Influence of Urban Network Features on Quality of Traffic Service

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The relation between street network geometric and control features and the network quality of traffic service is investigated. The goal is to quantify macroscopically the degree of improvements made when an urban street network undergoes modifications in its control or geometric features. The quality of traffic service in several city networks is assessed through field calibration of the two-fluid model. The model parameters are then correlated to 10 geometric and control features for each city network. It is found that under low traffic concentrations in the network, the average speed limit and the degree of signal progression are the most influential features. On the other hand, for high-concentration conditions, the fraction of one-way streets, the average number of lanes, and the fraction of signals actuated most affect the service quality. The density of signalized intersections affects peak and off-peak traffic. The signal density is beneficial during peak periods but detrimental during off-peak periods.

In traffic engineering practice, when an urban street network such as a downtown street system undergoes modifications in its geometric configuration or its control strategy, it is often desirable to obtain some quantitative measure of the resulting improvements. Similarly, when the need arises to improve the quality of traffic service in a street network, it is necessary to be able to predict the level of improvements to be attained as a result of any specific modifications in the network geometry or control features. This permits engineers to identify those strategies that yield the greatest level of improvement per unit cost of implementation.

The work reported herein presents a methodology to assess the degree of influence of various geometric and control features on the quality of service in an urban street network. From an initial list of some 20 potential factors, 10 key geometric and control attributes have been considered. They include

- Block length,
- Extent of one-way streets,
- Number of lanes per street,
- Intersection density,
- Signal density,
- Speed limit,
- Cycle length,
- Extent of on-street parking,
- Degree of signal actuation, and
- Degree of signal progression.

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Data on each of these features are collected for 19 urban street networks. The quality of traffic service across the networks studied is compared in light of the values of the geometric and control variables in each respective network. Statistical analyses are performed to identify those variables that most affect the traffic service quality as well as their respective degrees of impact.

The quality of service in each of the 19 networks is macroscopically quantified using the two-fluid model methodology. The model correlates the average travel time per unit distance to the stopped delay per unit distance in a network. Simply stated, under similar traffic loading conditions (same average concentration), a network with better quality of service will yield mile-long trips with shorter trip time and stop time values. Although the amount of traffic load on a facility is generally expressed in terms of volume, previous field and simulation studies (*1–3*) show a strong correlation between the averages of flow and concentration across a network, as is the case along a single roadway. As such, average concentration has been used in this study as a measure of traffic demand in a network since it is considerably easier to measure than the networkwide average flow.

The two-fluid model, formulated on the basis of this principle, has been used to quantify the quality of traffic service in several cities around the world (*4*). Subsequent visits to some of those cities has shown the model to be robust and accurate (*5*). The model parameters are hence used to characterize the service quality in the networks in this study. A more detailed description of the model is therefore merited.

TWO-FLUID MODEL

As discussed previously by Herman and Prigogine (*6*), the concept of a two-fluid model appeared in the kinetic theory of multilane highway traffic when the transition to the so-called collective flow regime was made at sufficiently high vehicular concentrations. For highway traffic, the speed distribution for the cars splits into two parts at the collective transition: one part corresponds to the moving vehicles and the other to the vehicles that are stopped as a result of local conditions such as traffic jams. Likewise, the traffic in a city network can be considered to consist of two traffic fluids: one part composed of the moving cars and the other of cars that are stopped as a result of congestion, traffic signals, stop signs, other traffic control devices, and obstructions resulting from construction, accidents, and such—but not parked vehicles. The parked cars are ignored since they are not a component of the traffic but instead form a part of the geometric configuration of the street.

In the two-fluid model the ideas in the kinetic theory of traffic are followed by assuming that the average speed of the moving cars, v_r, depends on the fraction of the cars that are moving, f_r, in the following form:

$$v_r = vf_r^{-1} = v_m f_r^{\mathbf{n}} = v_m(1 - f_s)^{\mathbf{n}} \quad (1)$$

where

f_s = average fraction of vehicles stopped,
v_m = average maximum running speed in the network system,
v = average speed of the traffic, and
$\mathbf{n}$ = parameter whose significance will be discussed later.

The boundary conditions are reasonably satisfied because for f_s = 0 and 1, the running speeds are v_m and 0, respectively. The following identities should also be noted:

$$f_r + f_s = 1 \quad (2)$$

$$v_m = 1/T_m \quad (3)$$

$$v_r = 1/T_r \quad (4)$$

$$v = 1/T \quad (5)$$

where

T_m = parameter representing the average minimum trip time per unit distance,
T_r = average running time per unit distance, and
T = trip time per unit distance.

