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TRAFFIC VOLUME AND COLLISIONS INVOLVING TRANSIT AND NONTRANSIT VEHICLES

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Abstract—This study reports an analysis of collisions occurring between public transit vehicles operated by the San Francisco Municipal Railway System (Muni), the public transit agency for the City of San Francisco, and nontransit vehicles. The analysis, focusing on weekday collisions during 1987, demonstrated a strong association between hourly transit collisions rates and hourly traffic volume. The collision rate varied from 0.01 per 1,000 Muni vehicle-hours of operation during the interval 5 A.M. to 6 A.M., a time of very low traffic volume, to 0.93 (approximately 1 collision per 1,000 Muni vehicle-hours of operation) during the interval 5 P.M. to 6 P.M., a time of very high traffic volume. Using a power function to predict either the total number of collisions, or the rate of collisions per 1,000 Muni vehicle-hours, almost 90% of total variation was accounted for by traffic volume. A very similar pattern was found for collisions judged either avoidable or unavoidable. A peak in the collision rate between 2 A.M. and 3 A.M. could not be accounted for by traffic volume alone. That peak occurred in the one-hour interval following the 2 A.M. closing of bars in San Francisco, and was composed entirely of a sharp increase in unavoidable collisions. Increasing traffic volume appeared to operate through two mechanisms: (i) an increase in the number of opportunities for a collision, defined as a quantity proportional to the product of the number of Muni and non-Muni vehicles; (ii) an increase in the probability of a collision occurring between any given pair of vehicles.

INTRODUCTION

In 1985 the 10 largest transit systems in the United States (having 1,000 or more vehicles) were involved in a total of 38,731 accidents, resulting in 14,082 injuries and 116 deaths (National Urban Mass Transportation Statistics 1985). In the same year, these 10 agencies spent millions of dollars for casualty and liability claims that stemmed from those accidents.

The San Francisco Municipal Railway (Muni), the public transit system for the city and county of San Francisco, ranks among the 10 largest city-transit systems in the United States. Muni carries over 900,000 passengers per day using several different types of vehicles, including diesel buses, electric buses, light rail vehicles, and cable cars. Muni experiences about 3,000 accidents of all kinds each year. The recorded cost to Muni in collision damages and claims ranges from $5 to over $6 million per year, and with probable additional uncounted costs. Over 1,000 injuries and one or two deaths occur each year as a result of Muni accidents.

Most studies of transit-related collisions have focused on driver characteristics. These have included analyses of years of driving experience (Adelstein 1952; Blom et al. 1987; Cresswell 1963; Cornwall 1961; Spratling 1961; Pelze and Schuman 1971; Brown 1982), prior collision record (Cresswell and Froggatt, 1963; van Nooten et al. 1985), and fatigue (Harris and Makie 1972). Other studies have focused on temporal characteristics of the working environment such as type, length, and time of shift. (Pokorny et al. 1987a; Pokorny et al. 1987b). Few studies of transit-related collisions have considered environmental factors such as weather conditions, type of roadway, or traffic volume (Jovanis et al. 1989).

This article describes the first part of a larger study of accidents in the Muni system, which will attempt to: (i) identify the important causes of accidents and (ii) design and evaluate interventions. The starting point for the analysis was the considerable hour-to-hour variation in the number of collisions and in the collision rates, defined as the number of collisions per 1,000 Muni vehicle-hours. Traffic volume, not previously studied in relation to transit accidents, was examined to determine the role of this potentially important factor in collision rates.

METHODS

Variables studied

Data on collisions during 1987 were obtained from the accident database maintained by Muni. Data are collected for each reportable collision including date, time of day, location (name of street and nearest intersection), type of Muni vehicle involved (diesel bus, electric bus, light-rail vehicle, or cable car), type of other vehicles involved (e.g. automobile, truck), and type of collision (e.g. side swipe, rear-end collision).

The database also records a post-investigation classification of driver responsibility for the collision. There are two categories for this classification: avoidable and unavoidable. This distinction is undoubtably subjective; however, it is widely used in the study of accidents and for legal purposes for assessing fault in the event of a collision. The variable was included here to see if there is a difference between the two categories in their association with traffic volume.

