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Analysis of Disruption Causes and Effects in a Heavy Rail System

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Abstract

Heavy rail systems traditionally known as Metros as well as other transit systems are continuously subject to disruptions which are caused by vehicle failures, communication failures and unexpected high demand among others. These situations cause ineffective system operations resulting in longer passenger waiting time, delays in the itineraries and trains bunching throughout the alignment.This paper presents the results obtained in a study of a year long database of a heavy rail transit system in operation in a major urban area of the US. The main objective of the work presented is to determine mathematical relationships that can be applied for analysis of disruptions of transit systems in terms of three main aspects namely, time between disruptions, disruption duration, and delay/headway ratio.

A brief description of the system is initially presented followed by descriptive analysis of the frequency of occurrence of the detected events causing disruptions and the resulting average delays. Statistical procedures are followed to obtain the relationships that arise from the data analysis. In addition, the disruption impacts over the system operation are presented. In terms of time between successive disruptions, an exponential relationship was found to be the best fit to the data obtained in the field. Regarding disruption duration, a triangular distribution was found as the best fit. Finally, the delay/headway ratio analysis provided insights in the use of this standardized variable to analyze system disruptions using simulation.

Keywords

Disruption, Transit Systems, Rail, Public Transportation

1. Introduction

Transit systems are frequently subjected to disruptions that affect the service quality. Disruptions are caused by several factors such as brake system failure, door failure, train control failure and incidents inside the vehicles.

This paper presents the results of a study of a comprehensive and accurate data set of a heavy rail transit system in operation in the United States. The metro system is automated and serves a vast population in a major metropolitan area. The data set represents the failures occurring during the year 2001 in one of the metro lines of the mentioned system. This particular line includes twenty-seven stations along a 47.9 km.

2. Disruption Causes and Effects

During the year 2001, there were a total of 1,156 incidents on the metro line that disturbed the system operation. Figure 1 presents a summary of the disruptions occurring on the line during the analyzed period. As seen in the figure, the first four major causes of disruption were failures associated with the brake system, doors, automatic train control (ATC), and station overrun. These disruption causes correspond to 66% of the overall disruptions during the analyzed period.

The metro line uses eight performance indicators to estimate the effect of disruptions on the system normal operation. Four of these performance indicators are Time related Indicators that measure the delay on the system and the other four are Reliability Indicators that measures the disruption effect on the system reliability.

The four Time Indicators and their description are shown below:

1. Duration: The length of time taken by the disruption
2. Train Delay: The delay on train “x” caused by disruption “y”.
3. Passenger Delay: The extension of the passenger waiting time or the on-board time caused by a disruption.
4. Line Delay: The delay on the overall system caused by disruption “y”

