Weather and Rail Delays: Analysis of Metropolitan Rail in Dublin

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Abstract

With changes in the global climate, the occurrence of severe weather events appears to be becoming ever more frequent. As a result of this, vital transport networks are becoming increasingly exposed to disruption or disablement due to weather related incidents. In order to adapt to these changing conditions it is important to gain an understanding of how weather currently impacts transport systems. This paper presents the results of a statistical analysis of the impact of weather conditions on the performance of metropolitan commuter rail based upon observations made on the Dublin Area Rapid Transit (DART) rail system. Utilising a dataset comprising daily performance observations for 30 train services operating across the DART network, this research applies a number of multiple regression models to gain an understanding of the role of weather, temporal effects, and resulting interactions, on delays experienced by the network. While research in this area has traditional focused on the impact of single events, this study presents an examination of the role of multiple factors and their interactions. With regard to temporal effects, the largest delays are observed in the last third of the year, with peak delays occurring in November. Delays due to adverse weather conditions are observed, with rain being the primary factor related to poor performance. Interactions between different weather conditions, particularly wind and rain, as well as between weather conditions and the month in which a journey took place were also observed to be significant and resulting in delays to services.

1. Introduction

The global climate appears to be undergoing significant changes due to increased concentrations of greenhouse gases within the atmosphere. One result of this is changes in the frequency and severity of weather events (IPCC, 2014). Within an Irish context this is likely to lead to warmer winters and increased large scale precipitation events (EPA, 2016). Changing weather patterns mean that there is an increasing need to understand how weather events impact upon existing public transport systems. Increases in heavy precipitation (mainly rain) and the frequency of high winds would appear to be an area of significant concern for network operators, however very little academic research currently exists regarding the quantification of the effects of weather events can have upon the performance of metropolitan heavy rail systems. This research provides an examination of the role of a number of weather parameters on a metropolitan heavy rail line in the Greater Dublin Area (GDA) in eastern Ireland.

2. Background

2.1 Climate Change and Transport

Within the scientific community there is a large degree of consensus that the global climate is undergoing a dramatic change (Bray, 2010). In terms of the impact on existing transport networks, the United Nations Intergovernmental Panel on Climate Change (IPCC) has stated that the resulting alteration of the climate is "likely to affect all transport modes to varying degrees" (IPCC, 2014). While some of these changes may be considered positive, with potential increases in the use of open air modes such as cycling and walking due to the potential easing of harsh winter weather conditions in northern latitudes (Broker et al, 2013 and Wadud, 2014), it would appear that current transport infrastructure may be highly vulnerable to the consequences of altered weather patterns. According to the IPCC "The transport sector will be highly exposed to climate change and will require extensive adaptation of infrastructure, operations, and service provision" (IPCC, 2014). Events such as coastal flooding and storm surges associated with sea level rise are likely to threaten transport infrastructure in low lying maritime areas, while increased precipitation may increase congestion and the frequency of traffic incidents (Koetse and Rietveld, 2009). Coastal areas (like the area in which the DART operates) have been highlighted as particuarly vulnerable to increases in sea level and extreme weather (Dawson et.al, 2016).

While it appears likely that changes in climate and weather may result in significant impacts upon current transport systems, it is not yet clear which services will be adversely affected, and how severe such impacts will be. With limited funding often available to network owners and operators, it is important to understanding how vulnerable given systems are to allow for prioritisation in adaptive works. With this in mind it is important to gain a better understanding of how weather impacts upon specific transport networks, in order to make predictions with regard to how changes in the climate are likely to affect such networks in the future.

2.2 Weather and Other Modes

While some work has been undertaken to assess the role that weather events play in the operation of railway networks, the majority of the research regarding the role of weather upon transport services is within the road traffic sector (Mesbah et al, 2015). Early research in this field in the late 1990's from Wales and England shows the strong relationships between extreme weather and the frequency of accidents (Edwards, 1996). Research examining the role of precipitation upon road networks, (Hooper et al, 2014) highlighted significant reductions in speed, and the potential knock on effects for journey times, as well associated economic costs, whereas Kwon et al (2011) has highlighted weather as one of the factors that leads to the decomposition of travel time reliability. Similar work by Theofilatos and Yannis (2014) has shown that precipitation can increase the likelihood of road traffic accidents, but that the role of other parameters such as wind speed, temperature, and visibility are not were not clear. However, in specific cities such as London, research using Automatic Number Plate Recognition techniques has been used to determine travel time increases associated with defined levels of both rain and snow, while also finding negligible impacts of temperature (Tsapalis, 2013). A number of studies have examined the role that winter weather can have on traffic collisions in both the United States and Canada (Andrey et al, 2013) (Black and Mote, 2015), but point out that it is hard to generalise these findings across cities.

Within the active transport sector research undertaken by Flynn et al (2011) found that bicycle commuting is significantly impacted by weather conditions with the absence of rain related to increased observed levels and the presence of snow leading to significant decreases. Similarly work undertaken in Toronto Canada has demonstrated the impact of weather conditions such as wind, rain, and low temperatures on non-motorised modes (Saneinejad et al, 2012).

2.3 Weather and the Rail Sector

While there is a large body of research assessing the impact of weather events on road networks, relatively little research has been carried out to date in terms of their impact upon main line rail services. Research into the likely effects of climate change on rail networks has highlighted potential delays resulting from extreme weather events (Koetse and Rietveld, 2009) due to factors such as very high wind speeds and flooding events, which can lead to network or line segment closures. These weather based delays can also lead to the loss of economic efficiency as a knock-on effect (Rosetti, 2002). An examination of the role of precipitation upon performance of Melbourne tram system by Mesbah et al (2015) showed that rainfall can produce detectable changes and delays to service levels. Similarly, research undertaken in the Netherlands has highlighted how weather events can result in direct effects upon train performance in terms of delays, as well as indirect effects as a consequence of impacts upon necessary infrastructure (Xia et al, 2013). When assessing how the 2010 winter weather affected rail freight operations in Norway, Sweden, Switzerland and Poland, Ludvigsen and Klæboe (2014) found that rail operators were totally unprepared to deal with the powerful and cascading effects of three weather elements. Specifically, these elements were long spells of low temperatures, heavy snowfalls, and strong winds. However, during this study it was difficult to establish clear causal relationships between the bad weather and occurrences of freight train delays and/or bad weather-induced technical problems affecting delay duration.

