Analysing the Effects of Weather on Light Rail Transit Performance in Dublin, Ireland

Gearoid Walsh
Trinity Centre for Transport Research
University of Dublin, Trinity College
Dublin 2.
Email: gwalsh1@tcd.ie

Margaret O'Mahony (Corresponding author)
Trinity Centre for Transport Research
University of Dublin, Trinity College
Dublin 2
Email: margaret.omahony@tcd.ie

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ABSTRACT

As climate change and greenhouse gas emissions receive increasing levels of attention, the need for sustainable transport solutions becomes increasingly apparent. The Luas is Dublin's Light Rail Transit (LRT) network and, since completion in 2004, it has become key component of the city's transport system, with plans for further expansion in the near future. Ensuring that sustainable transport options, such as the Luas, are attractive to users by providing a reliable service is a key step in increasing their usage and environmental benefits. This research investigates the effects of the weather on the reliability of the Luas trams, with a focus on identifying specific sections of the network and time periods that are increasingly vulnerable to weather-related disruption.

A large dataset of Automatic Vehicle Location (AVL) data was received from Transport Infrastructure Ireland (TII) from which the required headways for the analysis were derived. Precipitation, air temperature and wind speed for the same time periods were obtained from the Irish weather service (Met Eireann). The two datasets were then combined and analysed using multiple linear regression.

Precipitation was found to be the most influential weather variable for negative impacts on LRT performance. Unexpectedly, increases in wind speed resulted in decreases in headway times. Weather was found to have more substantial effects on the Luas Red Line than on the Green Line. The results of this study would be useful to transport authorities in their efforts to increase the resilience of the Luas network to adverse weather conditions.

Key words: Weather, Light Rail Transit, Headways, Performance

INTRODUCTION

In recent years, the issues of greenhouse emissions and resulting climate change have received increasing amounts of public attention. In Ireland, the transportation sector is one of the largest sources of CO_2 emissions, accounting for 20.3% of total emissions *(1)*. To facilitate a move away from private cars, public transport options must be attractive to users and ensure they function efficiently and effectively is necessary. All modes of transport have a degree of vulnerability to external conditions such as adverse weather. However, the degree of disruption varies depending on the specific characteristics of the transport system. Efforts have been made by researchers to investigate the effects of weather on various modes such as bus and heavy rail networks *(2,3,4)*.

Dublin's Light Rail Transit (LRT) network known as the Luas and shown in Figure 1 is an important component of the city's transportation system, having an average daily usage of 150,000 people *(5)*. It consists of two lines: The Red Line, currently 21km in length with 32 stops, begins on the south-west periphery of Dublin, in the suburb of Tallaght and proceeds northeast to Dublin City Centre before terminating at the Point in Dublin's Docklands. The Green Line with a length of 22km and 35 stops, runs from Bride's Glen in Southeast County Dublin to Broombridge in Dublin's Northern suburbs.

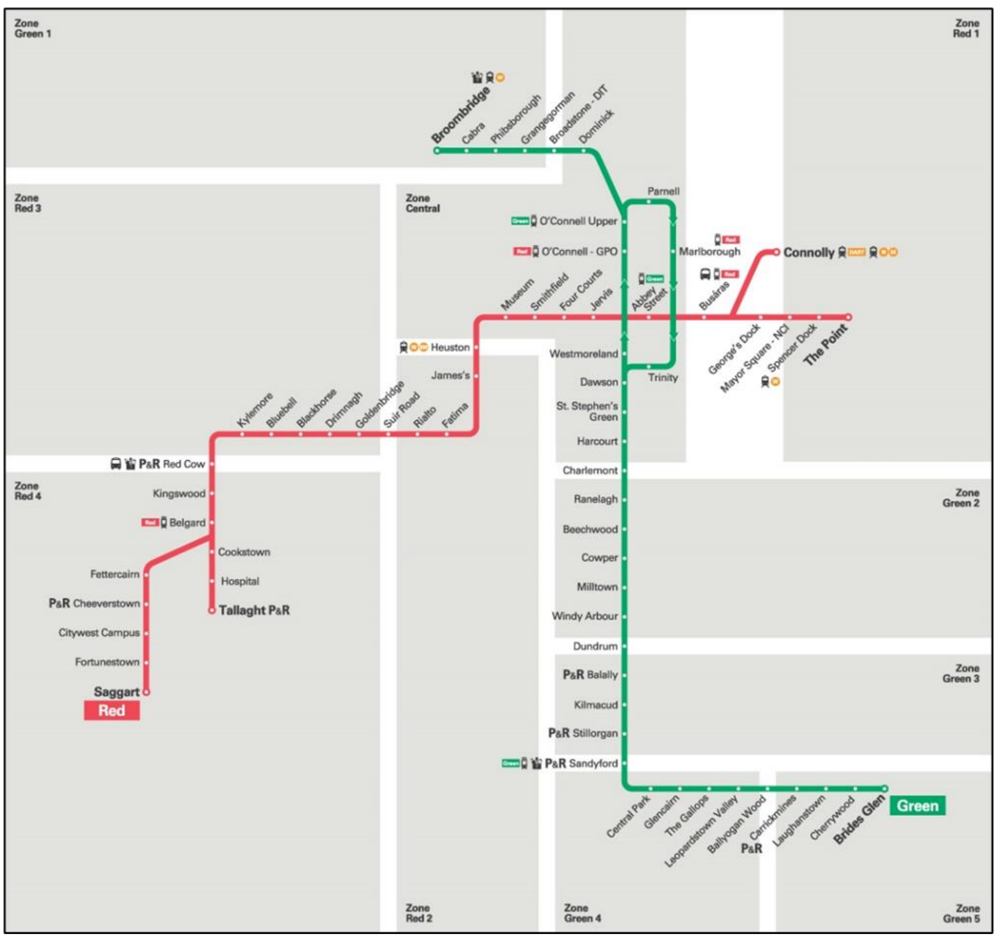

Figure 1. Luas Network *(6)*.

Dublin's climate, like the rest of Ireland's, can be classified as being oceanic and is strongly influenced by the country's proximity to the Atlantic Ocean. The North Atlantic Drift is a warm water current that ensures the sea temperatures around Ireland remain relatively warm year-round, giving Ireland a milder climate than other nations at a similar latitude. Irish winters tend to be cool and windy with snowfall irregular and infrequent. Summers tend to be mild with slightly less rainfall than the winter. The overall seasonal temperature variation is quite low, and rainfall is plentiful, occurring year-round *(7)*. Dublin's climate is summarised in Figure 2.