The analyses reported in this paper were based on data from collisions between Muni and other vehicles during 1987. Traffic patterns in San Francisco are very different for weekdays than for weekends; this report is limited to weekday (midnight Sunday to midnight Friday) collisions during 1987. We tabulated the number of collisions occurring during each hour of each weekday for the entire year, as well as the number of hours of Muni vehicle operation for the same periods. The collision rate per 1,000 Muni vehicle-hours of operation was then calculated for each hour of the day, as follows:

$$\text{collision rate} = \frac{\text{number of collisions}}{\text{number of Muni vehicle-hours}} \times 1{,}000.$$

To construct a measure of hourly traffic volume in San Francisco, we obtained from the city traffic engineer a single weekday count of vehicles per hour in both directions for four city streets. These counts were summed, yielding a total vehicle count for each hour. The total for each hour was then divided by the total for the entire day, yielding a percentage for each hour. We call this the *traffic index*, representing a relative measure of hourly traffic volume. This measure seems to be an adequate index of relative hourly traffic volume in the city for the following reasons. First, the streets sampled are all major arteries serving as commuting routes into and out of the city, as well as being geographically diverse. Second, despite the geographic diversity, the correlations among the individual measures were very high (the Pearson correlation coefficients ranged from 0.36 to 0.97; half of the 28 correlation coefficients were greater than 0.80). Finally, because San Francisco does not have significant seasonal weather changes, we considered single weekday counts to be representative of relative traffic volume for weekdays for the entire year.

Statistical analysis

Variables used in the statistical analysis were the number of collisions (n), the number of Muni vehicle hours in units of 1,000 (vh), and the traffic index (x). For the association between traffic volume and collisions, we focused initially on the number of collisions (n), rather than on the rate (n/vh) itself. A number of previous studies have used a power function to model the relationship between accidents and traffic volume (Satterthwaite 1981). In the present analyses, a power function of the general form

$$n = \kappa \cdot x^{\alpha} \cdot vh^{\beta}$$

was used as the basic model, where κ, α and β are model parameters to be estimated from the data (Scott 1983; Maycock and Hall 1984). One objective of the modeling was to determine the relative and absolute values of α and β. Are they about equal? Is either (or both) close to 1.0?

To evaluate the parameters of this model we used a generalized linear modeling approach (McCullagh and Nelder 1983) in which a Poisson distribution was assumed for the number of collisions. Analyses were done for total collisions and then separately for avoidable and unavoidable collisions. The statistical package GLIM was used to implement the analyses (Aitkin et al. 1989).

For each fitted statistical model, we assessed its adequacy in describing the observed data by calculating the percent of variance that could be explained by the model (Appendix A). Residual differences between model-predicted and actual hourly variations were examined graphically.

RESULTS

Collisions by time of day

A total of 1,562 collisions between Muni and other vehicles occurred during the weekdays of 1987. Table 1 shows the number and rate (number per 1,000 vehicle-hours of operation) of collisions by collision type (total, avoidable, and unavoidable) for each hour of the day. The rates are presented graphically in Fig. 1a. Overall, the lowest collision rate occurred in the two time periods 4 A.M.–5 A.M. and 5 A.M.–6 A.M. (0.02 and 0.01, respectively per 1,000 vehicle-hours). The highest collision rate occurred during 4 P.M.–5 P.M. (0.93 per 1,000 vehicle-hours). This peak was almost 100 times the lowest

Table 1. Number of collisions and accident rate per 1,000 vehicle-hours for total collisions, by hour-of-the-day, for the San Francisco Municipal Railway (Muni), 1987