Within the rail industry, the United Kingdom rail infrastructure owner and operator Network Rail identifies a number of sources of delay arising from weather events and categorises these into summer events, such as lightning strikes, rails buckling due to heat, and flooding, as well as winter delays arising from fog, snow and ice, high winds, and cold related rail fractures (Network Rail, 2015). Similar research examining the UK railway network has defined a number of thresholds for variables such as high and low temperatures, snow depths, and wind speed that can adversely impact operations, while less obvious phenomena such as humidity leading to engine malfunctions can also occur (Thornes and Davis, 2002).

2.4 Research Objectives

While some research has been carried out regarding the role of precipitation upon the performance of existing rail systems, it is clear that there is still a considerable gap in the literature regarding the role of other weather phenomena. This is especially true in terms of quantifying impacts weather events on services. Previous studies have tended to focus on the impact of individual conditions and events. More research is required with regard to combined effects and interactions between different weather phenomena, such as high winds and rain. Furthermore there are other factors that impact the performance of rail services and there is a need to better understand their interactions with weather conditions. In this paper, we attempt to address the following research objectives:

- Assess the underlying temporal trends that impact the DART service.
- Examine the role of weather in terms of its impact on service performance.
- Examine interactions between different weather events and temporal effects, in terms of their ability to produce delays across the network.

3 Description of the DART line

The DART is an electrified heavy rail service operating on the eastern seaboard of Dublin. The DART is Ireland's busiest heavy rail line, accounting for 56% of total annual patronage on Irish railways, and the line contains seven of the ten busiest stations on the entire network (NTA, 2013). The DART operates two separate services: one from Malahide in the north to Greystones in the south, and one from Bray (one stop north of Greystones) to Howth in the north east. The Malahide-Greystones service operates 48 times per day on a normal weekday, while the Bray-Howth service operates 78 times per day. However, the majority of services share the same portion of the network, with only 7 of the stops served by the DART not comprising part of both services. For the purposes of this analysis it was decided to only examine the Bray to Howth Junction section of the line as the stations along this section are covered by both services. In the year under examination (2013) the DART had a daily average ridership of 55,921 passengers, which was down very significantly from 83,618 in 2007 (NTA, 2013). This decrease in ridership is likely to be a result of the contraction of the Irish economy which began with the 2008 financial crisis and has seen a general reduction in commuter numbers throughout the GDA.

In terms of potential vulnerability of the service to weather events, the DART's proximity to the coast of Dublin Bay leave it quite exposed to both coastal flooding and high winds, which may result from storms in the Irish Sea. As it is a metropolitan rail service, its passenger demand profile is closely linked to commuter trends, with spikes in demand occurring in the morning between 7am and 9am and again in the evening around 5pm. More detailed passenger data was not available to the research team for the purposes of this analysis.

3.1 Weather and the DART

Due to the exposed nature of the large sections of the line, DART services have a history of experiencing severe delays and disruptions due to extreme weather events. Within the last ten years numerous closures and delays along the DART line have been experienced, such as flooding arising from heavy rainfall, high winds causing trees to fall onto overhead lines, and disruptions due to heavy snowfalls. Flooding events leading to the closure of the DART line appear to relatively common, in particular in vicinity of Dalkey station in the southern half of the line. This has caused repeated line closures on the Bray- Dún Laoghaire section (Irish Times, 2014). Flooding events have also occurred at Bayside station on the Northern portion of the line (Journal, 2011), while serious damage caused by the flooding of the Dodder river in 2011 lead to the curtailment of services between Grand Canal Dock and Sydney Parade stations for a period of two weeks in October/November 2011 (Journal, 2011). As the DART draws its power from overhead lines and has significant vegetation along portions of the line, trees falling as a result of high winds are a significant problem. Such events have resulted the suspension of services between the Dalkey and Dún Laoghaire stations (Irish Times, 2011) in 2011, at Landsdowne Road Station in 2013 (Irish Examiner, 2013), and on the Northern Section of the line in 2015. Heavy snowfall also has the ability to cause significant delays as seen in December 2010 (Herald.ie, 2010). While these events demonstrated that the DART line is vulnerable to disablement due to extreme weather events, they do not provide much in terms of contextual information regarding the impact of weather events on services which remain in operation but are still adversely affected.

3.2 Seasonal Factors and Leaves on the Tracks

One particular seasonal issue that tends to cause significant delays on the DART line is the presence of leaves on the tracks. This is caused by the shedding of deciduous trees along the track in the autumn and early winter. When such leaves fall on the rails, the rolling action of the train passing over them compacts them into 'mulch', which greatly reduces the coefficient of friction between the rail and wheels of the rolling stock. The consequence of this is a reduction in the possible safe acceleration rate of the carriages and also an extension in braking distances required by the trains. This in turn leads to a delay in scheduled services as trains have to operate below normal speeds. This problem is of significant magnitude that Irish Rail has invested in 86 traction gel applicators to help ease this problem and it provides regular updates to its users concerning this problem during the relevant season. See Irish Rail (2015) for more detailed information on this specific problem.