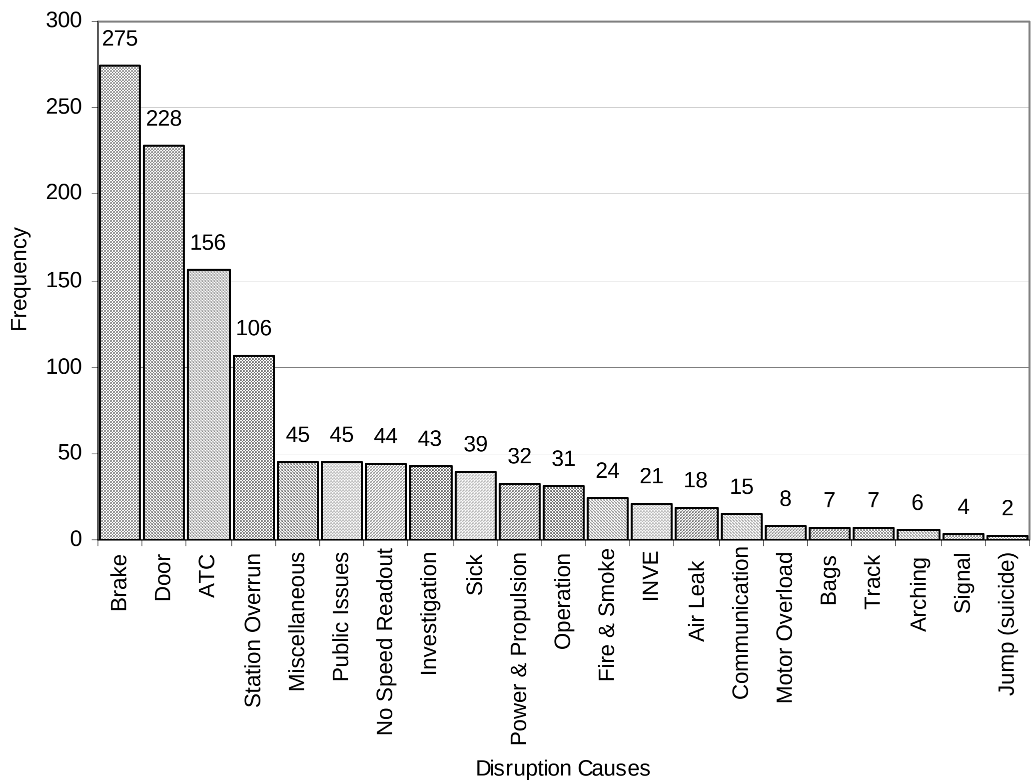

Figure 1: Metro Line Incident Frequencies for the 2001

The four Reliability Indicators and their description are shown below:

1. Partially Late: The number of trains with partially late trips (trains that partially fulfill the assigned schedule) due to an incident “y”
2. Offloaded: The number of trains that need be offloaded due to a disruption “y”.
3. Late Trips: The number of trains that arrive late to the final destination due to a incident “y”
4. Lost Trips: The number of trains that do not finish the assigned schedule due to a incident “y”

According to the analyzed data, the disruption that causes the longest delay for the train, passenger, and line is the jump (that is unauthorized person on the tracks possibly struck by the train), which causes an average delay of 215 minutes to the train and 22 minutes to the passenger and line. It is important to mention that this type of disruption is not frequent on heavy rail systems occurring twice in our disruption data set.

Without taking into consideration the disruption caused by Jump incidents, the four reasons for major train delay are fire and smoke, signal failure, track failure, and propulsion and power failure. The brake failure and door failure are the most frequent causes of disruption. On average, they result in 5.2 minutes and 4.9 minutes delay, respectively. Figure 2 presents the delay on the Train, the passengers and the Line due to the disruptions. As presented in the figure the causes for longest passenger delay and line delay is Arching which is pass power to a section without power.