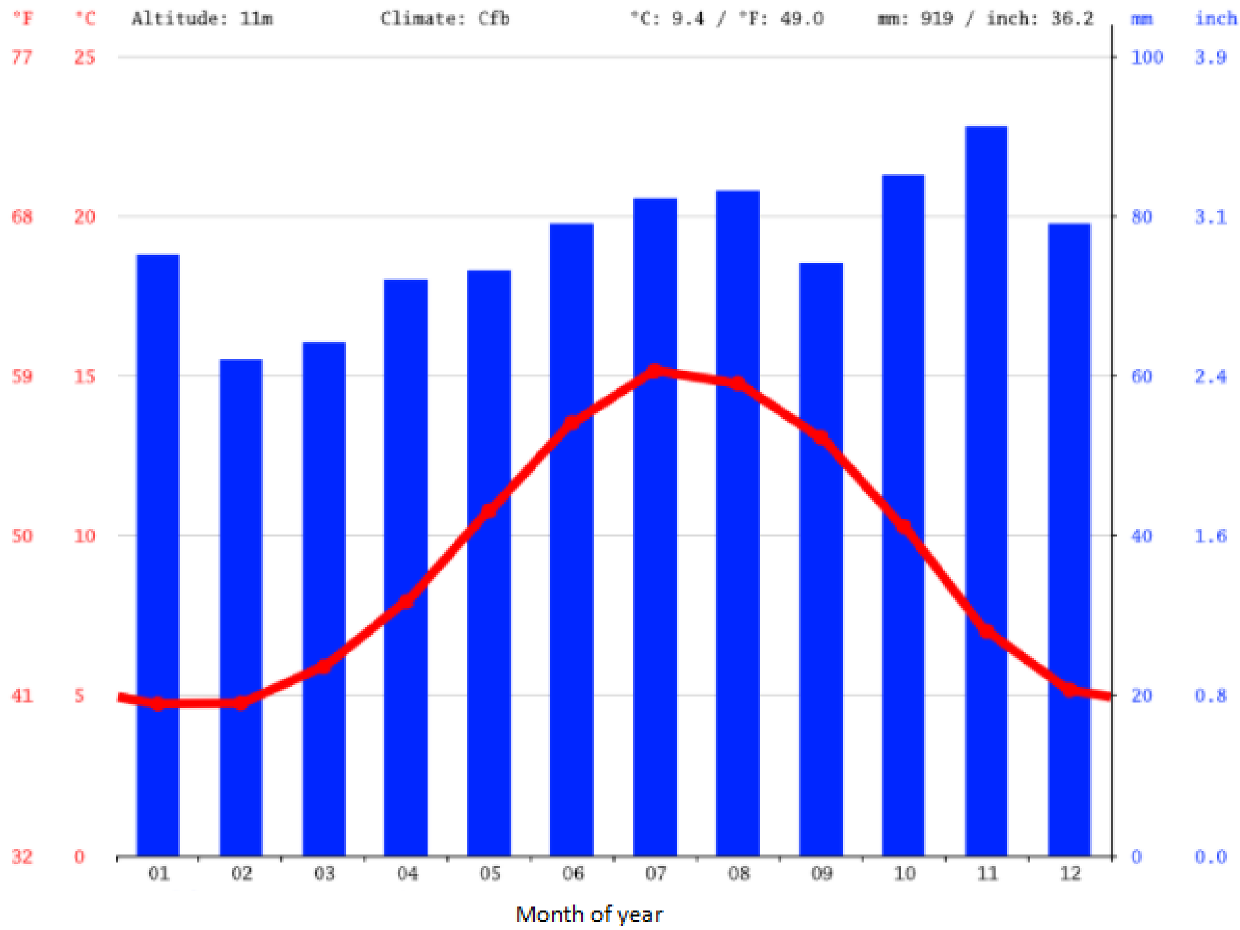

Figure 2. Summary of Dublin's climate *(8)*

It is expected that climate change may include an increase in both the frequency and severity of adverse weather conditions in combination with rising sea levels in the Irish Sea where an increase of 0.47m could occur by the end of the 21st Century *(9)*. These effects could be potentially result in devastating consequences for Dublin *(10)*. This is especially important in terms of the transportation sector, the fastest growing producer of greenhouse gases in Ireland between 1990 and 2016 *(11)*. The Luas system, due to its electrification, could prove to be an important asset in Ireland's bid to mitigate climate change. By better understanding the impact of weather on its performance, the operations of the network can be optimised ensuring maximum attractiveness to potential consumers and environmental benefits.

The main objectives of the research are as follows:

(1) To identify any sections of the Luas network which are increasingly vulnerable to disruption.
(2) To determine which weather variables have the greatest effect on the performance of the Luas.
(3) To explore if weather impacts the two Luas lines differently.
(4) To highlight any specific time periods where weather-related disruption is more likely to occur.
(5) To compare expected tram frequencies with actual values.

The next section of the paper will provide relevant background for the research. This will be followed by a summary of the methodology used. The results of the analysis will then be presented and discussed followed by conclusions of the work and relevant recommendations.

BACKGROUND

Rail networks have much lower densities than road networks resulting in fewer alternative routes *(12)*. Therefore, an isolated event can lead to a bottle-neck effect which disrupts all traffic along a railway section and this cascading effect often results in a decrease in transportation service quality and significant economic losses *(13, 4)*. Studies focused on weather-related disruption are often more difficult to draw conclusions from compared to those that relate to a random failure of a singular component or an intentional attack on the railway *(14)*. In an investigation by *(15)* on Melbourne's tram network, it was found that every additional 1mm of precipitation increased trip time by 8 seconds, while every 1°C deviation from 15°C resulted in an increase of 1 second of trip time.

Weather-Related Disruption in Ireland

The railway network in Ireland is composed of 1700km of track mainly concentrated on the east coast and the midlands with only a small number of stations on the wetter west coast *(16)*. An investigation of the incidence of landslides in the Irish railway network *(16)*, using weather data from The Irish Meteorological Service (Met Eireann) found that only 2 landslide failures had been reported in October on average despite it being the wettest month on average. However, 63% of reported events occurred between November and January indicating, the potential influence of antecedent rainfall on the likelihood of soil slope failures.

A study carried out by *(17)* focused on weather-related disruption on the heavy commuter rail line in Dublin, known as the DART. The greatest delays occurred during November, a period typically known for high winds and rainfall. A large proportion of the DART network is lined by deciduous trees and this combined with adverse weather conditions can result in a large amount of leaves blown onto the tracks limiting the speed at which the trains may operate.

Climate Change and Network Resilience

Climate change is expected to increase both the frequency and severity of certain weather phenomena in the foreseeable future *(18)*. The increase in extreme rainfall events will likely be seen in Ireland and will occur due to winter temperatures warming. Rises in sea levels will likely occur due to the melting of polar ice caps which may threaten transport infrastructure in low-lying maritime areas as coastal flooding and storm surges becomes more common *(17)*.

The concept of resilience describes a system's capacity to maintain its original function after a major disruption. It also may consider the speed at which the system can return to a state of normal operation *(19)*. Successful rail operations generally are considered to be less flexible and less robust systems of transportaton than travelling by private car. However, in the event of severe disruption the possibilities for coordinated restoration are greater with rail, and other forms of public transport, than with private transportation *(20)*.

One means of conducting vulnerability studies requires detailed information regarding supply and demand patterns in combination with sophisticated modelling software *(19)*. The potential decisions of passengers in the event of disruption are directly influenced by the amount of information available to them, such as the expected duration of the delay and details of possible diversions. This parameter can therefore be highly influential *(21)*. In a study by *(22)* the importance of informing passengers about disruption as soon as possible is highlighted. The robustness of the transport network in Stockholm was investigated by *(20)* and they found that increasing the capacity on key links within the network would help absorb unplanned disruptions and increase the overall robustness of the network.