While it is clear that DART services have a vulnerability to weather events, very little research currently exists regarding the specific effect of different weather parameters, in terms of the magnitude of their impact upon delays for service users. This research utilises both weather observations and DART performance records to produce a better understanding of the impact of the various weather conditions experienced by the service.

4 Descriptive Statistics

The principal dataset considered for analysis was a record of the arrival and departure times of DART services, and their corresponding published schedules, from 2013. The first step, in terms of initial analysis of the dataset was the identification of underlying temporal trends. For the purposes of this analysis it was decided not to include observations for weekends or public holidays. No significant differences were noted in travel times between the different weekdays, however temporal trends were identified during the day (in terms of hours) and over the course of the year (in terms of months). Also weekends and public holidays display very different operating schedules and travel behaviors. Analysis of the data showed that the longest journey times occurred in the morning peak period and again over a longer period in the late afternoon/early evening. This finding would appear to agree with intuition, as these time periods represent peak periods of commuter activity, and therefore, trains are likely to be delayed as more passengers attempt to board. While the dataset does not contain observations for journeys before 7am and after 6pm, it is expected that journey times in these periods would be lower than those seen at peak times. With regard to the differences between journey times throughout the year, the median journey time remains quite consistent for the first nine months of the year but increases in October, reaching a peak in November before falling off again. One possible explanation for this may be the presence of leaves on the track as alluded to previously.

The second dataset used for the purposes of this research, was the weather data collected from the Irish Meteorological service Met Éireann (Met Éireann, 2015). For this study the weather data collected from the Dublin Airport weather station for the 2013 calendar year is used as it is the closet station to the line. This dataset contained hourly records for occurrences such as wind and gust speed (km/hr), temperature (degrees C), snowfall and rainfall (mm), and visibility (m). As well as providing this information, Met Éireann also provides a number of criteria for their colour coded weather warnings (Met Éireann, 2015). Based upon these criteria, it was possible for the research team to define a good weather or "Green" condition within the dataset. This refers to a time period where none of the weather warnings are in place, and this condition is defined by the thresholds outlined in Table 1.

Table 1: Green Condition Criteria

Weather Event	Threshold
Wind speed	< 80 km/hr
Rain after 24 hours	< 30 mm
Rain after 12 hours	< 25 mm
Rain after 6 hours	< 20 mm
Temperature	< 27C
Temperature	> 2C
Visibility	> 1000m

5 Methodology

5.1 Data Filtering

The DART performance data was initially supplied by Irish Rail and was then filtered to remove observations that did not meet relevant criteria from the dataset. For the purposes of this research the term "journey time" was defined as the time that the train arrives at the last station considered for analysis minus the time it departed the first station considered. This does not consider whether or not the train was late into service, and therefore only the impact of weather conditions on trains already in operation is considered. The initial dataset was filtered to allow for the removal of known outliers arising from such sources as public holidays, major sporting events at Dublin's Aviva Stadium (football and rugby stadium with a capacity of 52,000), and non-weather related disruptions, such as traffic bridge strikes and level crossing failures that were reported in the media. To allow for more comparable analysis, all observations occurring on Saturdays and Sundays were also removed from the dataset.

The next step was to remove unknown outliers in line with common approaches within the literature (Mesbah, 2015). The aim of removing these unknown outliers is to take into consideration (a) other events affecting the demand not included previously, such as strikes in other public transportation modes; (b) non-specified maintenance or repair activities; and (c) the fact that very good weather conditions might related to an increment of the users travelling in a more relax manner (implying larger delays). This filter was only applied to observations in the data set that met Green Condition criteria, that is outliers that were not linked to incidents of bad weather. The reason for this is that it was desired to keep outliers that may be associated with extreme weather events as they related to the research objectives of the study. With a remaining sample size after initial filtering of approximately 6,000 observations plotted on a normal distribution, it is possible to argue that points furthest in tails of normal distribution that circa 1/6,000 (= 0.00015) could be viewed as outliers. First the mean and standard deviation of journey times was calculated. Points more than 3.29 standard deviations from mean were deleted (this corresponds to probabilities of 0.9995 and 0.0005). The mean and standard deviation were then recalculated and the process repeated. Having done this three times, all (Green Condition) data points fulfilled this criterion, removing 91 outliers from the dataset.

Once these filters had been applied the rail data set was considered to be in its final form. The overall effect of the removal of unwanted observations is a decrease in the total number of observations from 8,811 to 6,345, resulting in a slightly increased mean journey time of 60.56 minutes in comparison to 60.18, and a reduced standard deviation of 3.17 minutes in comparison to 3.81 minutes.

5.2 Regression Models

At first, a simple multiple linear regression model was fitted to the data. In this model, it is assumed that the effect of the explanatory variables on journey time will occur independently. This model is described in Equation 1.

$$Y_i = \beta_0 \quad + \sum_{P=1}^{P} \beta_p \, X_{ip} + \varepsilon_i \tag{1}$$

Where: Y_i is the dependent variable, β_0 is the intercept, β_p is the coefficient for the independent variable p, X_{ip} is the observed value, and ε_i is the error term.

5.3 Akaike's Information Criterion

For the purposes of the estimation of the models, Akaike's information criterion (AIC) (Akaike, 1973) was used to decide which variables to include and exclude. This approach rewards increased goodness of fit, given by the likelihood function, and penalizes the number of estimated parameters, avoiding the overfitting problem. The two main limitations of the AIC concern small sample sizes and complex collections of models and are not applicable to this situation.

Once the descriptive analysis of the two datasets had been undertaken, the next step was to attempt to model the impact of weather events upon the journey times of services along the DART line. This was done via a multiple linear regression analysis.