Hour of the day	Muni vehicle hours(units of 1000)	Total Collisions		Avoidable Collisions		Unavoidable Collisions	
		Number	Rate	Number	Rate	Number	Rate
12 Midnight	49	9	0.18	2	0.04	7	0.14
1 AM	29	4	0.14	2	0.07	2	0.07
2	12	4	0.35	0	0.00	4	0.35
3	13	2	0.16	0	0.00	2	0.16
4	43	1	0.02	1	0.02	0	0.00
5	109	1	0.01	0	0.00	1	0.01
6	170	18	0.11	6	0.04	12	0.07
7	190	84	0.44	24	0.13	60	0.32
8	177	109	0.61	27	0.15	82	0.46
9	150	82	0.55	15	0.10	67	0.45
10	133	75	0.56	18	0.14	57	0.43
11	133	93	0.70	22	0.17	71	0.53
12 Noon	137	104	0.76	21	0.15	83	0.61
1 PM	148	106	0.72	26	0.18	80	0.54
2	163	116	0.71	26	0.16	90	0.55
3	185	161	0.87	41	0.22	120	0.65
4	198	147	0.74	43	0.22	104	0.53
5	188	175	0.93	44	0.23	131	0.70
6	149	129	0.87	43	0.29	86	0.58
7	105	58	0.55	16	0.15	42	0.40
8	83	27	0.32	5	0.06	22	0.26
9	74	18	0.24	2	0.03	16	0.22
10	70	19	0.27	10	0.14	9	0.13
11	63	16	0.25	4	0.06	12	0.19
Total	2770	1558	0.56	398	0.14	1160	0.42

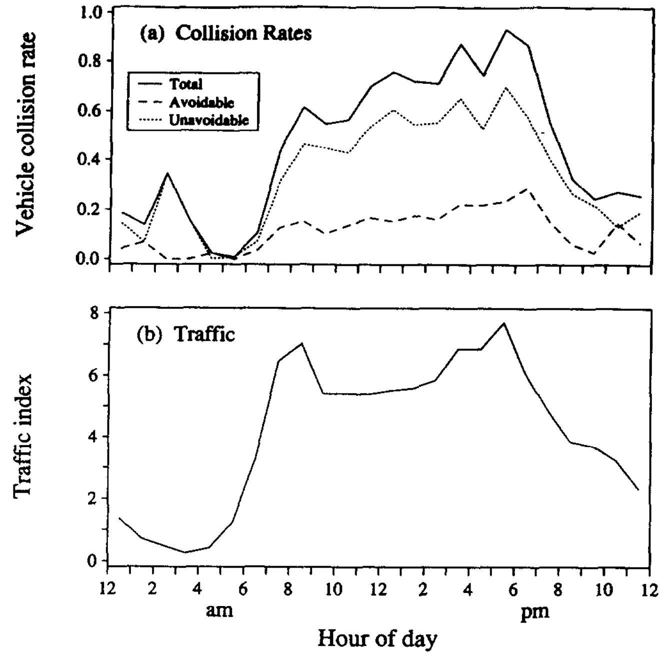

Fig. 1. (a) Vehicle collision rate (total, avoidable, unavoidable) in the San Francisco Municipal Railway (Muni) by hour of the day, weekdays, 1987, (b) Total traffic count (in units of 1,000) and traffic index, by hour of the day, weekdays, 1987.

collision rate. Avoidable and unavoidable collision rates showed comparable patterns of early morning troughs with peaks in the late afternoon.

Table 2 shows the values of the traffic index, using total traffic counts to generate an hourly percentage of the total. This index is plotted by hour in Fig. 1b. The hour of minimum traffic volume was 3 A.M.–4 A.M. when 201 vehicles (.3% of the total for the day) were counted at the sample locations. Traffic volume increased until 8 A.M.–9 A.M. at which time almost 5,200 vehicles (7% of the total for the day) were counted. The count dropped somewhat during the middle hours of the day and then increased to a maximum value between 5 P.M.–6 P.M., when almost 5,700 vehicles were counted (7.7% of the total for the day). This hourly pattern is similar to collision patterns reported for other urban areas (e.g. Box and Oppenlander 1976). Visually, the traffic index (Fig. 1b) shows a striking similarity to the collision rates (Fig. 1a) in the hour-to-hour pattern of variation.

Modeling of collisions and traffic volume

We conducted the initial modeling using the number of collisions (n) as the basic outcome variable, and with Muni vehicle-hours (vh) and the traffic volume index (x) as the predictor variables. Traffic volume and Muni vehicle-hours were first evaluated in separate models. The association between total collisions and Muni vehicle-hours was evaluated using the model:

$$n = \kappa \cdot vh^{\alpha}. \tag{1}$$

For this model, the estimated value of α (i.e. $\hat{\alpha}$) was 1.89 ($s.e.$ = 0.08). The association between total collisions and traffic volume was evaluated using the model:

$$n = \kappa \cdot x^{\alpha}. \tag{2}$$

For this model, $\hat{\alpha}$ = 2.07 ($s.e.$ = 0.09). Thus, for both Muni vehicle-hours and traffic volume, the variable of total collisions was proportional to the power of approximately 2, however, the parameter for traffic volume was a bit higher than that for Muni vehicle-hours.

