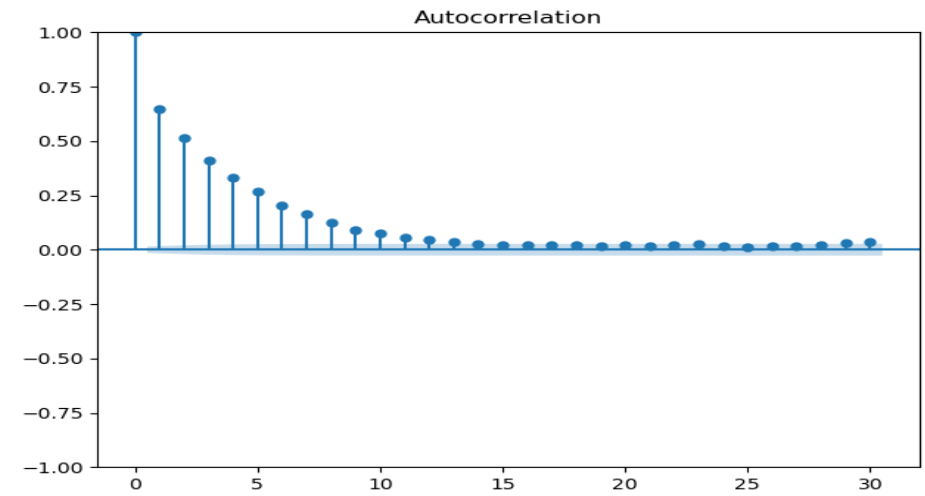

Fig 3.4: Autocorrelation of Arrival Delay

Display the 3- hour rolling mean of arrival delay over time, capturing both seasonal patterns and short term fluctuations.

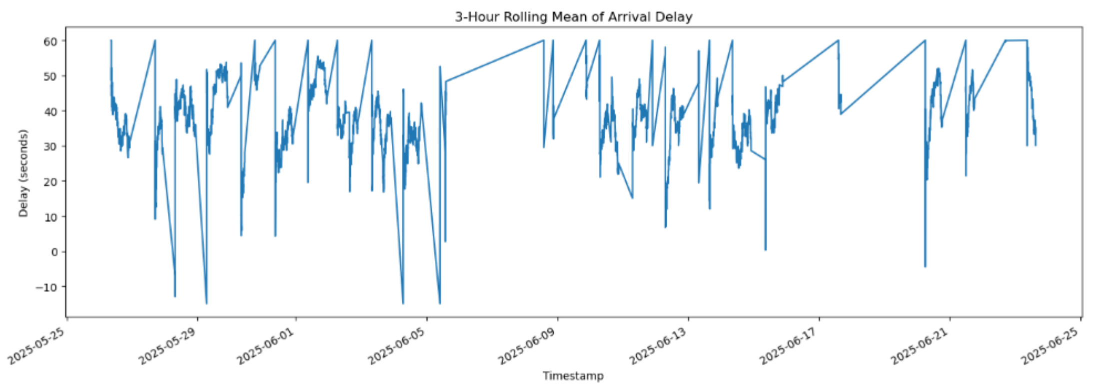

Fig 3.5: 3-Hour Rolling Mean of Arrival Delay

3.4 Feature Engineering and Transformation:

To enhance the predictive capability of the hybrid model, some of the feature engineering and transformation steps were applied to the dataset obtained from the Dublin bus data and weather APIs. These steps amied to capture both the temporal patterns and the external weather factors that are influencing the bus delays.

Lag Features and Rolling Statistics:

Lagged delay values(arrival_delay_Lag1, arrival_delay_lag2) were created to capture the temporal autocorrelation in the delay patterns.A rolling_mean_3hr features was created to help the model to avoid the outliers , noise and learn from the local trends.

Temporal Indicators:

Time based features such as hour_of_day, day_of_week, and is_weekend were extracted from the timestamps to find the cyclic patterns of urban transportation. As these features were numerical or binary values there was no requirement of categorical values.

Weather and Environmental Variables:
The weather API provided external features such as temperature, precipitation, humidity, wind speed and cloudiness.These are continuous features, which may have both linear and nonlinear influence on delays.

Normalization:

The Normalization technique was applied to numerical features while using GRU model for training. However the Prophet model can handle raw values, so we should be careful when handling the hybrid pipelines to avoid inconsistencies. After the transformation, the dataset consisted of both the static and dynamic attributes, helping to identified the factors that are influencing delay. This helps in model training, enabling the hybrid model to learn about the temporal sequences and then external environmental factors.