Responding to Disruption

When considering a railway's performance, a flexible service and recovery strategy was highly ranked in terms of importance yet poorly ranked in terms of performance *(23).* Although risk managers and logistics experts who work for rail companies are aware of the potential for disruption, effective mitigation strategies and tools are often scarce *(4).* In research by *(24),* similarities and differences between disruption management processes in several European countries were examined. They found that management systems vary significantly with some having highly centralized control centres, such as in Denmark, with others having their control more widely distributed, or decentralized, such as in Germany. Decentralized systems involve decisions made at a local level; therefore, they usually do not benefit the network as a whole and can contribute negatively to the overall performance of the system. A highly centralized structure can lead to railway operators being overloaded with information and decisions lagging behind the progression of the local situation.

Many papers in the literature focus on hypothetical scenarios in which disruption effects the network by making a specific section of track unavailable for a set period, while not many investigate the effects of actual weather events. The scenarios modelled in many studies often make assumptions regarding the behaviour or railway operators and passengers, such as consistent rational decision-making. Furthermore, a gap in the literature exists regarding disruption on LRT networks. There is a need to better understand this the vulnerability of LRT networks to weather as they increasingly become the back bone of urban public transport systems. The objective of the research here is to address this gap in the literature.

METHODOLOGY

Data

Luas Data

The Luas tram schedule is presented by frequency and not as a fixed schedule. The scheduled tram frequency is dependent on the time of day with peak hours having a typical frequency of 3 to 5 minutes and off-peak hours having a significantly lower frequency of 12 to 15 minutes *(25).* The Luas dataset received from TII contained entries relating to every actuation that occurred on the Luas network for the full year of 2020. With 360 data entries per minute, the data file contained over 200 million datapoints. To proceed with the analysis, it was necessary to filter the dataset into a more manageable size. The data for seven days in February 2020, a very wet and windy month, were extracted along with seven days of data for a much calmer and drier period in April 2020. The objective was to examine the differences between days with ideal and days with poor weather conditions. How ideal and poor weather conditions were defined are presented later. The numbers of tram arrivals analysed at each station were in the range 2,495 – 4,919.

The impact of weather on the timetabled arrival of trams at stations required filtering of the data to remove data entries corresponding to readings taken by the system when trams were between stations. Recoding was necessary to separate entries for the Luas Green Line and Red Lines, different stations, direction of travel, weekday, weekend and peak and off-peak hours. The headway calculation involved subtracting the time value of each actuation at a station by the proceeding time.

The dataset contained data for all 67 stations in the Luas network. Running an analysis for all stations would be unnecessary as adjacent stops are likely to be impacted in a similar way by local weather conditions. Therefore one stop was selected from each zone of the system (see Figure 1), for both lines, for consideration in the analysis. Stops serving as termini were omitted as trams often turn at termini. Stops near busy commercial areas such as Balally and Jervis were selected as these stations are likely to experience larger passenger numbers and could be considered more important in the context of the whole network. At Belgard, the Red Line deviates into two separate sections, heading towards Saggart and Tallaght respectively. As can be seen in Figure 1, these two distinct branches are in the same zone (Zone Red 4) and stations were selected on both branches. An additional station in this zone (Kingswood) was selected at the section before the deviation occurs. The Green Line stations chosen were: Phibsborough, Dawson, Cowper, Balally, Glencairn and Cherrywood. The Red Line stations chosen were: Spencer Dock, Jervis, Rialto, Bluebell, Kingswood, Citywest Campus and Hospital. A map showing the chosen stations in relation to the rest of the Luas network is shown in Figure 3. Descriptive statistics for each of the chosen stations are shown in Table 1.

Figure 3. Key stations chosen for analysis *(26)*

Table 1. Descriptive statistics relating to headways at key stations.

Station	Min (s)	Max (s)	Mean (s)	Standard Deviation	N
Phibsborough	58	1958	725	252	2495
Dawson	61	1966	416	238	4314
Cowper	41	1985	415	238	4318
Balally	37	1923	414	233	4315
Glencairn	38	1930	684	258	2734
Cherrywood	19	1983	685	259	2731
Spencer Dock	34	1991	552	269	3310
Jervis	49	1985	401	250	4566
Rialto	33	1982	405	249	4504
Bluebell	34	1851	403	250	4516
Kingswood	18	1986	383	240	4919
Hospital	38	1968	630	246	2991
Citywest	42	1921	636	217	2817

Weather Data

The weather data used in this study was obtained from the Met Eireann *(27)*. As the Luas network is located entirely within Dublin, only weather stations in Dublin were of interest. Furthermore, it was decided that weather data used in this study should be on an hourly basis. This ensured a higher level of accuracy and allowed weather data to be mapped with the Luas data more readily. Although there are 9 weather stations in County Dublin, only three record on an hourly basis: Dublin Airport, Phoenix Park and Casement, the locations of which are shown in Figure 4.

