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QUALITY OF TRAFFIC SERVICE

by

Siamak Ardekani  
Robert Herman

Research Report Number 304-1

Quality of Traffic Service  
Research Project 3-8-80-304

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The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Federal Highway Administration. This report does not constitute a standard, specification, or regulation.

## PREFACE

This is the first report on Research Study No. 3-8-80-304, entitled "Quality of Traffic Service." A major portion of this report is based on data collected by volunteer graduate and undergraduate students at the University of Texas at Austin. The authors wish to express their gratitude to these students. In addition, sincere thanks are extended to Charles Little, Diana Vazquez, Han-Jei Lin, Jim Anagnos, Leon Snider, and Thomas W. Stallworth for their assistance in collection of data in Dallas; and to Chris M. Tschirhart, Andrew G. Eng, and Mark P. Emerson for the collection of shuttle bus and automobile data in Austin. Finally, the efforts of Lyn Gabbert, Jose E. Saenz, and other staff of the Center for Transportation Research in typing, redaction, and publication of this report are deeply appreciated.

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## LIST OF REPORTS

No previous reports have been published in connection with Research Project No. 3-8-80-304 of the Texas State Department of Highways and Public Transportation.



## ABSTRACT

The Two-Fluid Model has been used to model the quality of service in Austin and Dallas traffic networks. In addition, the physical interpretation of the model parameters is closely examined. Furthermore, the Two-Fluid Model is slightly modified to better predict the average minimum trip time and stop time per unit distance. Finally, the results of two ergodic experiments as well as data in very light traffic conditions have been used to investigate the consistency of the underlying assumptions of the Two-Fluid Model. The interrelation between the Two-Fluid Model and other macroscopic traffic models such as a simple fuel consumption model is also discussed.

The report is concluded with a discussion of the use of time-lapse aerial photography in the investigation of the Two-Fluid Model assumptions and in the derivation of relations that may exist among the means of the speed, density, and flow in a traffic network.

KEY WORDS: Two-Fluid, Ergodicity, Urban Traffic Network, Fuel Consumption, Quality of Traffic Service, Fraction of Vehicles Stopped, Fraction of Time Stopped, Average Running Speed, Stop Time per Unit Distance, Trip Time per Unit Distance.



## SUMMARY

The Two-Fluid Model of Town Traffic has been used in this study to model the quality of traffic service in the central traffic networks of Austin and Dallas. The Two-Fluid Model is based on the view that traffic consists of two fluids, one consisting of the moving vehicles and the other, the vehicles that are stopped. Traffic observations have been made in two Austin street networks and in one Dallas central network. The model parameters for Austin and Dallas are compared to the parameters obtained in similar analyses for Melbourne, Sydney, Milwaukee, London, and Brussels. The results obtained for Austin and Dallas show qualities of traffic service which are much better than those in London and Brussels, while they are not significantly different from the qualities of traffic service in Melbourne, Sydney, or Milwaukee.

Furthermore, the physical interpretations of the Two-Fluid Model parameters are examined in detail. Data in Austin show that these parameters are sensitive to the vehicular mode used in data collection (e.g., transit buses compared to passenger vehicles). In addition, since in an urban network the average maximum fraction of vehicles running is always less than unity, the Two-Fluid Model has been slightly modified. This modification results in better predictions of the average minimum trip time per unit distance and the average minimum stop time per unit distance.

In addition, the consistency of the underlying assumptions of the Two-Fluid Model with the observational data is investigated. Two ergodic

experiments have been performed. The results indicate that the fraction of time a single test vehicle is stopped while circulating in the system is a good estimate of the mean fraction of the test vehicles stopped. This result is consistent with one of the two assumptions of the model. Moreover, midnight and early morning hours data show that the first assumption of the Two-Fluid Model, which relates the average running speed to the fraction of vehicles running, is also consistent with the observational results.

The interrelation of the Two-Fluid Model with the fuel consumption model (Ref 1) and with the formulation of the traffic intensity as a function of distance from the city center (Ref 2) is discussed in the theoretical chapter.

Finally, to outline the future course of our research activity, we have described the potential value of time-lapse aerial photography. We can determine from aerial photographs whether or not the fraction of vehicles stopped for a fair sample of the vehicular population is identical to the fraction of time stopped for a test vehicle utilizing the network under study during the same general time period. Furthermore, aerial photographs can be used to determine the space means of speed, density, and flow. Thus, we hope to derive relations that may exist among these variables. Lastly, the  $\alpha$ -relationship as an evaluation of traffic performance of road networks (Ref 3) may be investigated by means of time-lapse aerial photography. This relationship implies a specific functional dependence of average speed on concentration, which we hope to examine in a city network.