5.4 Modelling Steps

For the purposes of this analysis initial regression models were constructed and then additional variables added to increase the complexity and performance of the models. This involved first creating models based upon the DART schedule and the the unique Train_ID, and then adding weather and temporal variables. The Train_ID variable is a unique identifier for a given scheduled service and is likely to capture information such as passenger demand. The first of these weather models only considered whether or not the Green Condition defined previously was true or not, with the dummy variable taking a value of 1 when good weather was present and 0 when it was absent. The next model considered the impact of the various weather terms as independent variables, while the last model assessed the interaction of weather terms with each other and also temporal terms.

5.5 Model 1: Schedule and Train_ID models

The first two models developed were designed to create a base model. In the first model the published train schedules was the only independent variable, whereas in the second base model the Train_ID was used. The details of these models can be seen in Table 2. The results in Section 6 indicate that the published schedule does a very poor job explaining the observations within the data set and that the Train_ID, and the latent information contained within that variable, provides a better explanation of the variation. This model is labelled Model 1.

Table 2: Initial Models

Variable Examined	Description	Variable Type
Schedule	The published schedule for the service	Categorical
Train_ID	The unique ID of the train.	Categorical

5.6 Model 2: Green Condition Model

The next step was to create a model, which in addition to the Train_ID and the schedule also considered the weather conditions present during the trip. The first and simplest of these models simply considered whether or not the Green condition defined in Section 4 had been breached during the duration of the journey. If it had not been breached it could be considered that trip took place during good weather conditions. Table 3 outlines the variables that were included in this model. This model was labeled Model 2.

Table 3. Weather Effects Model (2) Variables

Variable Examined	Description	Variable Type
Schedule	The published schedule for the service	Categorical
Train_ID	The unique ID of the train.	Categorical
Green	Indicator variable for whether green conditions existed	Categorical

5.7 Model 3: Specific Weather and Temporal Variables Model

Model 3 expanded upon weather conditions examined in Model 2, however, rather than simply considering the whether or not the Green condition had been breached, this model assessed the role that the various weather conditions, for which there was data available, had in terms of producing delays to the service. This model also examined the role of temporal effects, specifically in the form of a Month variable relating to the calendar month in which the journey took place. The variables considered are outlined in Table 4 and this model is labeled Model 3.

Table 4. Specific Weather Effects Model (3) Variables

Variable Examined	Description	Variable Type
Schedule	The published schedule for the service	Categorical

Train_ID	The unique ID of the train.	Categorical
Month	The month of year in which the trip takes place	Categorical
Rain	The amount of rain (mm) that fell in the previous hour	Continuous
Rain_6	The amount of rain (mm) that fell in the previous six hours	Continuous
Rain_12	The amount of rain (mm) that fell in the previous twelve hours	Continuous
Rain_24	The amount of rain (mm) that fell in the previous twenty four hours	Continuous
Wind_Speed	The average hourly wind speed in kilometres per hour	Continuous
Temp	The average hourly temperature in degrees C	Continuous
Visibility	The visibility in metres	Continuous

5.8 Model 4: Interactions Model

The final regression model (Model 4) that was created considered impact of interactions between different weather terms, and between weather terms and temporal terms. Specifically, we were interested in whether the combination of heavy wind and rain had the potential to cause longer delays, particularly in the autumnal months, where wet leaves on the track were known to be an issue. As there were a large number of possible interaction terms for this model, AIC was used to determine which were to be kept in the model. Variables and interaction terms that did not improve the criterion were dropped from the model in a stepwise procedure. The retained model terms are outlined in Table 5.

Table 5. Interactions Model (4) Variables

Variable Examined	Description	Variable Type
Schedule	The published schedule for the service	Categorical
Train_ID	The unique ID of the train.	Categorical
Month	The month of year in which the trip takes place	Categorical
Rain	The amount of rain (mm) that fell in the previous hour	Continuous
Rain_6	The amount of rain (mm) that fell in the previous six hours	Continuous
Rain_12	The amount of rain (mm) that fell in the previous twelve hours	Continuous
Rain_24	The amount of rain (mm) that fell in the previous twenty four hours	Continuous
Wind_Speed	The average hourly wind speed in kilometres per hour	Continuous
Month.Wind_Speed	The interaction between wind speed and a given month	Interaction
Month.Rain	The interaction between rain in the previous hour and a given month	Interaction
Month.Rain_12	The interaction between rain in the previous twelve hours and a given month	Interaction
Month.Rain_24	The interaction between rain in the previous twenty four hours and a given month	Interaction
Wind_Speed.Rain_24	The interaction between wind speed and the rain in the previous twenty four hours	Interaction
Month.Wind_Speed.Rain_24	The interaction between the month, wind speed and rain in the previous twenty four hours	Interaction

6 Results

This section presents the results of the regression modelling process. In the case of each of the models the journey time is the dependent variable.

Model 1

The first model assessed the role that the published service scheduled and the unique train identifiers played in terms of predicting the observed trip lengths. Table 6 outlines the performance of the model if first Schedule and then Train_ID are used as the predictor variable. These results clearly indicate that the Train_ID variable provides more information than the scheduled times, which have poor predictive performance. This finding may be considered to be quite unexpected as it appears to indicate that the published schedules in fact bare little or no relation to the real world observations.

This is very much in contrast to other studies (Mesbah et al, 2015) where such timetables provide the greatest amount of explanatory power. As this result was so surprising it was re-checked, however it does appear to reflect underlying issues with timetable accuracy.

Table 6.R^2 Values

Model	R^2 Value (Adjusted)
Schedule	0.05
Train_ID	0.17

Model 2

In addition to the train's ID and schedule, Model 2 also considered the impact of weather, in terms of whether or not the green condition was breached. Table 7 displays the ANOVA values associated with this analysis.