Table 2. Total traffic counts from four locations and traffic index (percent of total traffic count), by hour-of-the-day, San Francisco, 1987

Hour of the Day	Traffic Count (in units of 1000)	Traffic Index (percent of total)
12 Midnight	1017	1.4
1 AM	537	0.7
2	362	0.5
3	201	0.3
4	316	0.4
5	926	1.3
6	2419	3.3
7	4767	6.5
8	5177	7.0
9	3988	5.4
10	3996	5.4
11	3974	5.4
12 Noon	4055	5.5
1 PM	4117	5.6
2	4308	5.9
3	5053	6.9
4	5049	6.9
5	5677	7.7
6	4473	6.1
7	3592	4.9
8	2825	3.8
9	2715	3.7
10	2377	3.2
11	1669	2.3
Total	73590	100.00

We then included both variables simultaneously in the model as follows:

$$n = \kappa \cdot x^{\alpha} \cdot vh^{\beta}. \tag{3}$$

The estimated coefficient for traffic volume was $\hat{\alpha} = 2.03$ ($s.e. = 0.18$); however, the estimated coefficient for vehicle-hours was $\hat{\beta} = 0.04$ ($s.e. = 0.17$). Since the two variables were highly correlated ($r = .91$, $p < .001$), the stronger of the two variables, traffic volume, statistically dominated the weaker variable, Muni vehicle-hours.

Next, we fitted a model in which the product of traffic volume and Muni vehicle-hours was evaluated, as follows:

$$n = \kappa \cdot (x \cdot vh)^{a}. \tag{4}$$

For this model, $\hat{\alpha} = 1.06$ ($s.e. = 0.05$); i.e. the number of collisions was proportional to the product of traffic volume and Muni vehicle-hours. From these models we conclude that it is reasonable to assume that accident numbers are proportional to Muni vehicle-hours, and that we are justified in modeling a relationship between collision rate (i.e. collisions per unit of Muni vehicle exposure) and traffic volume. To do this we removed vehicle hours (vh) as a predictor variable, and included it as a "variable constant" or, in the terminology of GLIM, an "offset" (Aitkin et al. 1989). This model,

$$\frac{n}{vh} = \kappa \cdot x^{\alpha}, \tag{5}$$

allowed us to express the results in terms of collision rates (i.e. number of collisions per 1,000 Muni vehicle-hours), while retaining the Poisson assumption for the distributional

Table 3. Parameter estimates (and standard errors) for the power function relating the hourly collision rate to hourly traffic index for total collisions, San Francisco Municipal Railway, 1987

Model	Parameter Estimates				Variance Explained
	k	a	β_1	β_2	
(4) $n = \kappa\cdot(x\cdot vh)^{\alpha}$	0.07(0.02)	1.06(0.05)	-	-	88.8
(5) $\frac{n}{vh} = \kappa\cdot x^{\alpha}$	0.07(0.01)	1.26(0.09	-	-	89.5
(6) $n = \kappa\cdot(x\cdot vh)^{\alpha}\cdot e^{\beta_1\cdot c_1}\cdot e^{\beta_2\cdot c_2}$	0.05(0.02)	1.13(0.05)	2.3(0.48)	-0.44(0.06)	95.5
(7) $\frac{n}{vh} = \kappa\cdot(x)^{\alpha}\cdot e^{\beta_1\cdot c_1}\cdot e^{\beta_2\cdot c_2}$	0.07(0.01)	1.33(0.10)	2.6(0.48)	-0.41(0.06)	95.7

properties of n. For this model, $\hat{\alpha} = 1.26$ (*s.e.* = 0.09), showing that the rate of collisions per unit of exposure for Muni vehicles was proportional to a power of traffic volume greater than 1.00.