## IMPLEMENTATION STATEMENT

The Two-Fluid Model of Town Traffic presents parameters  $T_m$  and  $n$  as characterizers of the quality of traffic service, where  $T_m$  is an estimate of the average minimum trip time per unit distance if all causes of stoppages are removed from a traffic network, and  $n$  is directly related to the change in trip time per unit distance,  $T$ , resulting from a unit change in the stop time per unit distance,  $T_s$ .

The studies presented in this report establish further grounds for the use of the parameters  $T_m$  and  $n$  as criteria for comparison of the quality of traffic service in various urban traffic networks around the world. In addition, we have modified the Two-Fluid Model to include theoretical predictions of the actual minimum trip time per unit distance,  $T_{\min}$ , and its corresponding minimum stop time per unit distance,  $T_{s(\min)}$ , which, despite the presence of traffic control devices exist in a network under very light vehicular concentrations. These two variables are also useful comparison criteria.

Furthermore, during the short test period of a few hours the mean fraction of test vehicles stopped,  $\langle f_s \rangle$ , and the fraction of time a single test vehicle is stopped,  $T_s / T$  are relatively independent but nearly identical variables. The values of these variables are directly proportional to the fuel utilization rate in a network for the following reason. The Two-Fluid Model and the observational data indicate that as the

value of  $T$  increases the values of both  $T_s$  and  $T_s/T = \langle f_s \rangle$  will also increase. Consequently, the fuel utilization rate which is directly proportional to  $T$  will also be directly proportional to  $T_s$ ,  $T_s/T$ , and  $\langle f_s \rangle$ . As a result, the variables  $T_s/T$  and/or  $\langle f_s \rangle$  can be used as relative measures of the operational efficiency and the quality of traffic service in a traffic network.

In summary, when comparing two urban traffic networks or rank ordering a number of networks based on their qualities of traffic service, the network with the smallest values of  $(T_{m, n})$ ,  $(T_{s(\min)}, T_{\min})$ ,  $\langle f_s \rangle$ , or  $T_s/T$  can be considered the best. Similarly, the network with the second smallest values of these parameters and variables would be considered to have the second best quality of traffic service. We note that the sensitivity of these parameters and variables must be studied in greater depth before they are used as quantifiers of the absolute quality of traffic service in a network.

The above-mentioned parameters and variables can also be used in before and after studies of a network which undergoes major changes in its control devices and/or its geometric configuration.

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## CHAPTER 1. INTRODUCTION

During the past thirty years a great effort has been made to develop a science of vehicular traffic. A wide variety of questions have been examined in this relatively new science, with special attention given to the details of the specified traffic processes, including the optimization of these processes by means of design and control techniques. More than two decades ago the idea that a science of vehicular traffic was a highly meaningful unexplored discipline began to be recognized by investigators in the physical sciences, applied mathematics, and engineering. There were those of us at that time who had the conviction that various aspects of the very involved problems inherent in the driver-vehicle road-complex and all of its ramifications and implications could be handled in a rational manner with the knowledge and equipment available in mathematics, theoretical and experimental physics, engineering, psychology, and medicine, to mention a few of the required disciplines. Since then many traffic problems have been handled using a mathematical approach coupled with experimentation and field observations. Some of the problems tackled have been in the areas of single lane flow described by car following theory; multilane flow described by a statistical approach similar to that used in statistical physics; highway crossing and merging processes analysed by means of the queueing theoretical approach; intersection and network problems; etc.

In order to synthesize broad systems knowledge it is generally necessary to comprehend various specific narrower textbook-like problems. We then require some general overall theoretical structure in which to fit the known details. From a historical point of view the earlier studies of single and multilane traffic flow provided the impetus to find some general broad view of traffic flow in a city network. There is always the hope that the examination of relations among variables in a complex system might lead to some simple relations as a result of collective effects.

We are keenly aware that great progress in science and technology is often made by virtue of creative ideas in rather narrow and specific problem areas. In recent years, however, we have become more and more aware that in the physical, chemical, and biological worlds and even in the sociotechnical world there are profound problems involving systems containing many variables that interact in a highly nonlinear manner. As already mentioned we have the hope that in such highly complex systems there are collective effects that result in simple relations among at least some of the pertinent variables.