Table 7. Model 2 ANOVA

Coefficient	DF	SSE	MSE	F value	P Value
Schedule	1	10.94	10.95	1.38	0.24
Train_ID	29	10994.54	379.12	47.77	$< 10^{-5}$
Green	1	181.80	181.80	22.90	$< 10^{-5}$
Residuals	6306	50051.28	7.94		

The estimates for the terms examined in Model 2 are outlined in Table 8 and demonstrate that journey time can vary considerably with regard to the specific service that is running. With regard to weather impacts, when the Green condition is observed to be true, that is there is good weather present, journey times are on average 0.7 of a minute or 42 seconds faster than when this condition is not met. This can be considered to be a significant delay.

Table 8. Model 2 Estimates

Coefficient	Estimate	P value	Coefficient	Estimate	P value
(Intercept)**	46.78	0.00005	Train 18	0.51	0.07
Train 1*	0.70	0.01198	Train 19	0.18	0.523
Train 2	-0.04	0.91	Train 20**	1.22	0.00945
Train 3	-0.46	0.10	Train 21**	1.26	0.00733
Train 4	0.10	0.75	Train 22**	-2.06	$< 10^{-5}$
Train 5	0.05	0.85	Train 23	-0.02	0.97
Train 6**	2.54	$< 10^{-5}$	Train 24**	-1.92	$< 10^{-5}$
Train 7**	1.57	0.00349	Train 25	-1.85	0.27
Train 8**	1.28	$< 10^{-5}$	Train 26*	0.66	0.01716
Train 9**	-1.01	0.00030	Train 27	2.64	0.35
Train 10**	-2.02	$< 10^{-5}$	Train 28	-0.02	0.97
Train 11	0.46	0.10	Train 29	0.94	0.20
Train 12	-0.22	0.44	Train 30	1.39	0.62
Train 13	-0.18	0.53			

Train 14**	-1.17	0.00009	Green	-0.70	$< 10^{-5}$
Train 15**	-2.56	0.00050	Schedule	0.24	0.21
Train 16**	-2.18	$< 10^{-5}$			
Train 17**	46.78	0.00005			

Residual standard error: 2.82 on 6306 degrees of freedom.

Multiple R-squared 0.18.

Adjusted R-squared: 0.18.

F-statistic: 45.47 on 31 and 6306 degrees of freedom.

* Significant at Alpha =0.05, ** Significant at Alpha=0.01

Model 3

The third model under consideration assessed the role of both individual weather events as well as the impact of temporal variables in terms of the calendar months of the year in which the journey occurred. Table 9 outlines the ANOVA values associated with this model. This model examined variables such as wind speed, visibility, temperature, and rain fall over one, six, twelve, and twenty four hours respectively.

Table 9. Model 3 ANOVA

Coefficient	DF	SSE	MSE	F value	P Value
Train_ID	29	10994.54	379.12	51.15	$< 10^{-5}$
Schedule	1	10.95	10.95	1.48	0.22
Month	11	3524.70	320.42	43.23	$< 10^{-5}$
Rain	1	73.57	73.57	9.93	0.00163
Rain.6	1	0.01	0.01	0	0.97
Rain.12	1	2.21	2.21	0.30	0.589
Rain.24	1	14.75	14.75	1.99	0.16
Wind.Speed	1	0.78	0.78	0.11	0.75
Temperature	1	3.09	3.09	0.42	0.52
Visibility	1	1.44	1.44	0.19	0.66
Residuals	6289	46612.54	7.41		

The variable estimates associated with Model 3 are presented in Table 10. The month variables are expressed in minutes and take January as the reference variable. Therefore negative coefficient estimates indicate that a journey taken in a given month is likely to be shorter than one taken in January and a positive coefficient indicates that it will be longer. The results indicate that all months with the exception of July can be considered to significant, with lower journey times than January being observed in all months except October, November, and December. The most significant delays can be seen to occur in November. With regard to the weather variables under examination, only rain that fell with an hour before a given journey was found to be statistically significant and a cause of delays.

Table 10. Model 3 Estimates

Coefficient	Estimate	P value	Coefficient	Estimate	P value
(Intercept)	43.60		Train 26	2.36	0.39
			Train 27	-0.10	0.79

Train 1**	0.70	0.00952	Train 28	0.71	0.32
Train 2	-0.06	0.88	Train 29	0.07	0.98
Train 3*	-0.55	0.04615			
Train 4	0.07	0.82	Schedule	0.29	0.13
Train 5	-0.05	0.84			
Train 6**	2.45	$< 10^{-5}$	Month_Feb**	-0.60	0.00039
Train 7**	1.44	0.00602	Month_Mar**	-0.70	0.00005
Train 8**	1.22	$< 10^{-5}$	Month_Apr**	-0.80	$< 10^{-5}$
Train 9**	-1.12	0.00004	Month_May**	-0.79	0.00002
Train 10**	-2.14	$< 10^{-5}$	Month_Jun**	-0.79	0.00032
Train 11	0.35	0.20	Month_Jul	-0.42	0.08
Train 12	-0.31	0.25	Month_Aug**	-0.73	0.00157
Train 13	-0.27	0.31	Month_Sep*	-0.40	0.04936
Train 14**	-1.15	0.00008	Month_Oct	0.35	0.07
Train 15**	-2.77	0.00012	Month_Nov**	1.54	$< 10^{-5}$
Train 16**	-2.24	$< 10^{-5}$	Month_Dec**	0.95	$< 10^{-5}$
Train 17	0.47	0.08			
Train 18	0.15	0.57	Rain**	0.30	0.00910
Train 19**	1.29	0.00478	Rain.6	0.01	0.82
Train 20*	1.16	0.01139	Rain.12	0.02	0.59
Train 21**	-2.12	$< 10^{-5}$	Rain.24	-0.02	0.15
Train 22	-0.22	0.68	Wind.Speed	0	0.70
Train 23**	-1.96	$< 10^{-5}$	Temp	-0.01	0.54
Train 24	-2.61	0.11	Visibility	0	0.66
Train 25*	0.62	0.02136			

Residual standard error: 2.72 on 6289 degrees of freedom.