The estimated coefficients for total collisions for models (4) and (5) are given in the top half of Table 3. The estimated value of the multiplier $\hat{\kappa}$ was the same for both models. The percentage of variation explained by both of these models was quite high; the model predicting the *number* of collisions (i.e. model [4]) accounted for 88.8% of the variance, and the model for collision *rate* (i.e., model [5]) accounted for 89.5% of the variance.

The entire sequence of analyses conducted for total collisions was repeated separately for avoidable and unavoidable collisions. The estimated values of the "power" parameters were very similar to those for total collisions. Considering the modeling of rates (i.e. model [5]), estimated coefficients for traffic volume were all between 1.25 and 1.30. The difference between the models was almost entirely in the multiplier coefficient (i.e. $\hat{\kappa}$).

Graphical presentations of actual versus predicted collision rates

In order to evaluate the pattern of correspondence between predicted and actual collisions, we made two different graphical presentations of the actual versus predicted rates. In the first comparison (Figs. 2a–2c) we plotted actual and predicted rates as a function of the hourly traffic volume. Predicted rates were generated using the parameters estimated from model (5). As seen in the graphs, and as reflected in the percentage of variance explained, the fit between the actual rates and those predicted by the power function was rather close.

In the second graphical presentation (Figs. 3a–3c), we plotted actual and predicted rates as a function of hour-of-the-day. For total collisions, the actual rate closely followed the predicted rate over most of the day (Fig. 3a). One exception was in the early morning hours (12 A.M.–3 A.M.) when the actual rate of collisions was substantially higher than the rate predicted based solely on traffic volume. During the hour 2 A.M.–3 A.M., the actual rate (0.35 per 1,000 vehicle-hours) was substantially higher than the predicted rate. For each of the hours between 4 A.M.–10 A.M., the actual rate was lower than the predicted rate. For much of the rest of the day, the actual rate was higher than the predicted rate. The same general pattern was seen for avoidable (Fig. 3b) and unavoidable (Fig. 3c) collisions.

Final model

Observed differences in the fit for different intervals of the day led to an additional, post hoc analysis of the association between traffic volume and collisions. We conducted this analysis by constructing a variable representing the different time intervals. The hours between 2 A.M.–4 A.M. constituted the first interval, the hours between 4 A.M.–10 A.M. represented the second interval, and all remaining hours made up the third

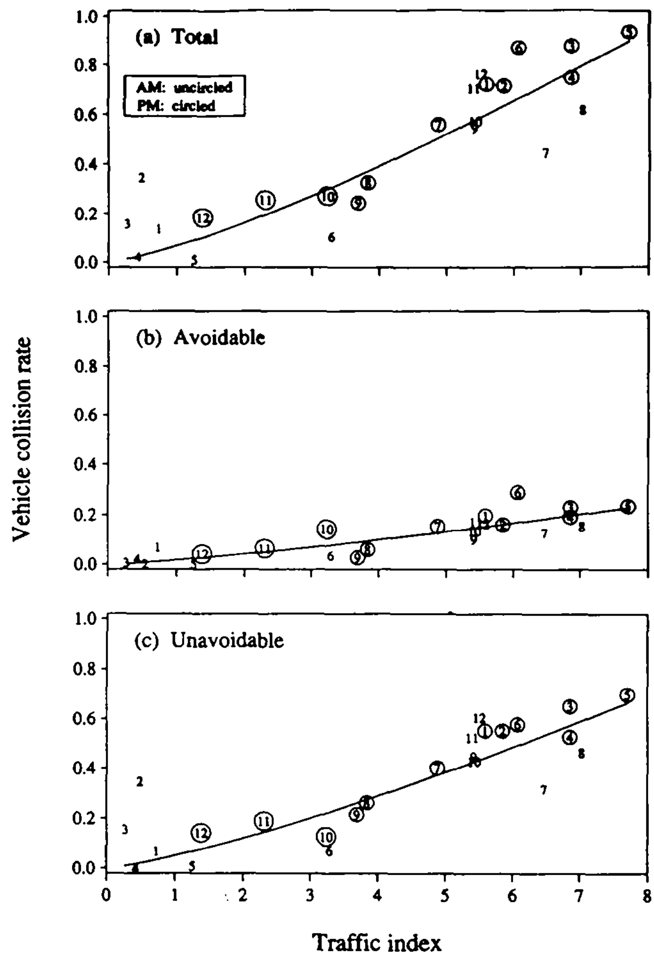

Fig. 2. Rates for (a) total (b) avoidable and (c) unavoidable collisions in the San Francisco Municipal Railway System as a function of hourly traffic index, 1987.