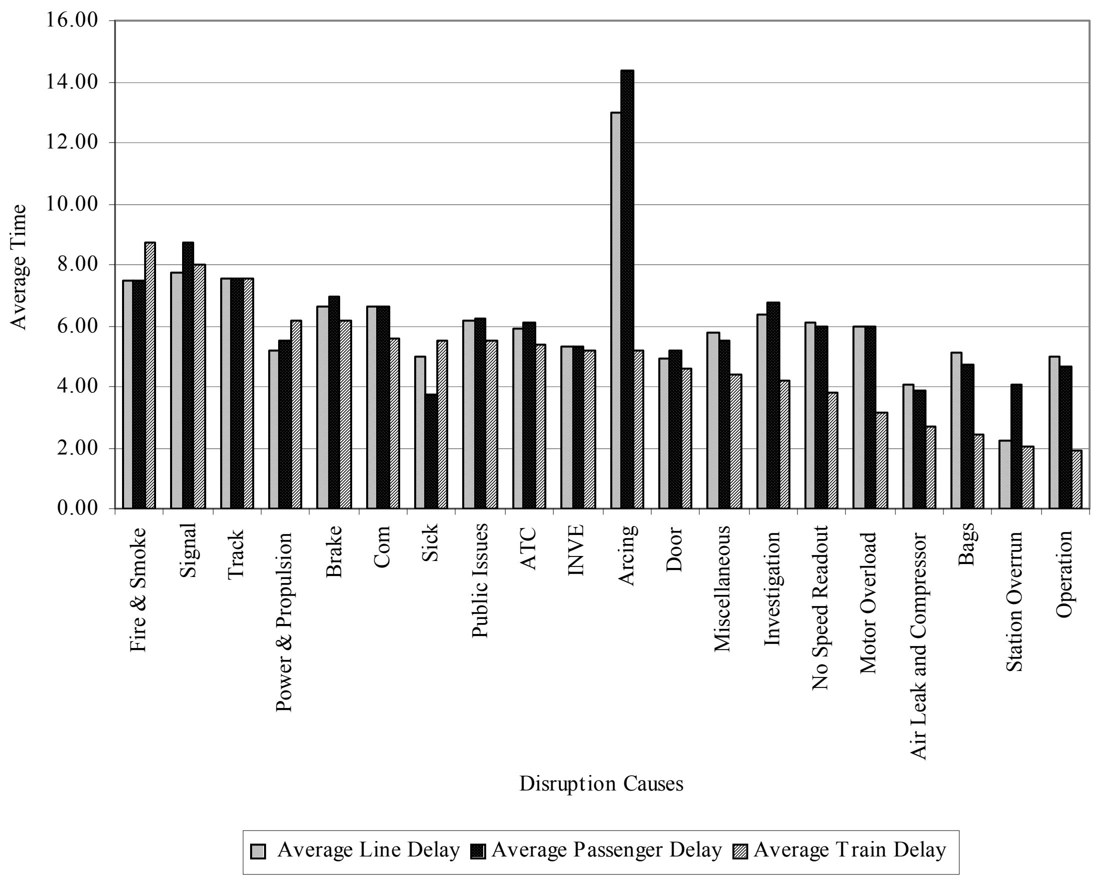

Figure 2: Average Delays Caused by the Disruption

In addition to delays, the disruptions otherwise affect the service reliability. During 2001, the metro line lost 30 trips, 48 trains arrived late at the final destination, 777 were partially late and 571 there were offloaded vehicles. The major reason for the late trips and lost trips were the brakes, which caused 20 late trips, 6 lost trips, 329 partially late trips and 236 offloaded vehicles. Figure 3 presents the performance disturbances caused by the disruptions. As seen in the figure, besides the brakes failure, the door failure, the ATC failure and no speed readout, were the major causes for partially late trips and offload. On the other hand, in addition to the brakes the major reasons for lost and late trips were doors failures, operator failure and other miscellaneous events.