Multiple R-squared 0.24.

Adjusted R-squared: 0.23.

F-statistic: 41.11, on 48 and 6289 degrees of freedom.

* Significant at Alpha =0.05, ** Significant at Alpha=0.01

Model 4

The final model created as part of this analysis concerned the interactions between the various weather events and temporal factors under consideration. As the examination of interaction terms was likely to produce a very large range of variables that could make the model unwieldy, the AIC was used for this model to determine which variables should be retained. Table 11 outlines the variables that were included in this analysis. Variables included in this model that are not considered in the previous models were: the interaction between the month and wind speed, the interaction between the month and the level of rain in the previous one, twelve, and twenty four hours respectively, the interaction between the wind speed and the rain in the previous twenty four hours, and the interaction between the month, the wind speed, and the rain in the previous twenty hour hours.

Table 11. Model 4 ANOVA

Coefficient	DF	SSE	MSE	F value	P Value
Train_ID	29	10994.54	379.12	52.06	$< 10^{-5}$
Schedule	1	10.95	10.95	1.505	0.22
Month	11	3524.70	320.43	44.00	$< 10^{-5}$
Wind_Speed	1	2.09	2.09	0.29	0.59
Rain	1	72.23	72.23	9.92	0.00164
Rain12	1	2.03	2.032	0.28	0.60

Rain24	1	14.88	14.88	2.04	0.15
Month_Wind_Speed	11	185.12	16.83	2.31	0.00800
Month_Rain	11	311.15	28.29	3.88	$< 10^{-5}$
Month_Rain12	11	263.51	23.96	3.29	0.00016
Month_Rain24	11	176.13	16.01	2.20	0.01210
Wind_Speed_Rain24	1	2.46	2.46	0.34	0.56
Month_Wind_Speed_Rain24	11	263.94	23.99	3.29	0.00016
Residuals	6236	45414.86	7.28		

As the interactions model contained significantly more variables than the previous models (over 100), Table 12 only displays the interaction terms and those terms that have not appeared in previous models. It is clear that there are a number of significant interactions such as the wind speed in November, the twelve hour rain fall November, the twenty four rainfall in a number of months, and interactions between wind speed, twenty four hour rainfall, and the month in which the journey occurred. It is interesting to note that a number of these interactions produce negative estimates suggesting that increased rainfall in certain months may be associated with reduced journey times.

Table 12. Model 4 Estimates

Coefficient	Estimate	P value	Coefficient	Estimate	P value
Feb_Wind.Speed	0.01	0.71	Aug_Rain12	0.16	0.37
Mar_Wind.Speed	0.01	0.51	Sep_Rain12	0.07	0.68
Apr_Wind.Speed	0.01	0.71	Oct_Rain12	-0.01	0.95
May_Wind.Speed	0	0.94	Nov_Rain12**	-0.58	0.001941
Jun_Wind.Speed	-0.01	0.63	Dec_Rain12	-0.18	0.20
July_Wind.Speed	0	0.84	Feb_Rain24**	-0.94	0.00037
Aug_Wind.Speed	0.02	0.22	Mar_Rain24	-0.93	0.00009
Sep_Wind.Speed	0.01	0.70	Apr_Rain24	-0.56	0.05
Oct_Wind.Speed	0.02	0.47	May_Rain24	-0.54	0.07
Nov_Wind.Speed**	0.08	0.00022	Jun_Rain24**	-0.66	0.00166
Dec_Wind.Speed	-0.02	0.38	Jul_Rain24	-0.75	0.00003
Feb_Rain	-0.89	0.14	Aug_Rain24**	-0.83	0.00583
Mar_Rain	-0.63	0.16	Sep_Rain24**	-1.48	0.00021
Apr_Rain	-0.91	0.08	Oct_Rain24**	-0.65	0.00023
May_Rain**	1.69	0.00253	Nov_Rain24*	0.86	0.03649
Jun_Rain	-0.37	0.54	Dec_Rain24**	-0.97	0.00024
Jul_Rain	-0.55	0.11	Wind.Speed_Rain24*	-0.02	0.01501
Aug_Rain	-0.55	0.16	Feb_Wind.Speed_Rain24*	0.03	0.01551
Sep_Rain	-0.43	0.47	Mar_Wind.Speed_Rain24**	0.03	0.00219
Oct_Rain	0.05	0.88	Apr_Wind.Speed_Rain24	0.01	0.34
Nov_Rain*	2.44	0.01	May_Wind.Speed_Rain24	0.02	0.17
Dec_Rain	-0.64	0.10	Jun_Wind.Speed_Rain24	0.02	0.10
Feb_Rain12	0	0.98	Jul_Wind.Speed_Rain24*	0.02	0.012
Mar_Rain12	-0.05	0.75	Aug_Wind.Speed_Rain24	0.02	0.09
Apr_Rain12	0.14	0.40	Sep_Wind.Speed_Rain24**	0.06	0.00553

May_Rain12	0.15	0.29	Oct_Wind.Speed_Rain24*	0.02	0.02527
Jun_Rain12	0.12	0.36	Nov_Wind.Speed_Rain24**	-0.06	0.00262
Jul_Rain12	0.12	0.31	Dec_Wind.Speed_Rain24*	0.02	0.01458
Residual standard error: 2.70 on 6236 degrees of freedom.					
Multiple R-squared 0.26					
Adjusted R-squared: 0.25					
F-statistic: 21.51					

* Significant at Alpha =0.05, ** Significant at Alpha=0.01

7 Discussion

This research set out to examine the role that weather events can play in producing delays along the DART network. Specifically this research was focused around three question research objectives, namely, to assess the underlying temporal trends that impact the DART service, to examine the role of weather on service performance, and to examine interactions between different weather events and temporal effects in terms of their ability to produce delays.