interval. This nonordered, categorical variable is equivalent to two "indicator" variables in which two of the three time intervals are represented in relation to the third interval (Aitken et al. 1989). Models (4) and (5) were rewritten to include the predictive effects of these indicator variables as follows:

$$n = \kappa \cdot (x \cdot vh)^{\alpha} \cdot e^{\beta_1 c_1} \cdot e^{\beta_2 c_2}, \tag{6}$$

$$\frac{n}{vh} = \kappa \cdot (x)^{\alpha} \cdot e^{\beta_1 c_1} \cdot e^{\beta_2 c_2}. \tag{7}$$

In these equations, c_1 represents the first interval and c_2 represents the second interval; these variables take values of 0 or 1, indicating whether or not an observation falls in the corresponding interval. The parameters β_1 and β_2 represent the effect associated with each interval in relation to the third interval.

The results for models (6) and (7) for total collisions are summarized in the bottom half of Table 3. The results show an increase in the variance explained (see Appendix A), from 88.8 to 95.5 for the model predicting *number* of collisions and from 89.5 to 95.7 for the model predicting *rate* of collisions. The results also indicate an increase in the predictive strength of traffic volume. As before, parallel analyses were conducted for avoidable and unavoidable collisions, yielding very similar results. The coefficients β_1 and β_2 in equation (7) can be interpreted to mean that, compared with the period 10 A.M.–2 A.M. (i.e. mainly the afternoon and evening period), the collision rate in the

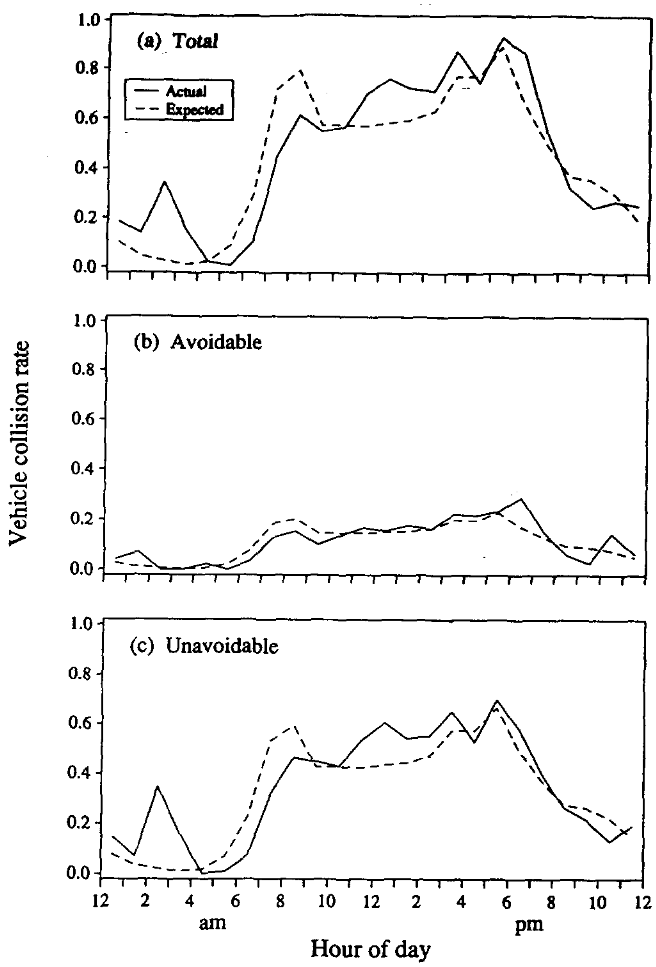

Fig. 3. Actual and model predicted rates for (a) total, (b) avoidable, and (c) unavoidable collisions in the San Francisco Municipal Railway System, by hour of the day, 1987.

early morning (2 A.M.–4 A.M.) is $e^{2.6}$, i.e. about 13 times higher than expected from traffic volume alone, and the later morning period (4 A.M.–10 A.M.) is $e^{-0.41}$, i.e. about 0.66 times, or 34% lower than expected on the basis of traffic volume alone.