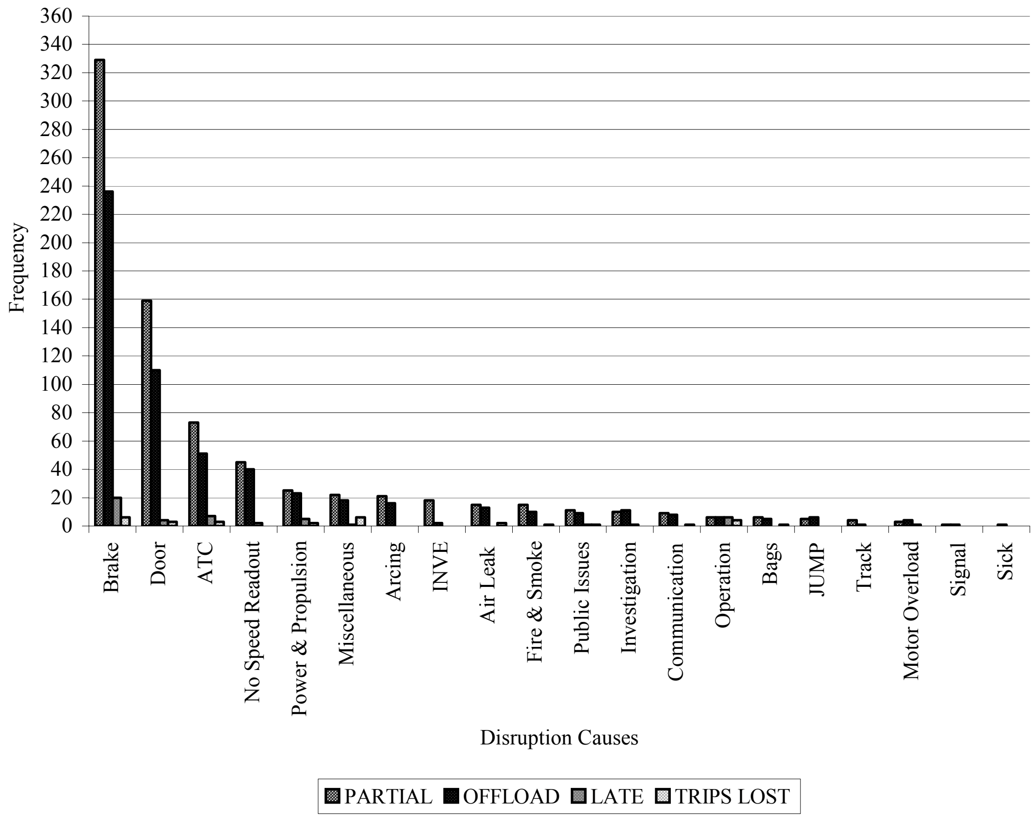

Figure 3: Performance Disturbances Caused by the Disruptions

3. Time Between Successive Disruption Events

The disruption analysis was concentrated on those that are less than ten (10) minutes, which is comparable to two times the Tren Urbano rush hour headway. Using the available metro line disruption data, the statistical distribution and its frequencies were estimated.

During the analyzed year in the metro line occurred 1,056 disruptions events with less than 10 minutes duration for 92 percent of the overall data. As presented in Figure 4 the histogram developed from this data has the shape of an exponential distribution. The calculated mean for the analyzed data is 454 minutes with an estimated variance of 547.3 minutes. Using an error of $\alpha = .05$ a Chi-square goodness of fit test was developed in order to prove the following hypothesis:

H_0= There is no significant difference between the disruption data and what would be expected from an exponential distribution with a mean of 454 minutes and a variance of 547.3. Table 1 presents the goodness of fit test developed to prove this hypothesis.

The degrees of freedom for the Chi-square test performed to validate the data are:

$$v = k - 1 - p = 13 - 1 - 2 = 10 \qquad (1)$$

In this case the parameter "p" is equal to two because use mean and the standard deviation from the observed data are used to obtain the theoretical frequencies. With $\alpha = 0.005$ and $v = 10$, the critical x^2 is 16.9[1]. Since the obtained x^2 is greater than the critical x^2 ($63.53 > 16.9$), the H_0 was rejected.

Because the Chi-square test result differs from the histogram on figure 7.1.4, a Q-Q plot was done in order to validate the presumption that the analyzed data followed an exponential distribution. The Q-Q plots amplify the differences that exist between the model exponential distribution and the observed data. If the variance between the observed frequency and the modeled frequency did not exist, the Q-Q plot would be linear with a slope of 1 and the Y tends to 0.

Table 1: Chi-Square Test for Time between Successive Disruption Events

ID	RANGE		OBSERVED FREQUENCY	OBSERVED FREQUENCY	EXPECTED FREQUENCY	X^2 STATISTICS
1	0	250	519	519	447.111	11.55871
2	250	500	189	189	257.908	18.41088
3	500	750	142	142	149.037	0.332262
4	750	1000	73	73	85.617	1.859312
5	1000	1250	58	58	49.679	1.393729
6	1250	1500	29	29	28.539	0.007447
7	1500	1750	12	12	16.912	1.426664
8	1750	2000	12	12	9.513	0.650181
9	2000	2250	6	6	5.285	0.096731
10	2250	2500	4	4	3.171	0.216727
11	2500	2750	4	4	2.114	1.68259
12	2750	3000	4	4	1.057	8.194181
13	3000	3250	0	5	1.057	14.70884
14	3250	3500	2			
[illegible]	3500	3750	0			
[illegible]	3750	4000	1			
17	4000	4250	0			
18	4250	4500	1			
19	4500	4750	1			
		Total	1057	1057	1057	60.53825