4 Design and Implementation Specifications:

This section explains the models used to forecast Dublin bus arrival delays, each selected for its distinct advantages in capturing the time series characteristics and the external factors such as weather and time based factors.

4.1 Prophet Model:

The Prophet model , developed by Facebook is a time series forecasting algorithm that effectively models three major components, they are trend,seasonality, and holidays.This model suits well for the time series data with the strong seasonal effects and historical data that repeats over time. The major advantage of this model is its robustness to missing data and outliers, making it a suitable model for the real world dataset like public transport , which often include irregularities and gaps.

The Prophet model was selected for its simplicity, interpretability and flexibility. To enhance its forecasting accuracy of the model, external regressor such as temperature, precipitation, hour of the day and lagged delay values were used.These additional features can allow the model to account for the external influences that affect the bus delay in urban environments.

This model also provides human readable and component wise forecasts, which makes the model more transparent and suitable for operational use by the government transport authorities.Additionally, its automated handling of the trend and seasonality can improve the accuracy in the urban transportation system.

4.2 GRU(Gated Recurrent Unit)

The Gate Recurrent Unit (GRU) is an advanced type of Recurrent Neural Network(RNN) which is design to overcome the limitation of the traditional RNN such as the vanishing gradient problem. The GRU model introduces two main gate they are update gate and the reset gate that allows the model to retain or clear the information over time.This architecture enables the GRUs to capture both the short term and long term temporal dependencies which makes them ideal for sequential time series forecasting tasks.

In this study, the GRU model was developed to predict the bus delay which are inherently temporal and also influenced by recent delay history, time of the day and dynamic external feature like weather. A stacked GRU model architecture was developed with multiple hidden layers to improve the model to learn deeper temporal relationships.The model also fed with range of features that include lagged delay features , temperature, precipitation, hour of the day , peak hours and weekend or weekdays.

The GRU model was chosen because of its computational efficiency ,ability to handle noisy data and high dimensional time series data. The compact architecture of the GRU model makes it well suited for real time applications.

4.3 Random Forest Regressor:

The Random Forest Regressor is one of the powerful ensemble learning method based on the decision tree,this model is well suited for capturing the non linear relationships in the structured data. In this research it was applied to predict the bus arrival delays by using both the historical and external features derived from the transport and weather API.

Before model training the dataset was scaled using the MinMax Scaler to ensure the uniform feature distribution.Label encoding was done to categorical features and lag features were constructed to provide temporal context. The dataset was then split into training and testing set. A grid search with 3-fold cross validation(GridSearchCV) was used to fine tune the hyperparameters, which includes the number of estimators, maximum tree depth, and minimum sample splits , The Random forest model was selected in this research for its robustness, interpretability and ability to handle high dimensional feature.

4.4 Hybrid GRU + Prophet Model:

The hybrid GRU + Prophet model exhibits the core innovation of this research. It integrates the strengths of Prophet a statistical time series model, with the deep learning Gate Recurrent Unit (GRU) network. The goal of the model is to capture both the long term trend and short term nonlinear dependencies in bus delay data which enhance the prediction accuracy in the complex network.

1. Prophet trend extraction:

Prophet is first applied to the historical bus delay data to separate the long term trend component (yhat). Instead of using the Prophet’s prediction as the final forecast, the models output is added as an extra input feature to the GRU model. This decomposition step allows the GRU model to learn the residual variation.

2. GRU for temporal and contextual learning:

The GRU model is then trained using the following features which includes:

- Prophets trend prediction
- Lag features(previous delays)
- Weather conditions(temperature, precipitation)
- Temporal indicators(weekday or weekend)
- Rolling means and
- Cyclic encoding (hour_of_day)

This allows GRU to capture both low-frequency stability from the trend and high frequency disruptions which is caused by weather.

3. Architectural Design:

Feature Fusion Layer :
The output from the Prophet Yhat values are combined with the other features is passed into the GRU layers.This ensures the GRU learns.This ensures the GRU learns temporal dependencies in the context of an already smoothed long term signal.