DISCUSSION

Previous studies

Although there have been no reported studies of traffic volume and transit-related collisions, there have been several studies of motor vehicle collisions in general as these relate to traffic density or traffic volume (Satterthwaite 1981). In one type of study design, accident rates are compared on roadways that carry different amounts of traffic. Excluding studies of single vehicle collisions, most studies using this design have shown a positive association between traffic volume and collision rate (Yu 1972; McKerral 1962; Rykken 1949; Turner and Thomas 1986). Some have shown a decrease in the rate at very high traffic volume (Raff 1953).

In another type of research design, a single roadway or set of roadways is studied, and traffic volume and traffic collisions are correlated over time. These studies have shown the same general pattern: i.e. a general increase in collisions with an increase in traffic volume (Belmont 1953; Mothe 1960; Brilon 1972; Scott 1983). Some of the studies, however, showed a decline in collisions at higher traffic volumes (Belmont 1953; Mothe 1960).

Studies using both types of designs (comparing roadways that differ in traffic volume and comparing temporal aspects of different traffic volume on the same roadway) have shown a relatively consistent pattern of results. The most frequent result is a positive association between a measure of traffic volume and collision rates. Collision rates at very high levels of traffic volume are a possible exception to this generalization.

Results from the present study are consistent with the usually positive association found by others between traffic volume (or traffic density) and collision rates; but the strength of the association we found appears greater as well as more consistent. The present study is different from previous studies in two ways. First, previous studies looked at general motor vehicle traffic, while this study examined collisions involving municipal transit vehicles with other vehicles. Second, most of the previous studies focused on individual rural or urban roadways or expressways, while this study examined collisions and traffic volume in a highly urbanized geographic area.

Modeling of traffic volume and collisions

Some of the previous studies of traffic volume and collisions used a statistical model that assumes that either the number or the rate of collisions is proportional to some power of the traffic volume (Satterthwaite 1981). Although it is fairly simple, the power model represents a wide family of monotonically increasing or decreasing functions, including linear functions. Furthermore, unlike a number of other possible models, this model will not produce a negative predicted accident rate (Maycock and Hall 1984).

For the data used in this study, different versions of the power model explained between 89% and 96% of the variation in the number of collisions or in the collision rate, an unusually high percentage for this type of statistical modeling. Although the power function may have produced a highly accurate prediction of collision rates from the traffic volume in this study, it may or may not provide some insight into the mechanism for this association. In the following section, using the model as a basis we have speculated about the possible mechanism.

Mechanism of the association

The statistical models shown above suggest that the number of collisions can be viewed in terms of the number of opportunities for a collision. In fact, if in models (4) and (6) vh and x can be regarded as proportional to the number of Muni and other vehicles in San Francisco during any particular hour, then $x \cdot vh$, can be interpreted as proportional to the number of opportunities for a collision. Using only traffic volume and Muni vehicle-hours (model [4]) the estimated coefficient for this expression was very near 1.00 (specifically, $\hat{\alpha} = 1.06$, $s.e. = 0.05$). Therefore, the number of collisions was approximately proportional to the number of opportunities for such a collision. From this perspective, the multiplier κ can be interpreted as the probability per hour of a collision between any particular Muni/non-Muni vehicle pair (rather, a multiple of that probability, since traffic volume is a relative measure, and the number of Muni vehicle-hours is expressed in units of 1,000 hours).

When the same model was expanded to include the variable for different time intervals (i.e. model [6]), the power coefficient increased from 1.06 ($s.e. = 0.05$) to 1.13 ($s.e. = 0.05$). If we accept this as a more appropriate model, then the increased number of collisions is not determined solely by the increased number of opportunities for a collision, but some additional factor is involved.