1 Introduction to Simulation Using SIMAN (8)

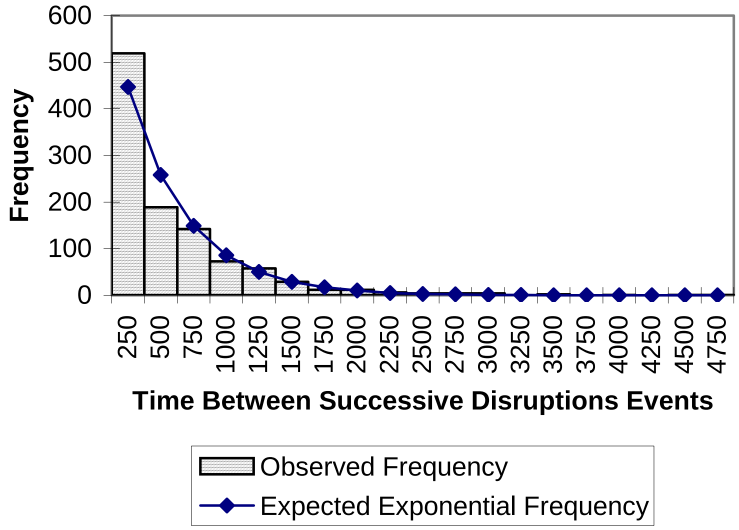

Figure 4: Time between Successive Disruptions Less Than 10 Minute

The Q-Q plot for the analyzed data is presented on Figure 5. By visual inspection, the analyzed data plot tends to be linear. In order to prove its linearity, a linear regression was done, setting the intercept to 0. As shown in the figure the linear regression slope approaches 1.0. The value of r^2 is .9638, so 96.4% of the observed variation in the modeled data can be attributed to an approximately linear relationship between the modeled data and the observed data. Taking into consideration those results, the analyzed data can be approximated using an exponential distribution with a mean of 454 minutes between incidents.

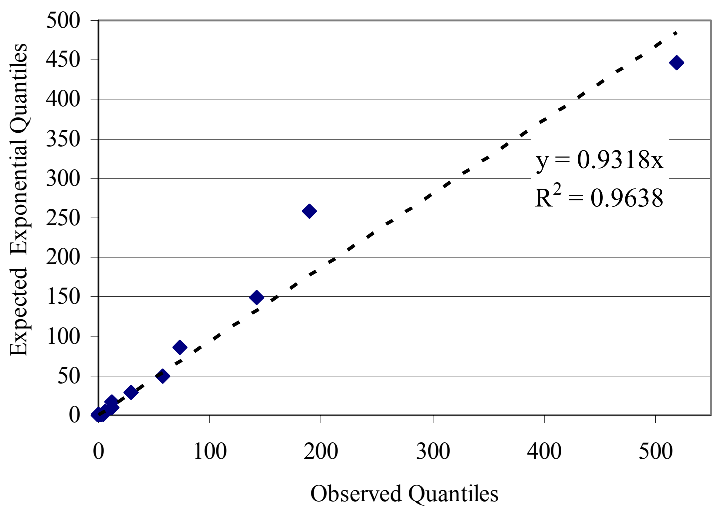

Figure 5: Q-Q Plot for Exponential Distribution and Successive Disruption Events Data

4. Disruption Duration

The disruption duration is defined as the time elapsed between the beginnings of the incident and when the incident was resolved and the trains return to operation. It is an important parameter since it represents vehicle delays.

The histogram presented in Figure 6, was developed for delays less than ten minutes. As shown in the figure, the analyzed data tend to be a triangular distribution, with an average of 3.96 minutes, median of 3 minutes and a standard deviation of 2.48. Using an error of α = .05 a Chi-square goodness of fit test was developed in order to prove the following hypothesis:

H_0= There is no significant difference between the disruption data and what would be expected from a triangular distribution with a Median of 3 min. and an average of 3.96 min. Table 2 show the goodness of fit test developed to prove this hypothesis.

Table 2: Chi-Square Test for the Disruption Events Duration

LOWER LIMIT	UPPER LIMIT	PROBABILITY OF OCCURRENCE	EXPECTED NUMBER IN CLASS	OBSERVED NUMBER IN CLASS	X^2
0	2	0.166	176.16	125	20.94
2	4	0.315	332.79	417	17.01
4	6	0.241	254.46	235	1.61
6	8	0.167	176.17	164	0.90
8	10	0.093	97.87	93	0.26
10	12	0.018	19.57	23	0.51
	Total	1	1057	1057	41.24

The degree of freedom for the chi-square test used to validate the data is:

$$v = k - 1 - p = 6 - 1 - 1 = 4 \qquad (2)$$

In this case the parameter "P" is equal to one since the median from the observed data was used to obtain the theoretical frequencies. With α = 0.005 and v = 4 the critical x^2 is 9.49[2]. Since the obtained x^2 is greater than the critical x^2 (41.24 > 9.49), the H_0 was rejected.