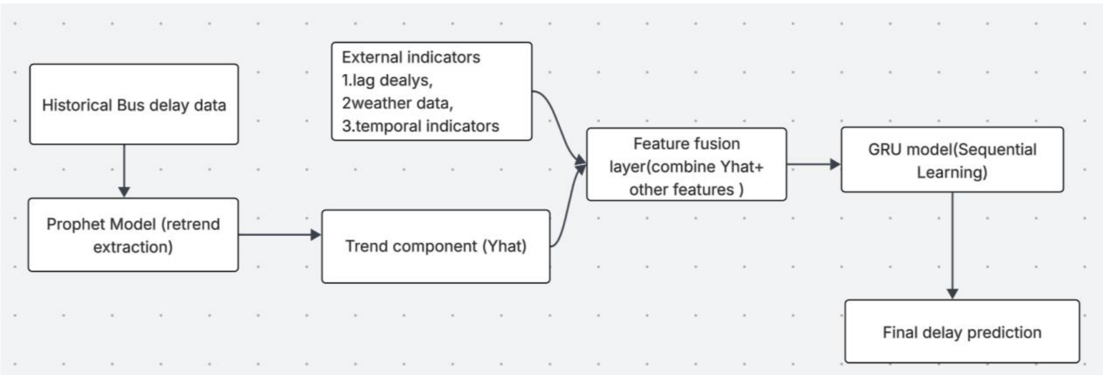

FIG 4.1 model architecture

Output Layer:
The GRU's output is passed through a dense layer to produce the final bus delay prediction.This prediction reflects both global seasonality and dynamic short term influences, which leads to more balanced and interpretable forecasting.

5.Result and discussion:

5.1: Introduction:

This chapter presents and analyzes the results which are obtained from the predictive models developed to forecast the Dublin bus delays. Four models were evaluated: Random forest with GridSearchCV optimization), GRU , Prophet and the proposed hybrid GRU+ Prophet model.The primary evaluation metrics include Mean Absolute error (MAE), Root Mean Squared Error(RMSE), and R^2 score, which collectively access the accuracy, variance, and overall explanatory power of each model. These results are compared to understand the relative strengths and limitations of each modeling approach and to evaluate the hybrid models performance.

5.2 Model Evaluation:

Evaluation metrics were used to find the effectiveness of each model in predicting the bus arrival delays.The metrics are:

- Mean Absolute Error (MAE):Reflects the average magnitude of errors in seconds, showing how far off predictions were for actual delays.

- Root Mean Squared Error (RMSE):Provides insight into the variance of error with higher penalties for large deviations

- R^2 score: Measures the proportion of variance in bus delay, which indicates the models generalization ability.

All the model prophet, GRU, Random Forest and the Hybrid GRU+ Prophet models were evaluated on the same dataset.The dataset was split into 80% for training and remaining 20% for testing. Scatter plots comparing actual vs predicted delay values were generated for each model to visually evaluate the prediction.

5.3 Model Performance Summary

The performance of each model is shown as below:

Model	MAE (s)	RMSE (s)	R^2 Score
Random Forest	0.20	1.86	0.9963
Hybrid GRU + Prophet	15.90	22.83	0.4496
Prophet (with regressors)	17.30	23.43	0.4222
GRU (Stacked Architecture)	21.12	26.99	0.2307

Table 3: Model performance comparision

5.4 Visualization of Results

To better understand each model,time series plots comparing actual vs predicted arrival delays were generated using a 30 minutes rolling average.

1.The random forest model closely follows the actual delay trend, despite its excellent R^2 score, some spikes were overly smoothed, indicates that the model may be over fitted.

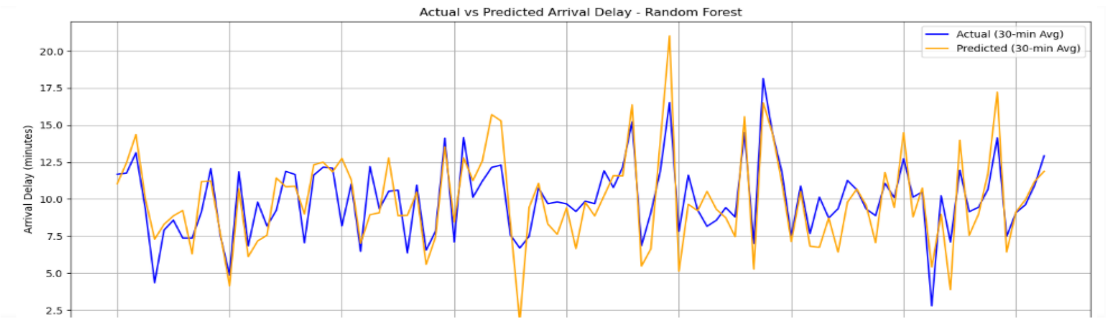

Fig 5.1:Actual vs. Predicted Delays (Random Forest)

2.The GRU model captures peaks and valleys but lags in accurately predicting the sharp changes.