If, in addition, the stop time per unit distance is denoted by T_s, it follows that

$$T = T_s + T_r \quad (6)$$

In the model it is also assumed that the fraction of the time stopped for an individual vehicle circulating in a network, (T_s/T), is equal to the average fraction of vehicles stopped in the system, f_s, over the same time period, namely,

$$f_s = (T_s/T) \quad (7)$$

It is important to remember with regard to the second assumption that, if the concentration varies widely—that is, fluctuates rapidly during the time of a trip—the condition stated in Equation 7 may not be satisfied (*4*). The concentration must vary slowly over the time scale during which (T_s/T) and f_s are measured.

The assumptions stated in Equations 1 and 7 lead to the two-fluid model relation between the trip time per unit distance, T, and the running time per unit distance, T_r, namely,

$$T_r = T_m^{1/(\mathbf{n}+1)} T^{\mathbf{n}/(\mathbf{n}+1)} \quad (8)$$

yielding the final result

$$T_s = T - T_m^{1/(\mathbf{n}+1)} T^{\mathbf{n}/(\mathbf{n}+1)} \quad (9)$$

It is emphasized that in the two-fluid theory the variables are always meant to be averages taken over the entire system.

It follows from Equation 8 that

$$\log T_r = [1/(\mathbf{n} + 1)]\log T_m + [\mathbf{n}/(\mathbf{n} + 1)]\log T \quad (10)$$

or

$$\log T_r = A + B \log T \quad (11)$$

with

$$\mathbf{n} = B/(1 - B) \quad (12)$$

and

$$\log T_m = A/(1 - B) \quad (13)$$

The parameters $\mathbf{n}$ and T_m associated with a traffic network can be obtained from Equations 12 and 13 by collecting trip time versus stop time data for a test vehicle circulating in that traffic network.

On a trip time–stop time diagram, the two-fluid model represented by Equation 9 plots as a slightly concave down curve. Figure 1 shows the curves for two hypothetical networks with the same value of T_m = 1.5 min/mi but different $\mathbf{n}$-values of 1 and 3, respectively. Also shown in Figure 1 is a line representing a fraction of vehicles stopped, $f_s = T_s/T$, of 0.25. It can be seen that for the same fraction of vehicles stopped, representing the same traffic loading conditions, the network with a smaller value of $\mathbf{n}$ = 1 yields considerably shorter trip time and stop time values. Previous studies have shown that the average fraction of vehicles stopped during a time period is a function of the average concentration in the network during that time (*1*,*4*). Furthermore, f_s has been shown, through the use of aerial photographs (*1*), to not vary greatly from one city to another for a given level of concentration.

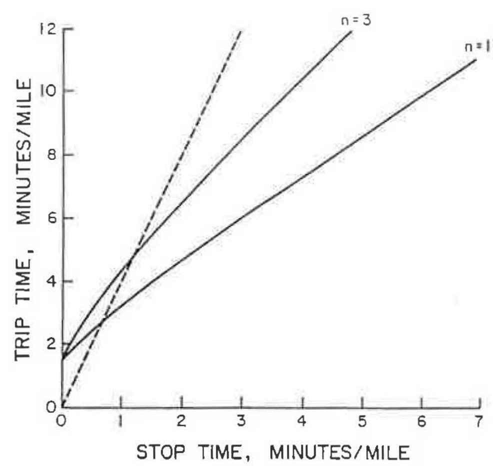

FIGURE 1 Two-fluid trends for two hypothetical networks with same T_m-value of 1.5 min/mi but different n-values of 1 and 3, respectively; dashed line corresponds to 0.25 fraction of vehicles stopped.

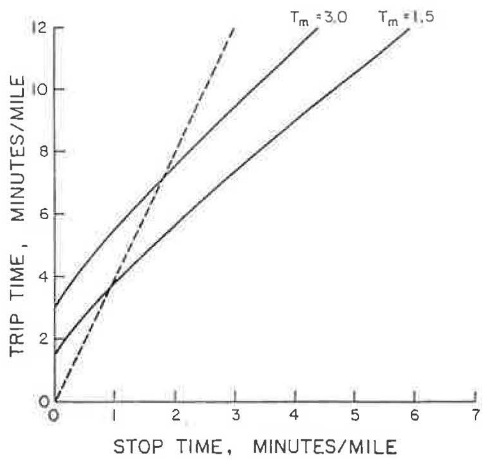

FIGURE 2 Two-fluid trends for two hypothetical networks with same n-value of 2 but T_m values of 1.5 and 3.0 min/mi, respectively; dashed line corresponds to 0.25 fraction of vehicles stopped.