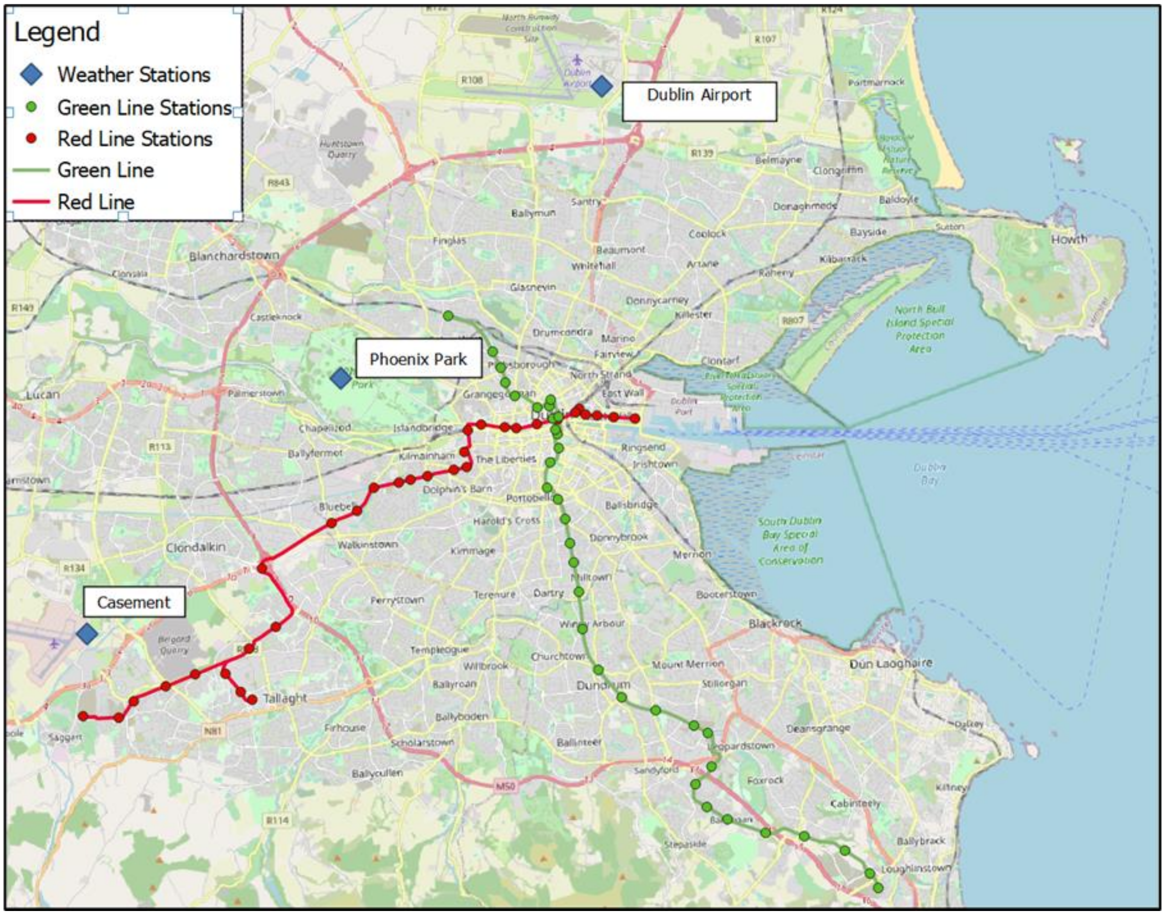

Figure 4. Location of weather stations in relation to Luas network *(26)*.

In keeping with other weather impact research, the key weather variables selected were precipitation, wind speed and air temperature *(17, 15)*. Data from the Casement weather station was excluded due to its location in the foothills of the Dublin Mountains and resulting elevation of nearly 100m above sea level. Most of the Luas network is closer to sea level. The Phoenix Park station is the closest to most of the Luas stations. However, values for wind speed are not measured at this station. It was hence decided that wind speed data would be taken from the Dublin Airport station. Data from both Phoenix Park and Dublin Airport would be used to determine the air temperature and precipitation values used in the analysis. Hourly data corresponding to air temperature, wind speed and precipitation for the two chosen weather stations was downloaded from the Met Eireann website *(27)*.

The average air temperature in April was higher at 9.3°C (48.8°F) that the average of 5.9°C (42.6°F) in February. February experienced much greater rainfall events, receiving an hourly maximum of 6.8mm/hour. The highest hourly total for precipitation in April was just 1.1mm/hour. The mean wind speed in February was also greater than April, averaging 6.7 m/s as opposed to 4.3 m/s.

Seven days were selected as having ideal conditions whereas the other seven had poor weather conditions. To decide which days were eligible for selection, numerical values were assigned to each hourly datapoint reading based on their weather conditions. Values were assigned in the 3 categories of air temperature, precipitation and wind speed with lower values being closer to ideal. For example, a datapoint with 0mm of precipitation would be assigned a value of 1 while another datapoint with a precipitation value between 0 and 1mm would be assigned a value of 2. For air temperature, ideal values were considered to be in the range 5-20 °C (41-68°F), with temperatures outside this range being assigned higher values in increments of 5°C (41°F). A similar process was carried out for wind speed with values being assigned in increments of 5 m/s with the ideal value less than 5 m/s. The values were then summed on an hourly basis and subsequently on a daily basis giving each day an overall score relating to its weather conditions.

To maintain the balance between weekday and weekend data, each of the 7 chosen days in February corresponded to a different day of the week; the same was true of the April data. Based on the scoring system, the 9th, 10th, 11th, 14th, 15th, 26th and 27th of April were selected to represent ideal weather conditions and the dates in February selected were the 6th, 8th, 9th, 18th, 19th, 21st and 24th representing poor weather conditions.

A bivariate Pearson Correlation was performed to assess correlation between the weather variables. A weak negative correlation (-0.011) was found between temperature and rain but it was not statistically significant ($p = 0.836$). Likewise, the relationship between air temperature and wind speed is not statistically significant ($p = 0.16$), however and very weakly correlated (0.077). There is a statistically significant ($p = 0.000$) greater positive correlation (0.3) between wind speed and rain.

Statistical Analysis

Multiple linear regression (MLR) *(28)* was selected as the most suitable analysis method due to its use in other studies with similar research objectives *(2, 15)*. Its ability to account for multiple predictor variables, in this case weather effects, meant it suited the scope of this research well. To address the first objective of the research i.e. to assess the impact of weather on headway, headway (s) was selected as the dependent variable and the independent variables were rain (mm), temperature in °C and wind speed in m/s.

Another research objective of this study was to identify any sections of the Luas network which are more vulnerable to weather related disruption. To carry out this comparison between different sections of the network, the MLR analysis was run separately for each of the chosen stations. The analysis was also run for each peak hour period to identify time periods which are increasingly sensitive to weather related disruption. This was carried out by separating the analysis file based on the numerical peak hour values.

RESULTS

Multiple Linear Regression Results for Chosen Stations

The MLR results for the chosen Luas Green Line stations are shown in Table 2. As can be seen the p-values (Sig. column) associated with the coefficients are less than 0.05 in most cases, indicating statistical significance. The exceptions are wind speed in the models for Phibsborough, Glencairn and Cherrywood, and air temperature for Cowper and Balally. Rain is statistically significant in all cases. The Durbin-Watson values range from 0.740 to 1.453, with all falling outside the ideal range of 1.5 – 2.5. Three stations (Dawson, Cowper and Balally) have Durbin-Watson values less than 1.0, indicating some levels of positive autocorrelation.

The adjusted R^2 values range from 0.011 to 0.023 indicating that 1.1% to 2.3% of the variance in headway can be explained by the weather variables. The Beta values (B column) for rain are positive in all cases, indicating a positive correlation between precipitation and headway times. Wind speed is negatively correlated with headway in all cases while temperature is positively correlated in half the cases and negatively correlated in the other half.