The collision rate, with respect to Muni vehicle-hours (models [5] and [7]), can also be viewed in terms of the number of opportunities for a collision. For models (5) and (7), a power parameter of 1.00 would indicate that the rate of collisions was exactly proportional to the traffic volume, which is proportional to the number of opportunities for a collision between any particular pair of Muni and non-Muni vehicles. However the actual power parameter for this function was substantially greater than 1.00 (1.26 for model [5], 1.33 for model [7]). The excess above 1.00 indicates that the increase in the collision rate was accelerated to some degree beyond a strictly linear function of traffic volume.

Whether the focus is on the number or rate of collisions, there appear to be two components to the association between traffic volume and collisions. The first is the number of opportunities for a collision, defined simply as the quantity proportional to the product of the number of Muni and non-Muni vehicles. The second is the probability of a collision between a given pair vehicles. The increase of this latter component with traffic volume may be the result of the interaction between environmental and vehicle operating factors. With increasing traffic density, the average distance between vehicles may become less than the minimum stopping distance (Homburger and Kell 1984). At the same time that decreased distance between vehicles reduces the drivers' margin for error, increased traffic density also increases the "task load" (Hulbert 1982), that is, the demand on the driver for perceptual, cognitive, and psychomotor performance increases. The interaction of operator capacity and increasing traffic density is an important question for further research.

Other contributing factors

During the course of this analysis, we noted that including a variable to distinguish different time intervals of the day improved the predictive power of the model, as well as the magnitude of association between traffic volume and collisions.

There were two time intervals of particular interest. An increase in collisions over those predicted from traffic volume alone began in midmorning and continued through the late afternoon. Some of this increase may have resulted from increased passenger levels and/or increased congestion due to pedestrian traffic. Another explanation may be driver fatigue, as many Muni drivers finish their daily shift during this interval.

The difference between actual collisions and those predicted as a function of traffic volume alone during the early morning hours may have been due to alcohol-related collisions. As noted before, this increase coincides with the 2 A.M. closing of bars in San Francisco and consisted entirely of unavoidable collisions, which are primarily collisions in which a Muni vehicle is hit by a non-Muni vehicle. These post hoc observations and subsequent analyses provide hypotheses for analyses using other data.

IMPLICATIONS

One implication of this study concerns research on transit collision rates. From the strong association between traffic volume and collisions, it is clearly necessary to control for traffic volume in any study of factors that may be correlated with traffic volume. In transit research, examples are those studies that examine such variables as type and time of shift (e.g. Pokorny et al. 1987a; Pokorny et al. 1987b).

Another implication is for preventing collisions. From the viewpoint of transit planners, what approaches can be made toward decreasing collisions? One obvious solution would be to decrease traffic volume. If the model developed above is correct, decreasing traffic volume would decrease the number of opportunities for collisions, and would also reduce the probability that any particular pair of vehicles would collide. Unfortunately, such a solution is generally beyond the reach of any individual transit system. An alternative approach would be to buffer, or otherwise compensate for, the impact of increased traffic volume. Possibilities include dedicated bus lanes, increased driver training for heavy traffic conditions, and adjustment of transit scheduling to compensate for increased traffic volume. Such measures, if effective, would have an impact at all levels of traffic volume; but the magnitude of savings, both absolute and relative, would be greater at higher traffic volume.

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APPENDIX. CALCULATION FOR PERCENT OF VARIATION EXPLAINED

The percent of variation in hourly collision rates explained by traffic volume was calculated by comparing the total variance in the collision rate with the residual variance. For example, using equation (1),

$$\hat{n}_i = \hat{\kappa} \cdot x_i^{\hat{\alpha}} = \text{predicted collisions for hour (i)}, \tag{A1}$$

where $\hat{\kappa}$ and $\hat{\alpha}$ are the estimates of κ and α, based on the data.

$$T_{\text{var}} = \text{total variance in hourly collisions over 24 hour period}$$
$$= \frac{1}{24}\sum_{i=1}^{24}(n_i - \bar{n})^2. \tag{A2}$$

$$R_{\text{var}} = \text{variance in residual collisions over 24 hour period}$$
$$= \frac{1}{24}\sum_{i=1}^{24}(n_i - \hat{n}_i)^2. \tag{A3}$$

$$P_{\text{var}} = \text{percent of total variance accounted for} = 100\left[1 - \frac{R_{\text{var}}}{T_{\text{var}}}\right] \tag{A4}$$