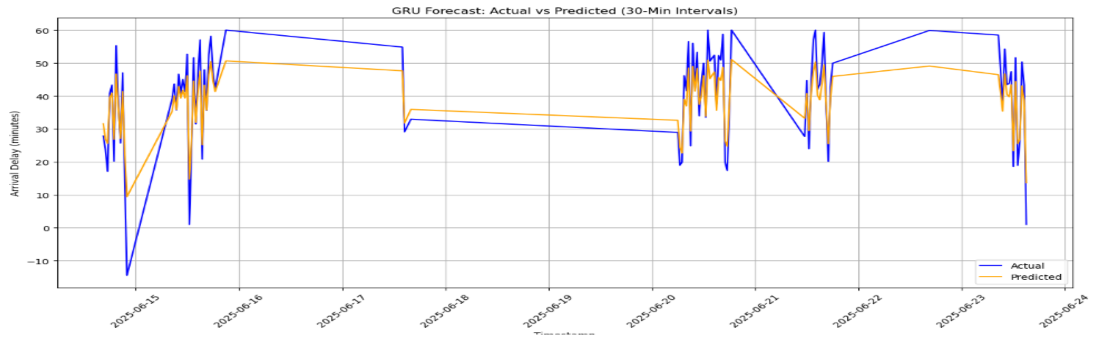

Fig 5.2:Actual vs. Predicted Delays (GRU)

3.Prophet performed well in capturing trend based delays but model failed to adjust to sudden disruption or in peak hours effetcts.

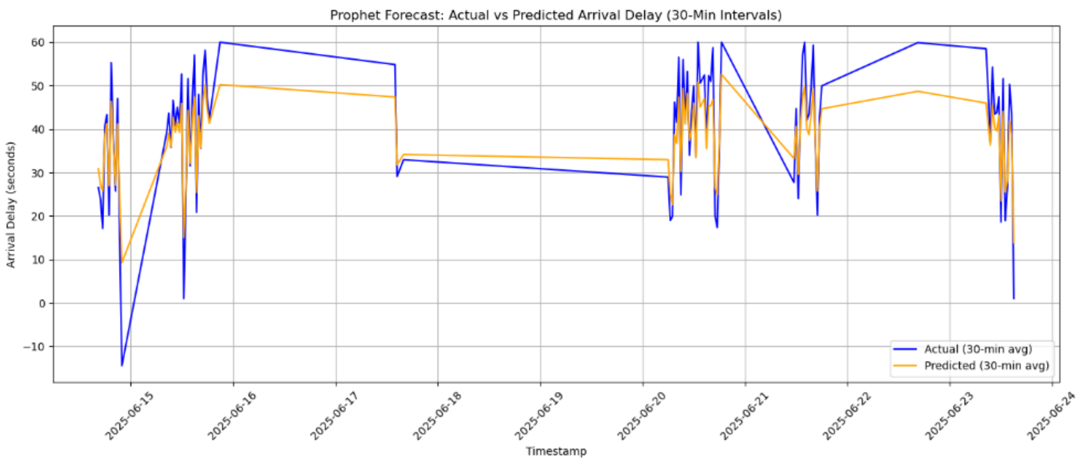

Fig 5.3:Actual vs. Predicted Delays (Prophet)

4.The hybrid model predicts both the macro patterns and micro variations more effectively than the other models