Table 2. MLR results for chosen Green Line stations

	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Adj R^2	D-W	ANOVA Sig.
Green Zone 1 (Phibsborough)										
Constant	678.572	15.400		44.063	0.000	648.373	708.770	0.020	1.453	0.000
Rain	48.745	9.034	0.111	5.396	0.000	31.031	66.459			
Temp	6.507	1.277	0.101	5.096	0.000	4.003	9.011			
Wind	-3.770	1.657	-0.047	-2.275	0.023	-7.019	-0.521			
Green Central (Dawson)										
Constant	459.592	11.431		40.205	0.000	437.181	482.003	0.022	0.740	0.000
Rain	70.104	7.721	0.142	9.080	0.000	54.967	85.242			
Temp	-2.811	0.913	-0.047	-3.079	0.002	-4.601	-1.022			
Wind	-4.956	1.197	-0.065	-4.142	0.000	-7.302	-2.610			
Green Zone 2 (Cowper)										
Constant	452.605	11.356		39.857	0.000	430.342	474.868	0.023	0.838	0.000
Rain	70.186	7.219	0.152	9.722	0.000	56.032	84.340			
Temp	-2.224	0.908	-0.037	-2.449	0.014	-4.004	-0.443			
Wind	-4.881	1.187	-0.064	-4.111	0.000	-7.209	-2.553			
Green Zone 3 (Balally)										
Constant	444.214	11.195		39.679	0.000	422.265	466.162	0.018	0.892	0.000
Rain	61.841	7.217	0.134	8.569	0.000	47.692	75.989			
Temp	-1.666	0.893	-0.028	-1.865	0.062	-3.417	0.085			
Wind	-4.231	1.168	-0.057	-3.622	0.000	-6.521	-1.941			
Green Zone 4 (Glencairn)										
Constant	628.866	14.866		42.304	0.000	599.717	658.015	0.011	1.302	0.000
Rain	27.388	8.751	0.062	3.130	0.002	10.229	44.548			
Temp	6.149	1.254	0.093	4.904	0.000	3.691	8.608			
Wind	-0.752	1.627	-0.009	-0.462	0.644	-3.942	2.438			
Green Zone 5 (Cherrywood)										
Constant	629.249	14.879		42.292	0.000	600.075	658.424	0.011	1.200	0.000
Rain	25.050	8.571	0.058	2.923	0.003	8.244	41.857			
Temp	6.252	1.259	0.095	4.965	0.000	3.782	8.721			
Wind	-0.739	1.627	-0.009	-0.454	0.650	-3.929	2.451			

The analysis results for the chosen Luas Red Lines are shown in Table 3. All results from this analysis are statistically significant (p-values less than 0.05) apart from temperature at Citywest Campus (0.660) and Hospital (0.322). The Durbin-Watson values for the Red Line stations range from 1.049 and 1.735. Two stations, Citywest and Spencer Dock have values in the ideal range of 1.5 – 2.5. None of the Durbin-Watson values were under 1.0 or over 3.0, indicating that autocorrelation is not present.

The adjusted R^2 values range from 0.011 at Citywest to 0.064 at Rialto indicating that 1.1% to 6.4% of the variance in Red Line headway times can be attributed to the variation in weather conditions. In all cases increases in precipitation correspond to increases in headway time. Wind speed is negatively correlated in all cases. Temperature is negatively correlated in all cases apart from Citywest.

Table 3. Multiple Linear Regression Results for Chosen Red Line Stations

	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Adj R^2	D-W	ANOVA Sig.
Red Zone 1 (Spencer Dock)										
Constant	687.899	14.885		46.213	0.000	658.713	717.084	0.047	1.619	0.000
Rain	77.235	8.768	0.155	8.808	0.000	60.043	94.427			
Temp	-8.867	1.182	-0.128	-7.504	0.000	-11.184	-6.551			
Wind	-11.732	1.499	-0.138	-7.828	0.000	-14.671	-8.794			
Red Central (Jervis)										
Constant	553.692	11.959		46.299	0.000	530.247	577.138	0.062	1.049	0.000
Rain	84.102	7.533	0.165	11.165	0.000	69.334	98.869			
Temp	-10.414	0.933	-0.162	-11.158	0.000	-12.244	-8.585			
Wind	-11.884	1.183	-0.149	-10.046	0.000	-14.204	-9.565			
Red Zone 2 (Rialto)										
Constant	556.030	11.986		46.391	0.000	532.532	579.528	0.064	1.128	0.000
Rain	88.488	7.641	0.172	11.580	0.000	73.507	103.469			
Temp	-10.434	0.932	-0.163	-11.195	0.000	-12.261	-8.606			
Wind	-11.542	1.187	-0.145	-9.723	0.000	-13.869	-9.214			
Red Zone 3 (Bluebell)										
Constant	555.376	11.995		46.299	0.000	531.859	578.893	0.062	1.217	0.000
Rain	85.123	7.647	0.165	11.131	0.000	70.131	100.115			
Temp	-10.311	0.934	-0.161	-11.035	0.000	-12.143	-8.479			
Wind	-11.904	1.190	-0.149	-10.000	0.000	-14.238	-9.571			
Red Zone 4 (Kingswood)										
Constant	505.924	10.766		46.994	0.000	484.818	527.029	0.048	1.447	0.000
Rain	72.230	6.980	0.149	10.349	0.000	58.546	85.913			
Temp	-8.088	0.852	-0.133	-9.490	0.000	-9.759	-6.417			
Wind	-10.441	1.100	-0.137	-9.490	0.000	-12.598	-8.284			
Red Zone 4 - Branch 1 (Hospital)										
Constant	695.732	13.765		50.544	0.000	668.720	722.721	0.021	1.465	0.000
Rain	34.847	7.702	0.085	4.524	0.000	19.745	49.950			
Temp	-1.135	1.147	-0.018	-0.990	0.322	-3.383	1.113			
Wind	-11.358	1.457	-0.147	-7.795	0.000	-14.216	-8.501			
Red Zone 4 - Branch 2 (Citywest Campus)										
Constant	663.855	12.957		51.236	0.000	638.449	689.261	0.011	1.735	0.000
Rain	29.729	6.964	0.083	4.269	0.000	16.074	43.383			
Temp	0.465	1.056	0.008	0.440	0.660	-1.605	2.535			
Wind	-6.870	1.342	-0.100	-5.119	0.000	-9.501	-4.238			

While the R^2 are generally relatively low for both lines, the values for the Green Line stations are relatively consistent and lower than the Red Line values. Acknowledging that the R^2 values are quite low generally, some further exploration of the results was conducted using QGIS, shown in Figure 5. Sections of the network were assigned a colour based on their adjusted R^2 value. The section appearing most sensitive to weather disruption is between George's Dock and Red Cow, while the section between Belgard and Saggart shows the least variation in headway. The section of the Green Line closer to Dublin City Centre, from Broombridge to Dundrum shows a higher sensitivity to weather related disruption in comparison to the more peripheral section, from Dundrum to Bride's Glen.