Because the Chi-square test result differs from the histogram on Figure 7; a P-P plot was performed in order to validate the asumption that the analyzed data followed a triangular distribution. The P-P plots allows us to analyze differences that exist between the model triangular distribution and the observed data. If variance between the observed frequency and the modeled frequency does not exist, the P-P plot must be linear with a slope of 1 and the Y intercept tending to 0.

[2] Introduction to Simulation Using SIMAN (8).

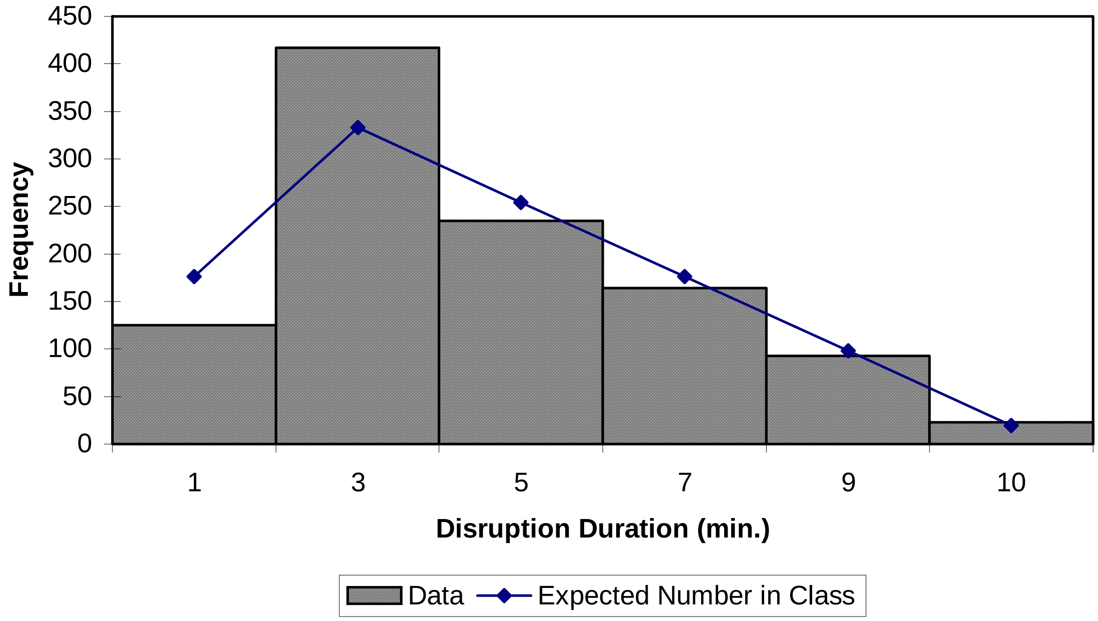

Figure 6: Disruption Duration Histogram

By visual inspection of the P-P plot on Figure 7, the analyzed data plot tends to be linear. In order to prove its linearity, a linear regression was performed, setting up the intercept to 0. As shown on the figure the linear regression has a slope 1.0041 and the r^2 value is .994, so 99.4% of the observed variation in the modeled data can be attributed to an approximately linear relationship between the modeled data and the observed data. those results, the analyzed data can be approximated using an exponential distribution.