Scheduled Journey Times

One of the most striking results to emerge from this analysis is the apparent lack of relationship between the schedule of journey times published by the DART operator and the journey times observed within the dataset. This is a very significant finding as published schedules tend to provide a large amount of exploratory information, in terms of the dependent variable.

Temporal Trends

An examination of temporal trends highlighted two distinct underlying factors: the time of day, and the calendar month in which the journey took place. With regard to the effect of a given month, it was apparent that greater delays occur within the winter months, with especially large delays being experienced in November.

Weather

The impact of weather events was analyzed in two distinct ways. Model 2 assessed the impact of the good weather indicator titled the Green Condition being breached, and found a significant effect, with estimated average delays of 0.7 minutes or 42 seconds. Model 3 assessed the impact of individual weather events, and found that only rain within the hour previous to a journey had a significant effect, in this case contributing to delays.

Interactions

The final area under examination was the impact of interactions between temporal terms and weather events, and varying types of weather event. We detected a number of double interactions between rain at varying levels and month, especially for November, and a triple interaction between wind speed, rain over the previous 24 hours, and month.

In particular, heavy rain in the past hour caused longer delays in May and November in comparison with January. A majority of months, with the exception of November, were less badly affected by heavy rain over a 24 hour period in comparison with January, but were more badly affected by high winds and heavy rain together in comparison to January.

Controlling for these interactions, differences between months are much less pronounced. This suggests that rain levels and wind per month may partially explain why these differences occur, and may be reflecting issues such as leaves being blown onto the tracks and lowering operating speeds.

8 Study Limitations

While this research was fortunate enough to have access to two large data sets in the forms of the DART performance data and the annual weather data, there were a number of factors that limited its ability to provide a totally comprehensive analysis of the factors impacting the performance of the service. Specifically data was not available regarding daily passenger numbers and the increases in boarding times that are likely to be associated with more users. In addition information was not available regarding any delays that may have been experienced by the DART due to issues related to other services sharing which also share sections of the network in central Dublin, though the influence of the demand on the daily delay is partially represented by the Train_ID variable. While the models produced provided an interesting insight into the role of weather in terms of producing delays, there is still a large amount of unaccounted for variance. Table 13 displays the R^2 values associated with the models. While these can be considered poor, this is in the main due to the lack of explanatory power present within the schedule, which should greatly contribute to these values (Mesbah et al, 2015).

Table 13. Model Comparisons

Model	R^2 Value (Adjusted)
Model 1	0.17
Model 2	0.18
Model 3	0.23
Model 4	0.25

An added difficulty is the complex nature of weather, with specific weather instances regularly co-occurring. This can lead to collinearity between explanatory variables, and care must be taken when assessing our results. For example, some of the coefficient estimates for parameters relating to the month of November are difficult to interpret, and may be due to the fact that the data is only partly explained by a simple linear model. While we attempted to control for this by, for example, reducing the correlation between cumulative rainfall for different numbers of hours, this is impossible to remove from the dataset entirely. Despite this, there is still ample evidence of the effect that weather events can have on rail journeys.

9 Conclusions

Changes in the global climate are likely to lead to new challenges in terms of managing and operating existing transport infrastructure. As weather conditions become less predictable it is important to gain an understanding how such events currently impact transport services to enable informed future planning. While a large body of work has been undertaken within the road transport sector with regard to the impact of weather on journey times, relatively little work has been done within the rail sector, specifically with regard to commuter heavy rail. This research utilized data collected from the DART service in Dublin to assess how such conditions can result in delays on a metropolitan rail service. The results of this analysis demonstrate that bad weather can have a significant and negative impact on journey times, with rain being the principal cause of observed delays. It is also clear from this analysis that there are a number of significant interactions between weather conditions, such as wind speed and rainfall in a given preceding period. There are also significant interaction effects between the various weather conditions, weather interactions, and temporal factors such as the calendar months in which they occur. It is theorised that one of the observed effects may be linked to operational issues relating to the compaction of deciduous leaves during the late autumn and early winter, however this needs more research, and is likely to be specific to the DART line, rather than generalizable. While weather events did create detectable delays within the service, there appear to be a number of other issues, specifically the apparent lack of relationship between the published DART schedules and the observed journey time contained within the dataset. This research sought to expand the literature relating to the impact of weather events, and specifically interactions and temporal effects, by applying it to a large amount of observations recorded for a suburban service. However, it must be noted that the DART line operates along the coast of Dublin Bay, and is therefore very exposed to high winds and maritime conditions for large stretches. This would suggest that while the authors believe that this research yields valuable insights, there is a need for further research be undertaken examining services operating in different geographic locations and in different climates.

Acknowledgements

This research forms part of the RAIN project which is funded under the European Commission's Seventh Framework Programme Grant Number N° 608166.

References

Akaike, H. 1973. Information Theory and an Extension of the Maximum Likelihood Principle. In Second International Symposium on Information Theory, pp. 267-281. Akadémiai Kiadó.