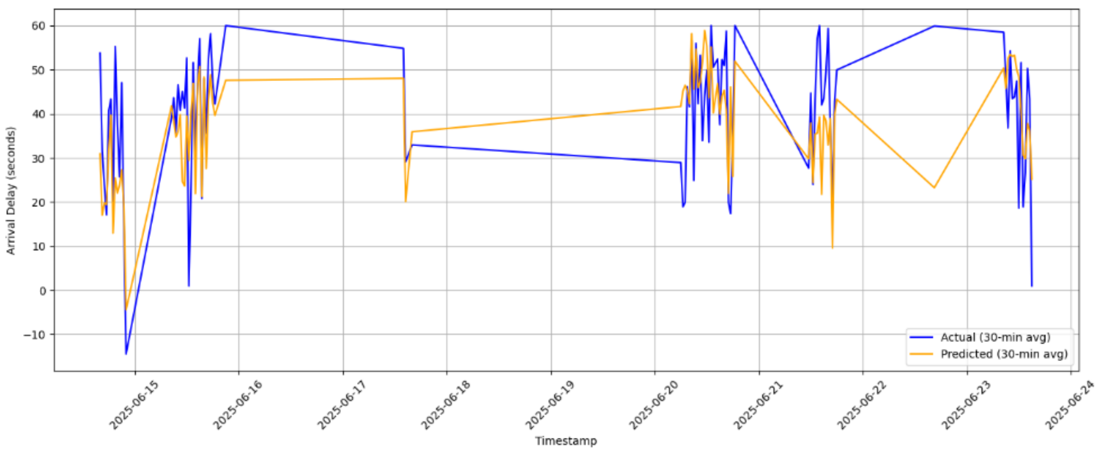

Fig 5.4:Actual vs. Predicted Delays hybrid (GRU+Prophet)

5.A bar chart compares the evaluation metrics of all the standalone models and hybrid model

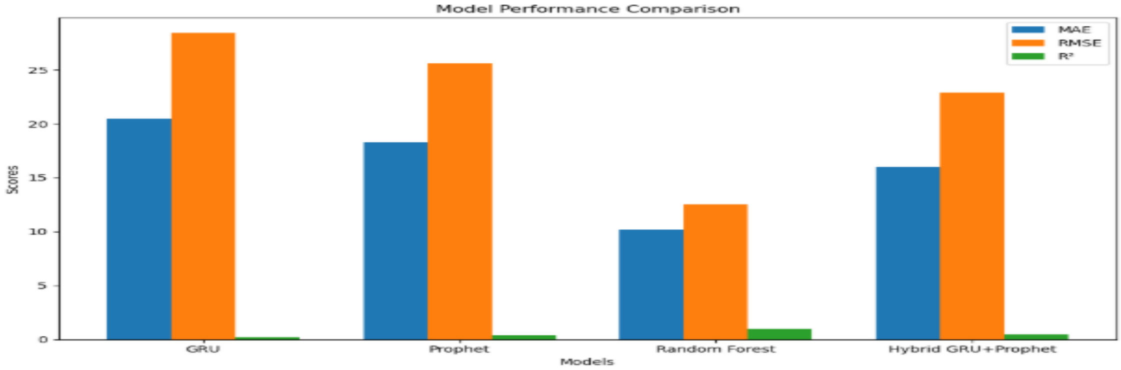

Fig 5.5:Model performance comparison

6.A histogram shows how residual errors are distributed for each model, useful for identifying the bias.

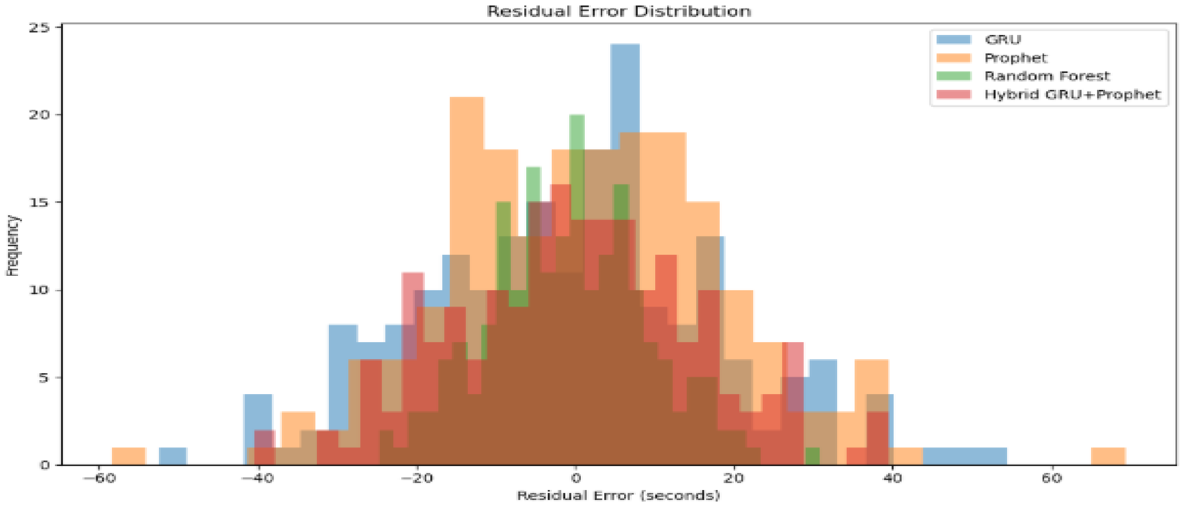

FIG 5.6 Residual Error Distribution

6. Discussion

6.1 Performance Analysis

Random Forest Regressor:

The Random forest model achieved near perfect performance(MAE=0.20s, RMSE=1.86, R^2=0.9963),these values are unusually high for a noisy real world data which indicate overfitting or temporal data leakage. Still the models strength lies in capturing the non linear feature interactions among the lag delays, weather variables, and time based features.This finding is aligned with Sarhani et al., 2023 showing that ensemble tree models excel at feature based regression but are less interpertable for the sequential patterns.