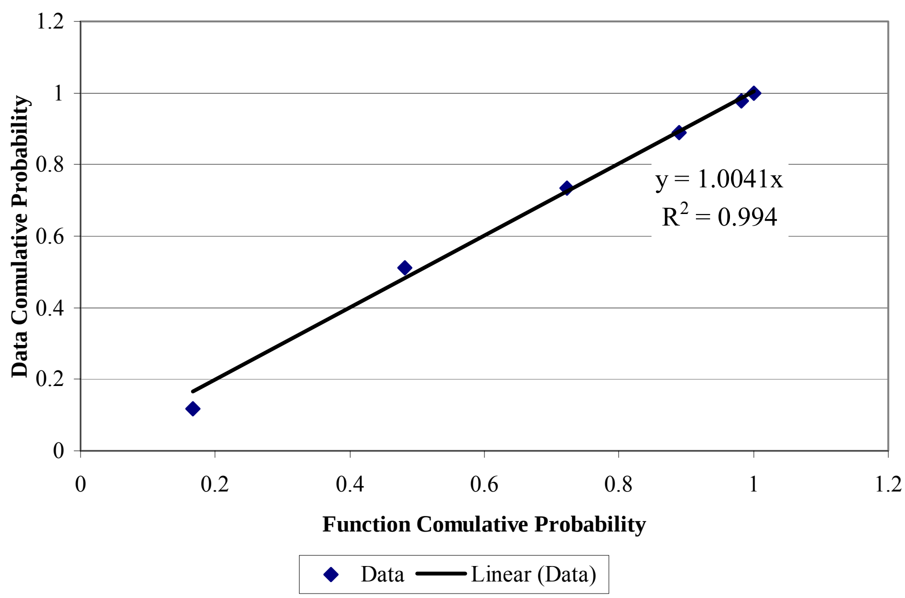

Figure 7: P-P Plot for Triangular Distribution and Disruption Duration Data.

5. Delay/Headway Ratio

The fundamental idea of this research is to analyze the implications of Scheduled Based and Headway Based operational logic in order to allow a better service when short and medium disruptions occur. For the purpose of this research, a disruption was considered in the range of short to medium when it is within the range of 0 to 2 times the headway.

The Delay/Headway ratio is a measure that explains how large or small the delay is compared with the headway at the time when the disruption occurs. During the 2001 on the metro line 88% of the occurred disruptions was less than two times the headway when they occurred. Figure 8 presents a cumulative density plot, which describes the overall delay/ headway data distribution.

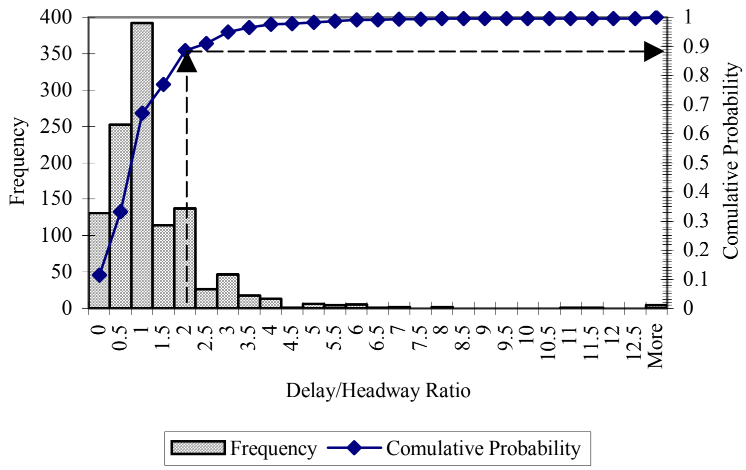

Figure 8: Overall Data Delay/Headway Ratio

Peak Hour will have modeled disruptions in the range of 0 to 10 minutes. This range was arbitrarily selected, considering the designed Tren Urbano five minutes headway for the peak hour. In order to determine whether the arbitrarily selected delay range differs from the overall data, the delay was standardized using the Delay/Headway ratio.

Kolmogorov-Smirnov (K-S) goodness of fit test was performed, in order to ensure that the modeled data do not defer from the overall data. With an error α of 0.05, the goodness of fit test was performed in order to prove the following hypothesis:

H_0= There is no significant difference between the analyzed and the overall data. Table 3 shows the K-S goodness of fit test developed to prove this hypothesis.

The maximum K-S Statistic calculated is 0.04147. The critical value for significance at α =0.05 and degrees of freedom = 1057 is given by the following expression[3]:

$$K\text{-}S\ Critical = 1.36/\,n^{1/2} = 0.04183 \qquad (3)$$

Since 0.04147 < 0.04183, the H_0 hypothesis of no significant differences between the analyzed data an overall data is not rejected. According to the data presented in Figure 9 and the goodness of fit test result, it was not possible to observe any significant difference between the studied delays (0 to 10 minutes) and the overall data. For this reason, the asumption that the delay is within the range of 0 to 10 minutes is valid and does not differ from reality.