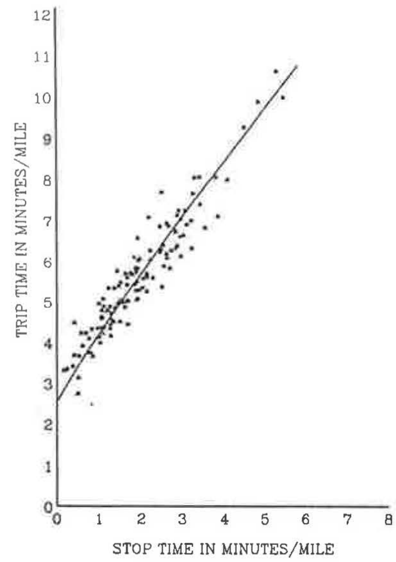

FIGURE 3 Trip time–stop time data and resulting two-fluid trend for 1990 Fort Worth CBD; T_m = 2.52 min/mi, n = 0.88.

A similar case can be made for the parameter T_m. Figure 2 shows two networks with the same **n**-value (**n** = 2) but different T_m-values of 1.5 and 3.0 min/mi, respectively. Again, the network with a lower T_m-value yields much lower trip time and stop time values for a given fraction of vehicles stopped.

A street network with a better quality of traffic service can be said to be one that yields smaller trip time and stop time per unit distance for a given level of traffic demand. Through the use of aerial photographs, it has been shown that for a level of traffic concentration (demand) a network with smaller values of T_m- and **n**-parameters offers lower trip time and stop time per unit distance (*1*). Parameters T_m and **n** can therefore be considered to be meaningful and reliable indicators of the quality of traffic service in an urban street network. Thus, the study described sets out to determine the degree of influence of the various network features on the parameters T_m and **n** as measures of network service quality.

DATA COLLECTION

The data collection phase of the study was performed in two steps. A number of networks for which the two-fluid model had already been calibrated were selected. These included downtown networks of Albuquerque, New Mexico (1983); Austin, Texas (1984); Dallas, Texas (1983); Lubbock, Texas (1984); Houston, Texas (1983); San Antonio, Texas (1984); Mexico City, Mexico (1983); and Matamoros, Mexico (1983). With the exception of the two cities in Mexico, all other networks were revisited in 1990 and the two-fluid model was recalibrated for each network. Trip time–stop time data were also collected in Texas cities of Arlington and Fort Worth in 1990. Figure 3 shows the trip time–stop time data and the resulting two-fluid trend for the Fort Worth central business district (CBD). Each point represents a 1-mi-long trip while circulating in the CBD network using a chase-car technique (*4*). Observations were made, as in all other cities, during various times of day and traffic conditions.

Additionally, Arlington, Dallas, and San Antonio underwent major changes in their control or street geometry in their downtown systems during the 1990–1991 period and were restudied in 1991. In Arlington, Cooper Street, a major arterial in the CBD, was reopened to traffic following a multiyear widening and reconstruction project. In Dallas, a portion of the previously studied network was closed to traffic for several weeks during filming of the motion picture "JFK." Early in 1991, a major signal retiming plan was implemented in the San Antonio CBD, and a number of street construction projects were concluded, improving the network geometry.

In all, 19 CBD networks were calibrated. The number of miles of data collected in each city varied from 80 to 120 mi depending on the network size. In each city, data were collected under a wide range of traffic demand conditions. In Texas cities in which concentration was measured, the average concentration varied from 5 vehicles per lane mile during off-peak to 35 vehicles per lane mile during peak (*1*). Table 1 summarizes the two-fluid model parameters obtained in each of the networks under study. As shown in this table, T_m-values range from 2.98 min/mi for Matamoros to 1.72 min/mi for Mexico City; **n**-values range from 2.10 for Matamoros to 0.61 for the 1991 Arlington network.