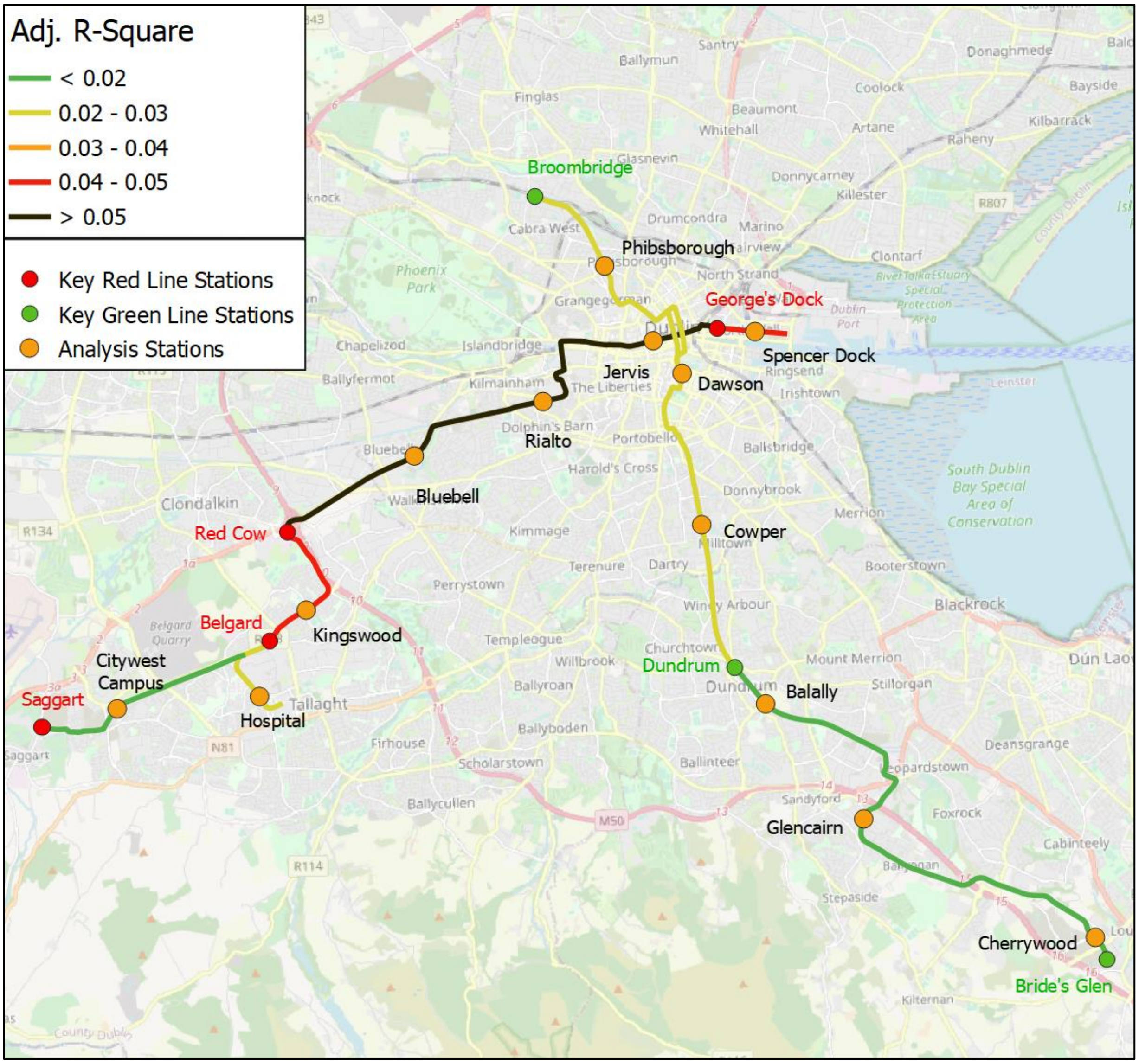

Figure 5: Map of Adjusted R^2 values at different sections of the Luas network

Analysis of the Effects of Each Weather Variable on Luas Performance

To better understand the effects of each of the three weather variables, the Beta coefficients from the MLR analysis were examined in Figure 6. Precipitation is positively correlated with headway in all cases and in 10 out of 13 stations, precipitation is the weather condition with the most influence on headway.

Interestingly, wind speed is negatively correlated in all cases and has a more substantial influence on performance at the Red Line stations. Temperature is negatively correlated at most stations with the exceptions being Phibsborough, Glencairn, Cherrywood and Citywest. The impact of temperature varies significantly based on each station. For example, at Citywest it is almost negligible while at Cherrywood it is the most significant factor.

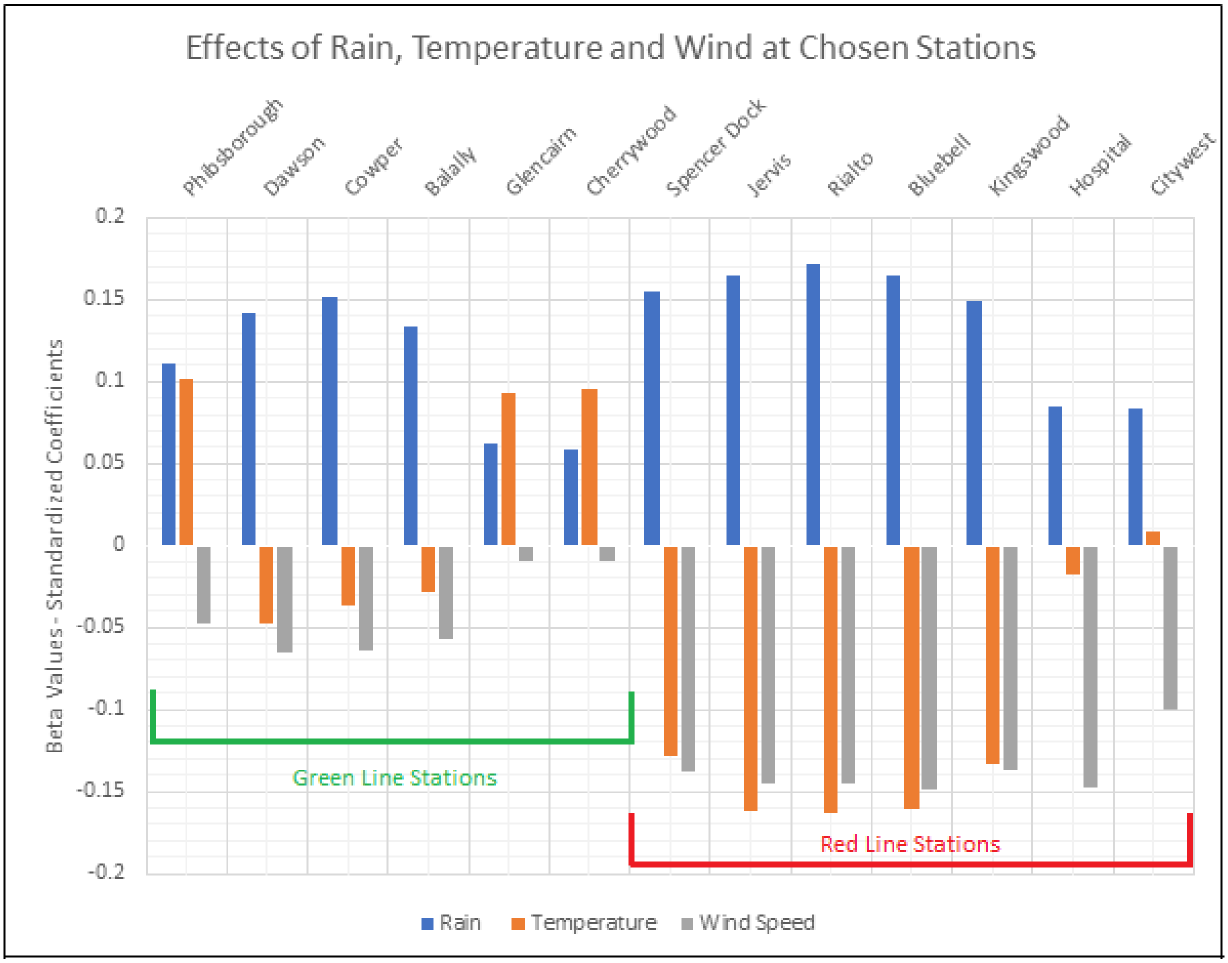

Figure 6. Beta coefficients at chosen stations

Weather Related Disruption at Different Time Periods

Ideal weather compared with poor weather days

An MLR analysis was carried out to assess the differences in impact on headway of the weather variables on days of ideal conditions and those with poor weather conditions. The table of results are not presented due to paper length considerations but a summary of the key findings are discussed here. All results were statistically significant at the $p < 0.05$ level. The Durbin-Watson values are both slightly outside the range of ideal values (1.5 - 2.5). The standard error value associated with the unstandardized coefficient for precipitation is noticeably large (413.336) and is most likely due to the very low number of datapoints in April having precipitation values associated with them. The adjusted R^2 value is slightly lower for the period of non-ideal conditions in February than it is the ideal conditions in April, 0.037 compared to 0.046. This indicates that in April, a larger amount of the variance in headway can be attributed to the weather conditions in comparison to February.