[3] Introduction to Simulation Using SIMAN(8)

Table 3: Delay-Headway Kolmogorov-Smirnov Goodness of Fit Test

LIMIT	OBSERVED FREQUENCY	OBSERVED RELATIVE FREQUENCIES	OBSERVED CUMULATIVE FREQUENCY	EXPECTED CUMULATIVE FREQUENCIES	K-S
0	124	0.11731	0.11731	0.11495	0.00236
0.5	248	0.23463	0.35194	0.33276	0.01918
1	381	0.36045	0.71239	0.67156	0.04083
1.5	103	0.09745	0.80984	0.76837	0.04147
2	125	0.11826	0.92810	0.88678	0.04132
2.5	22	0.02081	0.94891	0.90925	0.03966
3	40	0.03784	0.98675	0.94987	0.03688
3.5	14	0.01325	1	0.96543	0.03457
4	0	0	1	0.97666	0.02334
4.5	0	0	1	0.97753	0.02247
5	0	0	1	0.98271	0.01729
5.5	0	0	1	0.98617	0.01383
6	0	0	1	0.99049	0.00951
6.5	0	0	1	0.99136	0.00864
7	0	0	1	0.99309	0.00691
7.5	0	0	1	0.99309	0.00691
8	0	0	1	0.99481	0.00519
8.5	0	0	1	0.99481	0.00519
9	0	0	1	0.99481	0.00519
9.5	0	0	1	0.99481	0.00519
10	0	0	1	0.99481	0.00519
10.5	0	0	1	0.99481	0.00519
11	0	0	1	0.99568	0.00432
11.5	0	0	1	0.99654	0.00346
12	0	0	1	0.99654	0.00346
12.5	0	0	1	0.99654	0.00346
More	0	0	1	1.00000	0
				MAX	0.04147

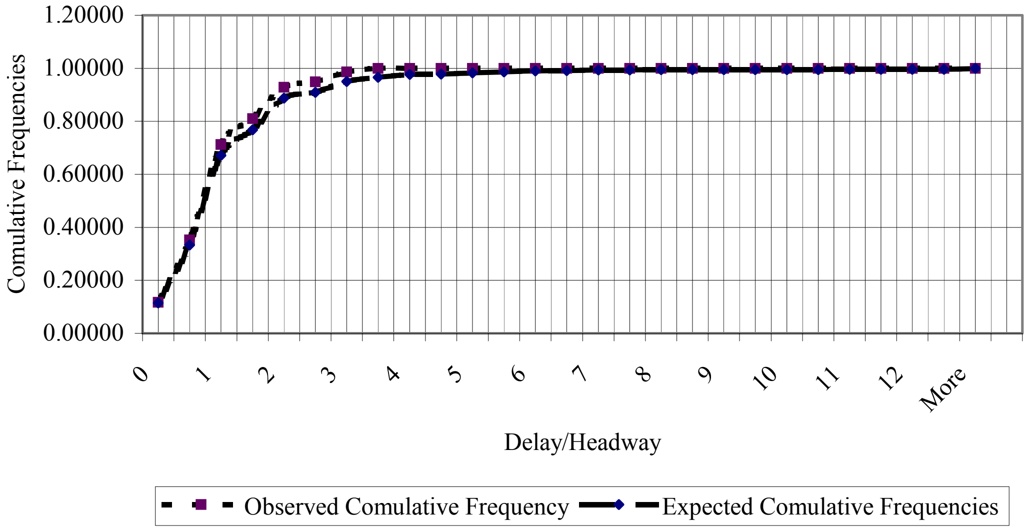

Figure 9: Delay Headway Cumulative Probability Data Analysis

6. Conclusions

This paper concentrated on the analysis of disruption causes and effects in a heavy rail system focusing on developing mathematical relationships in three areas namely time between disruptions, disruption duration and delay/headway ratio.

It was found that the delay/headway ratio analysis has the potential to be used as a good indicator for heavy rail system disruption analysis. Good use of this indicator will result in identifying strategic actions that could be taken to improve the operation in the medium and long range and save costs by generating actions that anticipates and attend disruption situations.

It is important to highlight that an updated and accurate database of the disruptions occurring in a system is a must for the application of the processes presented in this paper.

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