The parameter values reported in Table 1 have been tested for serial correlation. The test is necessary because the trip time–stop time data used in estimating the parameters are obtained from consecutive 1-mi microtrips. It is therefore reasonable to expect that the random error terms in the least-squares estimation technique violate the normal independence assumption and exhibit serial correlation. Consequently, a formal test for serial correlation was performed (*7*). Six of the field data sets showed first-order serial correlation and required slight corrections using a procedure detailed elsewhere (*7*).

TABLE 1 Two-Fluid Parameters for Downtown Networks Under Study

Downtown NETWORK	T_m* (minutes/mile)	n*
Arlington 1 (90)	1.98	1.06
Arlington 2 (91)	1.95	0.61
Fort Worth (90)	2.52	0.88
Dallas 1 (83)	2.12	1.36
Dallas 2 (90)	2.79	0.77
Dallas 2 (91)	2.77	0.80
Austin (84)	1.95	1.58
Austin (90)	2.14	1.46
Lubbock (84)	2.03	0.97
Lubbock (90)	1.78	1.27
Houston (83)	2.70	0.80
Houston (90)	2.24	1.11
San Antonio (84)	1.99	1.33
San Antonio (90)	2.52	1.14
San Antonio (91)	2.40	1.05
Albuquerque (83)	1.93	1.62
Albuquerque (90)	2.32	0.94
Matamoros (83)	2.98	2.10
Mexico City (83)	1.72	1.63

* Adjusted for serial correlation

The T_m- and **n**-values represent a wide variation in the traffic qualities from one network to another. A preliminary list of network features that could help explain such variations in traffic service quality was devised. From this list, 10 geometric and control features that were potentially influential yet not difficult to quantitatively measure were selected. They include

- X_1 (average block length). Calculated as the ratio of the total route miles to the total number of blocks in the network.
- X_2 (fraction of one-way streets). Calculated as the ratio of the total length of one-way streets to the total route miles in the network.
- X_3 (average number of lanes per street). Calculated by dividing the total number of lane miles open to traffic during the p.m. peak hour by the total route miles in the network.
- X_4 (intersection density). Calculated as the total number of intersections in the network divided by the total network land area (in square miles).
- X_5 (signal density). Calculated as the total number of signalized intersections in the network divided by the total network land area (in square miles).
- X_6 (average speed limit). Calculated by weighting according to the lengths of streets for which the speed limit (in miles per hour) is posted.
- X_7 (average cycle length). Calculated as the average of signal cycle lengths (in seconds) in the network during the p.m. peak hour. No weight based on approach volumes was used.
- X_8 (fraction of curb miles with parking allowed). Calculated as the ratio of the total number of curb miles on which parking was allowed during the p.m. peak period to the total curb miles in the network.
- X_9 (fraction of signals actuated). Calculated as the ratio of the total number of signal actuated intersections to the total number of signalized intersections in the network.
- X_{10} (fraction of approaches with signal progression). Calculated as the ratio of the number of intersection approaches in the network that are part of a progression scheme to the total number of signalized intersection approaches in the network.

The values of X_1 through X_{10} were determined for each of the networks under study. City maps, city transportation departments, and field surveys were the major data collection sources. Fairly accurate city maps were used to determine the average block length (X_1), the fraction of one-way streets (X_2), and the intersection density (X_4). Data related to signalization (X_5, X_7, X_9, X_{10}) were obtained through the traffic engineering offices in each city. Field surveys were performed to determine the values for lanes per street (X_3), speed limit (X_6), and curb parking (X_8). The data for the latter variables had already been recorded for the networks studied in 1983 and 1984 (*8*). Table 2 summarizes the data obtained.

DATA ANALYSIS AND RESULTS

Stepwise regression analyses were performed to identify those network geometric and control variables that most affected the quality of service parameters T_m and **n**. The data in Tables 1 and 2 were used in the analyses.

Stepwise regression is a procedure to select among a number of potential variables those that are best suited for inclusion in the regression model. Stepwise regression examines all candidate variables for the one that best explains the variation in the dependent variable. This variable enters the model. The significance of each variable entering the model is assessed by the F-statistic at a level of significance specified by the modeler. The process is repeated to find the next most influential variable to enter. At each step, however, the correlations between pairs of independent variables already in the model are examined. For strong correlations between independent variables, the least significant of those variables exits the model. Exiting the model is also determined from the F-statistic at a user-specified level of significance. Stepwise terminates and a model is output when either of these cases is met: (a) none of the variables outside the model has an F-value higher than specified by the user for entry into the model, and every variable in the model has an F-value higher than the user-specified value for leaving the model, and (b) the variable outside the model, which is significant enough to enter the model, is one that was discarded at the last step.