Problems of this type, i.e., problems complex in the interrelational sense can be termed symplectic problems. The word symplectic derives from the Greek word symplektikon meaning intertwined or complex precisely in the interrelational sense. We stress that many of our modern problems are of this complex type.

One of the main reasons for mentioning the class of symplectic problems is that a purely theoretical approach to the solution of a highly complex problem is problematical. It is rather clear that the science of traffic is basically an empirical science that cannot go forward effectively solely on theoretical grounds. Over the past years there has been far too little observational and experimental work pointed toward the development of the

fundamentals of the subject. We would hope that through the examination of the various traffic processes it will prove possible as time goes on to discover some of the simple "Ohm-like Laws" that hold in the domain of traffic and transportation.

As a brief excursus we wish to point out that it is, indeed, remarkable that so much of our knowledge of the physical world, for example, has been capable of being codified in what are extremely simple appearing relations such as the following:  $E = iR$ ,  $F = m\alpha$ ,  $E = h\nu$ ,  $p = h/\lambda$ ,  $E = mc^2$ , etc. These very "simple" appearing equations very likely express collective effects in what are otherwise highly complex situations. For example, Mach's Principle, which states that the inertial mass of a body is the result of all the forces exerted on it by all the other bodies in the universe, may well be at the core of such a simple law of motion. It is interesting to mention that John Muir in his book In My First Summer in the Sierra, 1916, wrote - "When we try to pick out anything by itself, we find it hitched to everything else in the universe."

An ultimate objective of the science of traffic is to understand traffic in large cities. It is rather difficult to fathom how this might be accomplished on a purely microscopic basis since as a minimum it would involve knowing about the movement of the traffic on all the links and through all of the nodes, i.e., intersections, of the network under consideration. For some time we have been reaching for an overall description that might relate a few of the most pertinent variables to one another in a simple way. The hope then is to attempt to organize information about fuel consumption, vehicle emission, trip time, stop time, average speed, fraction of the vehicles that are moving and stopped, etc., in a way that would characterize the traffic in a large city network quantitatively if

possible and, moreover, provide a scheme for estimating the quality of the traffic in various cities and sections of cities.

Much of our work over the past ten years has been focussed on attempts to examine general traffic characteristics in various cities with the goal of relating the character and quality of traffic to pertinent traffic variables, such as average speed, stop time per unit distance, standard deviation of acceleration, etc., as well as to the associated fuel consumption and exhaust emissions. An analysis by us of Chase Car data generated by Johnson et al (Ref 4) in nine metropolitan areas in the United States showed that variables such as stop time per unit distance, levels of acceleration or braking, as well as the magnitude of the speed variations, are all highly dependent on the average speed, i.e., the reciprocal of the average trip time per unit distance. We have also examined the effects of traffic concentration and roadway types on the speed distribution function and the acceleration distribution function. As is now well known it was found that the average speed is a traffic variable that can be used effectively to characterize urban traffic in many respects. For example, in terms of trip time, stop time, acceleration, noise, etc., the higher the average speed in an urban network the better the quality of traffic in general. It is interesting to note that there are rather clear trends among various of the traffic variables in many cities around the world. This is an encouraging sign and we have continued to pursue this and other aspects precisely to reach for some global representation of traffic in large city networks.

An excellent example of collective effects arose in our studies of the interrelation of fuel consumption and urban traffic. Early studies in the Detroit metropolitan area showed that the fuel consumed per unit distance was in first approximation linearly related to the trip time per unit distance.

This result was predicated on the test vehicle sampling the entire network for example by means of Chase Car techniques. We had examined the effect on fuel consumption of about 20 variables and found the above mentioned simple relation by means of a multivariate analysis. It is noteworthy that many of the other variables are strongly correlated with the average speed. This simple result was intimated by Pelensky et al (Ref 5) as well as Everall (Ref 6). We have shown that it is possible to derive such a simple relation by making simplifying assumptions in the theoretical description of the engine-drive system (Ref 7). Without going into any of the details at this juncture, what is important is to emphasize that in such a complex system with perhaps two dozen or more variables operating, there must, in the final analysis, be collective effects which reduce the complicated non-linear interrelations to relatively simple functional dependences. For additional information on these questions the reader is referred to the list of references.