The Beta values for both sets are shown in Figure 7. An increase in rainfall correlates with an increase in headway, while an increase in temperature correlates with a decrease in travel time. Although precipitation has a greater impact on headway in February compared with April a decrease in temperature has a greater impact on headway in April compared to February. Interestingly, wind speed is both positively and negatively correlated with headway times in February and April respectively but the coefficient is very small in both cases and so no conclusion can be drawn.

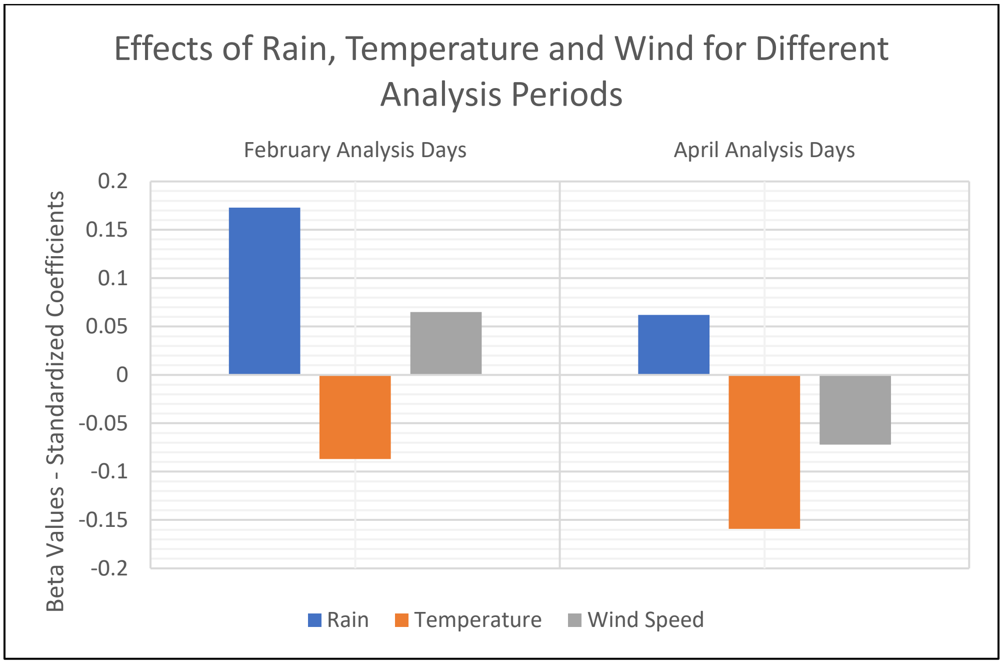

Figure 7. Beta Coefficients for February and April Analysis Periods

Peak Hours

In order to investigate the effects of weather on headway at different time periods, another MLR analysis was conducted. The four time periods under consideration were weekday morning peak hour, weekday evening peak hour, and weekend peak and off-peak times. Descriptive statistics for each time period are shown in Table 4.

Table 4. Descriptive Statistics for Headways at Different Time Periods

Period	Min (s)	Max (s)	Mean (s)	Standard Deviation	N
Weekday Morning Peak	41	1930	371.4	231.5	7785
Weekday Evening Peak	39	1707	370.9	203.1	7742
Weekend Peak	33	1928	561.8	216.9	6052
Off Peak	18	1991	542.6	291.6	26951

The p-values for weekend peak and off-peak were all statistically significant. For weekday evening peak the results for rain and wind are not statistically significant. All but rain is statistically significant for weekday morning peak and for the evening peak, rain and wind are not statistically significant. The Durbin-Watson values for 3 out of the 4 time periods lie within the ideal range of 1.5 – 2.5, the one exception being the off-peak time period, which is slightly less than 1.5 (1.392), indicating some positive autocorrelation.

The Beta coefficients for all 4 time periods are graphed in Figure 8. Precipitation is positively correlated in all cases, although its effect is negligible for the weekday evening peak. Wind speed is negatively correlated for 3 out of the 4 time periods. Temperature is positively correlated with increases in headway for both the morning and evening weekday peak hours, however, it is negatively correlated during weekends and off-peak times. This may indicate that there are other factors which influence Luas performance differently during peak periods in comparison to off-peak periods, such as congestion or the effects of larger passenger demand. The adjusted R^2 values range from 0.012, for the weekday morning peak hour, to 0.077, occurring at both the weekend peak and off-peak times indicating that 1.2% to 7.7% of the variance in headway can be attributed to weather impacts.