Two sets of stepwise regression analyses were conducted, with T_m and **n** as dependent (prediction) variables. In each case, independent variables X_1 through X_{10} (Table 2) were considered for entry into the model. A level of significance

TABLE 2 Network Geometric and Control Features

Downtown Network	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
Arlington 1 (90)	496	0	2.77	108	17	30.6	94.0	0.375	1.000	0.537
Arlington 2 (91)	479	0	2.92	124	25	30.3	91.0	0.315	1.000	0.557
Fort Worth (90)	300	0.71	3.0	355	268	30.0	75.0	0.360	0.110	0.50
Dallas 1 (83)	350	0.40	2.6	160	80	30.0	80.0	0.218	0.324	0.328
Dallas 2 (90)	338	0.65	3.2	282	224	30.0	80.0	0.131	0	0.488
Dallas 2 (91)	340	0.67	3.1	270	215	30.0	84.0	0.130	0	0.290
Austin (84)	430	0.52	3.0	209	82	30.3	64.0	0.834	0	0.32
Austin (90)	409	0.43	2.9	175	82	30.2	68.0	0.834	0	0.32
Lubbock (84)	380	0.30	3.1	187	45	31.1	81.0	0.602	0.01	0.27
Lubbock (90)	446	0.15	3.05	153	30	31.1	97.1	0.602	0.02	0.37
Houston (83)	324	0.76	4.3	309	213	30.0	80.0	0.366	0	0.77
Houston (90)	324	0.76	4.3	309	213	30.0	80.0	0.366	0	0.77
San Antonio (84)	365	0.45	2.7	244	144	30.0	100.0	0.280	0.008	0.327
San Antonio (90)	365	0.41	2.6	240	150	29.8	89.3	0.280	0.008	0.395
San Antonio (91)	365	0.40	2.82	252	147	30.0	61.8	0.269	0.008	0.451
Albuquerque (83)	381	0.47	2.7	222	111	25.5	61.0	0.441	0.171	0.52
Albuquerque (90)	381	0.46	2.7	221	113	25.5	62.2	0.428	0.169	0.53
Matamoros (83)	380	0.67	1.2	269	22	12.9	70.0	0.850	0	0
Mexico City (83)	359	0.72	3.9	225	47	31.2	120.0	0.110	0	0.613

X_1: Avg Block Length (ft)

of 30 percent was used as the criterion for including or removing variables from the model. A sensitivity analysis on the level of significance indicated that the model structure in terms of variables retained varied a great deal for significance levels below 30 percent while at this level and higher stable T_m- and **n**-models were obtained.

At the 30 percent level of significance, T_m was shown to be most influenced by the signal density (X_5), average speed limit (X_6), and fraction of approaches in the network with signal progression (X_{10}). The parameter **n** was most influenced by four variables at the 30 percent level of significance or higher. They included the fraction of one-way streets (X_2), the average number of lanes per street (X_3), the signal density (X_5), and the fraction of signals actuated (X_9). The resulting models for T_m and **n** are as follows:

$$T_m = 3.93 + 0.0035X_5 - 0.047X_6 - 0.433X_{10}$$

$$R^2 = .72 \quad (14)$$

$$\mathbf{n} = 1.73 + 1.124X_2 - 0.180X_3 - 0.0042X_5 - 0.271X_9$$

$$R^2 = .75 \quad (15)$$

The parameter T_m is an estimate of the average minimum travel time per unit distance or the reciprocal of the average maximum speed in the network. T_m is, therefore, expected to be highly influenced by the speed limit, with a higher speed limit yielding a lower T_m-value. It is therefore expected that the variable X_6 appears in the T_m-model and has a negative coefficient, as is the case in Equation 14. Equation 14 also indicates that the greater the signal density in an area, the greater the value of T_m, that is, the lower the quality of traffic service. This is also somewhat intuitive, because a higher number of signals per unit area generally results in greater delay to off-peak traffic, hence a greater T_m-value. On the other hand, a greater number of approaches in signal progression will result in a lower T_m-value (negative X_{10} coefficient), as is to be expected.