Andrey, J., Mills, B., Leahy, B. and Suggett, J. 2003. Weather as a Chronic Hazard for Road Transportation in Canadian Cities. Natural Hazards, Vol. 28, pp 319-343

Black, A.B, and Mote, T., L. 2015. Effects of winter precipitation on automobile collisions, injuries, and fatalities in the United States. Journal of Transport Geography. Vol. 48, pp165-175

Bray, D. 2010. The scientific consensus of climate change revisited. Environmental Science and Policy, Vol. 13, pp-340-350

Dawson, D., Shaw, J., Gehrels, R.W. 2016. Sea-level rise impacts on transport infrastructure: The notorious case of the costal railway line at Dawlish, England. Journal of Transport Geography, Vol. 51, pp. 97-109

Environmental Protection Agency. 2016. What impact will climate change have for Ireland? Available at:http://www.epa.ie/climate/communicatingclimatescience/whatisclimatechange/whatimpactwillclimatechangehaveforireland/#d.en.42707

Edwards, J. B. 1996. Weather-related road accidents in England and Wales: a spatial analysis. Journal of Transport Geography, Vol. 4, pp. 201-212

Flynn, B. S., Dana, G. S., Sears, J., and Aultman-Hall, L. 2012. Weather factor impacts on commuting to work by bicycle. Preventive Medicine. 54, 122-124

Hooper, E., Chapman, L., and Quinn, A. 2013. The impact of perception on speed-flow relationships along a UK motorway corridor. Theoretical and Applied Climatology, pp 1-14

Herald.ie. 2010. Available at. http.//www.herald.ie/news/morning-misery-as-dart-and-luas-halted-by-snow-havoc-27968147.html

Irish Examiner. 2013. Available at: http://www.irishexaminer.com/breakingnews/ireland/winds-force-closure-of-lansdowne-rd-dart-station-582828.html#!

Irish Rail. 2012. Available at. http.//www.irishrail.ie/blog/post?a=330

Irish Rail. 2015. Station and Route Maps. Available at. http.//www.irishrail.ie/travel-information/station-and-route-maps

Irish Times. 2014. Available at. http.//liveblog.irishtimes.com/92f6d661b5/LIVE-Weather-updates/

Irish Times. 2014. Available at: http://www.irishtimes.com/news/environment/more-rainfall-warnings-issued-after-flooding-disrupts-travel-1.1886186

Jaroszweski, D., Chapman, L., and Petts, J. 2010. Assessing the potential impact of climate change on transportation: the need for an interdisciplinary approach. Journal of Transport Geography, Vol. 18, pp. 331-335

Jounal.ie 2011. Available at: http://www.thejournal.ie/transport-returns-to-normal-following-flooding-263869-Oct2011/

Journal.ie. 2013. Available at. http.//www.thejournal.ie/dart-line-between-dalkey-and-dun-laoghaire-closed-over-fallen-tree-759295-Jan2013/

Kass, R. E., & Raftery, A. E. 1995. "Bayes factors". Journal of the American Statistical Association, *Vol. 90 No.* 430, pp. 773-795.

Koetse, M.J., and Rietveld, P. 2009. The impact of climate change and weather on transport: An overview of empirical findings. Transportation Research Part D. Vol. 14, pp205-221

Kwon, J., Barkley, T., Hranac, R., Petty, K. and Compin, N. 2011. Decompostion of Travel Time Reliability into Various Sources.

Ludvigsen, J., & Klæboe, R. (2014). Extreme weather impacts on freight railways in Europe. Natural hazards, 70(1), 767-787.

Mesbah, M., Lin, J., and Currie, G. 2015. "Weather" transit is reliable? Using AVL data to explore tram performance in Melbourne, Australia

Met Éireann. 2015. Historic Climate Data, Available at http.//www.met.ie/climate-request/

Met Éireann. 2015. National Weather Warnings. http.//www.met.ie/nationalwarnings/warnings-explained.asp

Met Office. 2015. Weather Warnings Guide. Available at. http.//www.metoffice.gov.uk/guide/weather/warnings

National Transport Authority (NTA). 2013. Heavy Rail Census. Available at. https.//www.nationaltransport.ie/news/heavy-rail-census-for-2013/

Network Rail. 2015. Summer Weather Explained Available at . http.//www.networkrail.co.uk/timetables-and-travel/delays-explained/summer-weather.aspx

Network Rail. 2015. Winter Weather Explained Available at .http.//www.networkrail.co.uk/timetables-and-travel/Delays-explained/Winter-weather/

Rosetti, M. A. (2002). Potential Impacts of Climate Change on Railroads, The Potential Impacts of Climate Change on Transportation Workshop, Oct. 1-2, 2002. DOT Center for Climate Change and Environmental Forecasting, http://climate. volpe. dot. gov/workshop1002.

Saneinejad, S., Roorda, M. J., and Kenndey, C. 2012. Modelling the impact of weather conditions on active travel behaviour. Transportation Research Part D, 17, 129-137

Schwarz, G. 1978. "Estimating the dimension of a model". Annals of Statistics, Vol. 6 No. 2, pp. 461-464.

Sims R., R. Schaeffer, F. Creutzig, X. Cruz-Núñez, M. D'Agosto, D. Dimitriu, M. J. Figueroa Meza, L. Fulton, S. Kobayashi, O. Lah, A. McKinnon, P. Newman, M. Ouyang, J. J. Schauer, D. Sperling, and G. Tiwari, 2014: Transport. In: Climate Change 2014: Mitigation of Climate Change.

Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J.

Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Theofilatos, A. and Yannis, G. 2014. A review of the effect of traffic and weather characteristics on road safety. Accident Analysis and Prevention, Vol. 72, pp 244-256

Tsapalis, I., Cheng, T. and Bolbol, A. 2013. Impacts of weather conditions on macroscopic urban travel times. Journal of Transport Geography. Vol. 28, pp204-211

Thornes, J. E., & Davis, B. W. (2002, April). Mitigating the impact of weather and climate on railway operations in the UK. In Railroad Conference, 2002 ASME/IEEE Joint (pp. 29-38). IEEE.

Wadud, Z. 2014. Cycling in a changed climate. Journal of Transport Geography. Vol. 35, pp12-20

Xia, Y., Van Ommeren, J. N., Rietveld, P., and Verhagne, W. 2013. Railway infrastructure disturbances and train operator performance. The role of weather. Transportation Research Part D, Vol. 18, pp 97-102