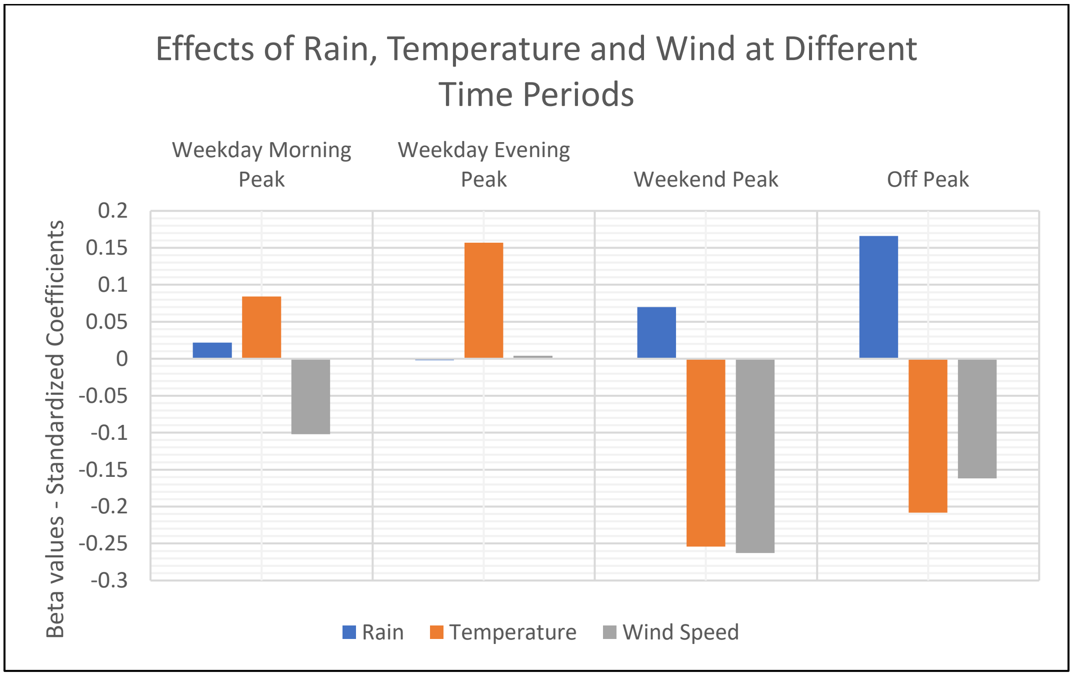

Figure 8. Graph of Beta Coefficients at Different Time Periods

Comparison of Actual and Scheduled Headway Times

This section investigated the variation between the actual Luas headways and scheduled tram frequencies. The actual headway values for each time period were average values taken from the descriptive statistics table, shown in Table 5, along with scheduled. Maximum scheduled values were obtained from the Luas website *(25)*. In peak hours this was 5 minutes (350 seconds) and for off-peak hours it was 15 minutes (900 seconds). The headways during the peak hours were slightly greater than the scheduled values. The measured weekend peak headway of 561 seconds substantially exceeds the scheduled value of 350 seconds. The off-peak service, at an average frequency of 542.6 seconds, was more frequent than the maximum scheduled value of 15 minutes. It was also more frequent than the minimum scheduled value of 12 minutes.

Table 5. Headway Comparison

Period	Average Headway (s)	Max. Scheduled Headway (s)	Difference (s)
Weekday Morning Peak	371.4	350.0	21.4
Weekday Evening Peak	370.9	350.0	20.9
Weekend Peak	561.8	350.0	211.8
Off Peak	542.6	900.0	-357.4

DISCUSSION

Increases in precipitation resulted in increases in headway times at all chosen stations and for all studied time periods. In the case of most of the chosen stations, precipitation was the weather variable with the most influence on headway times. This result was somewhat expected as similar studies found that increases in rainfall leads to an increase in the travel time of both light and commuter rail *(15, 17)*.

Decreases in wind speed corresponded to increases in headway times and this was true in the cases. This was an unexpected result and was different to the findings of other studies *(2, 17, 29)*. The absence of severe wind events in the analysis period may explain this result. The maximum wind speed over the course of the analysis period was 12.9 m/s. This value falls significantly short of the wind speed needed for a yellow warning to be issued, which is 65 km/hr, roughly 18 m/s *(27)*. It would be interesting to explore this on a larger dataset with a greater range of wind speeds.

Air temperature was the least consistent of the analysed predictor variables. Increases in temperature were both positively and negatively correlated to increases in headway with the results varying on a station-by-station basis. At some stations, such as Glencairn, temperature was the most significant predictor variable, while at other, such as Citywest, its influence was negligible. As in the case for wind speed, the variance in temperature over the analysis period was not large, -1.5°C to 19.6°C. Dublin's mild climate and lack of extreme temperatures limits the influence of air temperature on the performance of the Luas.

The adjusted R^2 values at Red Line stations were generally greater than those for Green Line stations. The section of the Red Line from the Red Cow station close to the M50 motorway in the west of the city to the George's Dock station located just east of Dublin City Centre. The exposed nature of the landscape surrounding this section of track could be influencing this result. For much of this section, the Luas runs parallel to the Grand Canal with the tracks located quite far from buildings or trees. In contrast, the sections of the Green Line that have lower R^2 values have much better shelter. Interestingly, the R^2 values of both lines are lower at locations nearer the termini at the periphery of Dublin in comparison to stations closer to the city centre. These areas would generally be expected to have lower passenger numbers than their more central counterparts and it is likely that this may be a factor that affects the headway analysis.

The adjusted R^2 values at weekday peak times, both morning and evening, are significantly lower than those at weekend peak and off-peak times. This illustrates that during the weekday peak the frequency of the Luas is not as strongly influenced by the weather as it is at weekends. Once again, this indicates that passenger activity is likely to be having more influence on Luas performance than weather. It is also possible that congestion could be influencing headway times during peak hours.

Policy Implications

Given the effect of precipitation on performance, it is recommended that rainfall should be prioritised for policy measures to be introduced to improve the resilience of the Luas to adverse weather conditions. Examples of such policies might include increasing Luas frequency by giving trams an increased level of priority at signalized junctions on shared roadways to reduce dwell time or increasing the number of trams running on the network. The operation of these policies could be carried out in conjunction with Met Eireann with the measures coming into effect during periods of high rainfall.

Climate change will result in the increase in both the frequency and severity of adverse weather events (9) and this will likely affect the performance of the Luas as extreme rainfall events and flooding become commonplace. Measures to improve the resilience of the Luas network should therefore be made sooner rather than later. One of the key targets set out by the Dublin City Council Climate Action Plan is to make Dublin a climate resilient region *(10)*. From the findings of the research presented here, the section of the Red Line from Red Cow to George’s Dock should be one of the first areas to be addressed. Putting measures in place to protect the Luas line from flooding at the Grand Canal could be an option to protect the network from the effects of increasingly adverse weather conditions.

The analysis methods used in this study could be used to examine weather impacts on other public transport networks. Analysing the effects of weather in a climate with much greater seasonal variation would be very interesting. The findings of such work could further enhance the collective knowledge of interactions between the weather and transport systems, leading to improvements in design and operation.

CONCLUSIONS

The main findings of the research are as follows:

- Increases in precipitation correlate with increases in headway at all analysed locations and time periods. In most cases, precipitation was the weather variable with the greatest influence on LRT performance.
- At all analysed stations, increases in wind speed correlated with decreases in headway. This was an unexpected result and may be influenced by the absence of extreme wind speeds over the course of the analysis period.
- The impact of air temperature on Luas performance was found to be inconclusive as its effects varied significantly at different stations and analysis periods.
- Weather had a more substantial effect for stations on the Luas Red Line in comparison to their counterparts on the Green Line.
- Based on the results of the MLR analysis, the section of the Luas Red Line from Red Cow to George’s Dock was identified as the area of the network that is most sensitive to the effects of the weather. Generally, its landscape is more open and this is considered to be a contributing factor.
- It was found that headway times during weekday peak times were not as strongly influenced by weather conditions as weekend peak and off-peak times. This may indicate that during these periods, other factors such as congestion have a greater influence on Luas performance.

With the increasing threat of climate change and planned expansions to rail networks in Ireland and at an international level, it is recommended that similar studies that investigate the effects of the weather on transport systems should be carried out. Future work relating specifically to the Luas should have a larger analysis period and a focus on more stations. It is also recommended that similar studies be undertaken in regions with different climatic conditions, as the results of these could provide valuable insight regarding the interactions between weather and transport systems, leading to improvements in design and operation.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: G. Walsh and M.O'Mahony; analysis and interpretation of results: G. Walsh and M. O'Mahony; draft manuscript preparation: G. Walsh and M. O'Mahony. All authors reviewed the results and approved the final version of the manuscript.

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