The influence of speed limit (X_6) on the value of T_m and its consequent degree of impact on the service quality are graphically illustrated in Figure 4. Figure 4 shows the two-fluid trend for the current network of downtown Fort Worth. Also shown is the line $f_s = T_s/T = 0.36$ corresponding to the current peak-period conditions in the Fort Worth CBD. Under the scenario examined, the average speed limit in Fort Worth is to be increased by 30 percent. By rewriting Equation 14 in the form

$$\Delta T_m = 0.0035\Delta X_5 - 0.047\Delta X_6 - 0.433\Delta X_{10} \quad (16)$$

the expected T_m-value for a 30 percent increase in speed limit can be calculated.

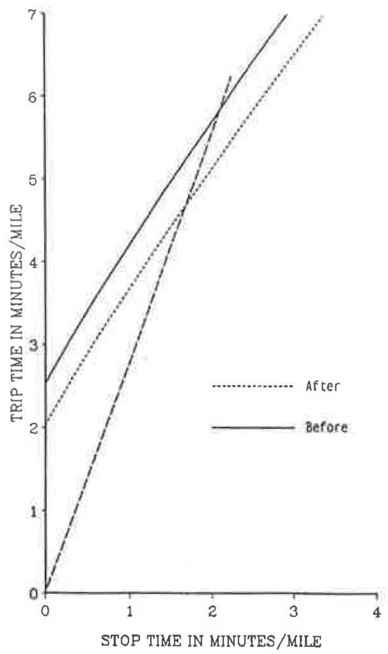

FIGURE 4 Two-fluid trends before and after 30 percent increase in average speed limit (X_6) in network; dashed line corresponds to fraction of vehicles stopped (0.36) in network during p.m. peak period.

The dashed curve in Figure 4 represents the expected two-fluid trend should such a change be implemented. The new curve is obtained by a decrease in T_m of 0.42 min/mi from the current 2.52 to 2.10 min/mi. As can be seen, for the current peak-period fraction of vehicles stopped in Forth Worth, the peak-period trip time and stop time per unit distance would be decreased on the average by about 0.97 and 0.35 min/mi vehicle, respectively—a 16.7 percent reduction in each. By the same token, a 30 percent increase in networkwide signal progression (X_{10}) would save 0.65 and 0.23 min/mi in peak-period trip time and stop time, respectively.

Whereas T_m is mostly influenced by the network control features, the parameter **n** appears to be more a function of the geometric characteristics of the network. As depicted by Equation 15, the value of **n** is increased as the fraction of one-way streets (X_2) is increased, thus implying a poorer quality of traffic service. At first glance this may be counterintuitive. It must be noted, however, that in an urban street network, in which land access is the primary function, one-way streets generally do result in a poorer traffic circulation pattern. This could translate into a higher level of interactions among vehicles and therefore a lower service quality. On the other hand, if the primary objective is to serve the through traffic at relatively high speeds and volumes, one-way streets will be most suitable. However, traffic in a CBD network generally has either its origin or destination within the CBD itself.

The impact of a 30 percent reduction in fraction of one-way streets (X_2) is examined in Figure 5. Figure 5 shows the current two-fluid trend for Fort Worth as well as the expected trend should the fraction of one-way streets be reduced by 30 percent. As can be seen, for the peak-period conditions in Forth Worth, as represented by the line f_s = 0.36, the peak trip time and stop time values would decrease by about 0.59 and 0.21 min/mi (10 percent each), respectively. This reduction would result from a decrease in the Fort Worth CBD **n**-value from the original 0.88 to 0.64.

A similar analysis is performed by the effect of a 30 percent increase in the average number of lanes per street (X_3) in Forth Worth, say, by prohibiting curb-side parking, by re-striping, or by widening streets. Keeping all other variables the same, the value of **n** would decrease to 0.72, resulting in an expected improvement in the quality of traffic service. The peak-period trip time and stop time would be reduced by about 0.40 and 0.15 min/mi (7 percent each), respectively.

Likewise, a 30 percent increase in the fraction of actuated signals (X_9) is examined. As expected, the trip and stop times would both decline should fixed-time signals be converted to actuated signals. However, as is also to be expected, the magnitude of the impact of this change would not be significant during the peak period when an actuated signal is likely to max out every cycle, thus operating virtually like a fixed-time signal. In this case, the reductions would be only about 0.02 and 0.01 min/mi (0.3 percent each) in the peak-period trip and stop times for the Fort Worth CBD.