GRU :

The GRU model showed the least performance with an MAE of 21.2 seconds RMSE of 26.99 second and R^2 score of 0.2307, this is due to:

- **Unable to capture the trend:**The GRU model is only suitable for sequence learning, it struggles to model both seasonal patterns and irregular changes.

- **Insufficient training data:** It requires large dataset and the hypertuning to avoid under-performance (Zhang & Kabuka, 2017).

Prophet:

The Prophet model performed slightly better that the GRU with an MAE OF 17.3 seconds, RMSE of 23.43 second and R^2 score of 0.4222, It effectively captured the long term trend but it failed to react dynamically to short term variation caused by sudden weather changes or peak hour effects which leads to increased prediction errors which was noted by Arslan(2023).This is because Prophet assumes relatively stable seasonal components and does not model sequential dependencies.

Hybrid GRU + Prophet:

The proposed hybrid model which integrates the prophets trend output as input to a stacked GRU network , this model outperformed both GRU and Prophet with an MAE OF 15.90 seconds, RMSE of 22.83 second and R^2 score of 0.4496. It takes the strength of both the models. Although still less accuracy than the random forest,Because GRU's data and tuning limitation still applied.However, the hybrid model is more interpretable and more generalize, especially suited for time series data with both recurring and irregular patterns, this aligning with findings of Du et al,(2022) and Zeng et al.(2023) on the benefits of hybrid models.

6.2 Discussion and Implications

The results between accuracy and interpretability:

- Random Forest: High accuracy but low transparency, difficult for transport agencies to interpret decisions.

- GRU: Can model sequence but requires large amount of training data and hypertuning.

- Prophet : The model is transparent, and robust to missing values, but lacks the depth to model high frequency variation.

- GRU+Prophet: This model balances both the long term trend and short term dependencies and adaptability; making it ideal choice for scenarios requiring both operational insights and responsiveness.

6.3 Limitations of the Study

Despite its contributions, this study has several limitations:

- **Data Constraints:** The dataset was geographically limited to Dublin and specific time frame, different seasonal, and geographical coverage needed.

- **Model Complexity :** Sequential training of Prophet and GRU increases runtime and resource demand.

- **Missing Features:** This model currently don't have a live traffic congestion, road events, or social factors ,which may impact delay in prediction in real-world scenarios.

7. Conclusion and Future Work

7.1 Conclusion

This research focuses on the growing challenge of forecasting bus arrival delays in urban passenger systems and Dublin's public transport network. Reliable and interpretable forecasting solutions are essential to supports transit optimization, enhance passenger satisfaction and data-driven traffic management.The limitations of traditional time series methods and standalone deep learning, this model proposed hybrid forecasting architecture connecting Prophet and GRU. It was used for modeling long-term trends and seasonal components, GRU takes short-term, nonlinear dynamics from lagged delays, weather and time-based features. The hybrid model can handle both structured patterns and unpredictable variations in arrival delays.The results shows that independent models like GRU and Prophet performed reasonably well, the hybrid GRU and Prophet model exceeds them by, providing the strengths of both model. Random Forest achieved the high predictive accuracy, but it lacks temporal interpretability, makes the hybrid model more balanced and insightful solution. Overall, study highlights the value of combining statistical decomposition with deep learning for complex transport forecasting tasks. The proposed approach is applicable not only for Dublin but also for other cities facing same challenges.

7.2 Future Work

Building on the current findings, future research can advance this work in the following ways:

Data Enhancement: Incorporate real-time GPS data, event logs, or traffic congestion indicators to improve contextual awareness.

Model Expansion: Explore transformer based hybrids or attention augmented GRUs for better performance.

Explainability Tools: Use SHAP or attention mechanisms to interpret feature importance within the GRU component.

Deployment : Implementing a real-time dashboard or API service for the authorities to use in operational planning.

Efficiency : Investigate lighter-weight alternative hybrid approach for deployment on edge devices.

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