In studying the influence of signal density (X_5) on the traffic service quality, it should be noted that although an increase in signal density would reduce the value of **n** (Equation 15), the opposite would be true for T_m (Equation 14).

Figure 6 examines the impact of increasing the signal density in the Fort Worth CBD by 30 percent. Such an increase would

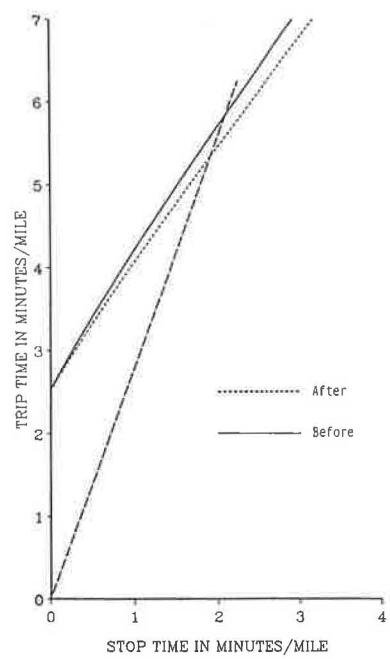

FIGURE 5 Two-fluid trends before and after 30 percent decrease in fraction of one-way streets (X_2) in network; Fort Worth CBD, f_s = 0.36.

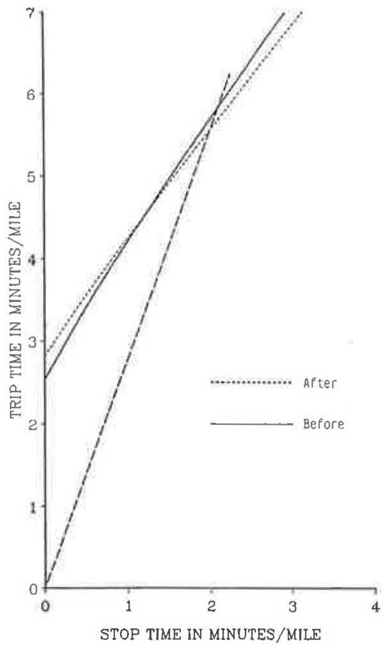

FIGURE 6 Two-fluid trends before and after 30 percent increase in signal density in network; Fort Worth CBD, f_s = 0.36.

lower the **n**-value to 0.54 and increase the T_m-value to 2.80. Consequently, the new two-fluid trend would have a higher intercept but a flatter slope, thus crossing the existing trend. The net result would be a 4.5 percent reduction each in peak-period trip time and stop time. However, the trip time and stop time values would increase during the off-peak period should more intersections in the area be signalized. It can be concluded that increasing the number of signals would harm the off-peak traffic operations but benefit peak traffic. This provides a strong argument for converting signals to flashing operation during off-peak periods.

Although these conclusions are somewhat intuitive, the procedure enables the traffic engineer to quantify the impact of such policy in terms of reductions in trip time and stop time.

CONCLUSIONS AND DISCUSSION OF RESULTS

The influence of the geometric and control features studied on the traffic service quality may be intuitive, but the degree of impact of each is not. The models derived provide analytical tools for quantifying the impact of such changes on the quality of traffic service. Without resorting to network simulation models that are time-consuming and expensive to code, engineers can use these macroscopic tools to examine the consequences of various policy decisions such as converting a two-way street to one-way, prohibiting on-street parking, adding or removing signals, converting signals to flashing operations, and adding or removing lanes.

Although the proposed methodology is promising, the models presented are based on a limited data base. More networks with varied geometric and control conditions must be added. More network features should also be considered. To perform a robust statistical analysis, the number of city networks should be more than twice the number of variables to provide a reasonable degree of freedom.

Despite the need for more field data, obtaining such data is expensive and extremely labor-intensive. The use of simulation may be an alternative in expanding the data base. NETSIM has been used successfully to calibrate the two-fluid model (*2,3,9*). The simulation environment will also allow a much wider range of variation to be achieved in the network feature variables. Furthermore, a higher number of variables can be examined without much additional effort, since the characteristics of the simulated network are readily known during the coding process. Simulation studies are being conducted using the TRAF-NETSIM package. The Fort Worth CBD network, with about 180 intersections and about 400 street links, has been coded for this purpose, and initial runs have been successful. The simulation studies will allow a more detailed examination and expansion of the relationships developed on the basis of field studies reported.

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