Another aspect of this entire problem is associated with urban evolution, self organization, and decision making. Ilya Prigogine and his collaborators have for many years been examining the consequences of non-equilibrium conditions and feedback on the properties of open systems. All "living" systems must continually exchange energy with the environment, i.e., what lies outside of that particular local world. As a consequence, whether it be a unicellular organism, a human being, or a city, the system will die once it is isolated and its internal reserves have been depleted. This is a very different situation from an equilibrium structure such as a crystal, which once formed can be stored indefinitely without the expenditure of energy. It is clear that a town when isolated from the surrounding area will immediately begin to decay. This is, of course, the concept behind the

establishment of a siege. Structures such as those mentioned above are capable of being maintained only by the dissipation of energy. For this reason Prigogine in 1967 termed systems of this type "dissipative structures" in contradistinction to "equilibrium structures" such as crystals mentioned in the example given above (See for example Ref 8).

The evolution of cities, in which vehicular traffic is one of the significant elements, is being studied in the above spirit by Allen and co-workers. In a series of articles they have outlined new aspects in the modelling of the evolution of a system of central places (See for example Ref 9). This work is based on the concepts that underlie the evolution of dissipative structures in the physical sciences. Thus, a new perspective is offered in which the interdependencies of the different variables of the system give rise to its "self organization". Structure and organization can be "created" as well as destroyed as the system evolves as a whole. As such a system evolves we have the interplay of determinism specified by the equations of the model which interrelate the pertinent variables specifying the system; on the other hand "chance" or "indeterminacy" which is associated with instability from which changes in structure may occur.

The work reported here is a continuing attempt to organize our knowledge about traffic in an urban network in such a way that it gives rise, hopefully, to global relations that have a validity over a wide range of conditions in many cities everywhere. It is only in this way that we will lose the constraints of specificity which prevent us from making general statements. Moreover, we hope that our work will eventually provide a simpler basis from which it will be possible to include the traffic and transportation elements into the modelling of a city and perhaps in the study

of the competition and evolution among cities, which like living creatures are born, develop, and often decay.



## CHAPTER 2. THEORY

Traffic observations of trip time per unit distance (reciprocal of the average speed) and stop time per unit distance for vehicles driven in urban, non-freeway networks indicate a consistent simple linear trend between these two variables (Refs 10 and 11). The Two-Fluid Model of Town Traffic has been developed in an attempt to establish a theoretical basis for this observational relation (Ref 12).

The Two-Fluid Model considers the traffic in a non-freeway city network to consist of two fluids, namely, the moving cars and the stopped cars. The motionless fluid does not include the cars stopped due to non-traffic related causes, such as parked cars. The kinetic theory of multilane highway traffic (Ref 13) has already shown that at sufficiently high traffic densities the speed distribution of vehicles includes a delta function at the origin, representing the motionless fluid or the fraction of the vehicles that are stopped. This is analogous to the Bose-Einstein condensation, which at sufficiently low temperatures leads to the splitting of the distribution function into two parts, one representing the molecules in the ground state and the other, the molecules in excited states (Ref 14). The thermal energy of the excited molecules is proportional to a power of the fraction of the excited molecules present. Similarly, it is suggested that speed of the moving vehicles,  $V_r$ , depends on the fraction of the vehicles that are in

motion,  $f_r$ , namely,

$$V_r = V_m f_r^n, \quad (1)$$

where  $V_m$  is the average maximum running speed and  $n$  is a parameter. This is the first assumption of the Two-Fluid Model. Note that

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

where  $f_s$  is the fraction of vehicles stopped.

Moreover, the model assumes that the fraction of the time stopped for a single vehicle circulating in a network,  $(T_s/T)_i$ , is equal to the mean fraction of the population of cars stopped,  $\langle f_{s,p} \rangle$ , over the same time period, namely,

$$\langle f_{s,p} \rangle = (T_s/T)_i. \quad (3)$$

For convenience the symbol  $\langle x \rangle$  is used interchangeably with the notation  $\bar{x}$  to represent the average value of  $x$ .

This relation (Eq 3) can be theoretically proven for steady state traffic conditions. To do this, we will first prove that even under non-steady state conditions the mean fraction of time stopped for all the vehicles in a network is equal to the mean fraction of all the vehicles stopped in that system.

Assume a traffic network with a population of  $N$  vehicles. Over an observation period  $\tau$ , the probability of the  $i^{\text{th}}$  vehicle of this population being stopped,  $p_i$ , can be expressed as the fraction of time

stopped for this vehicle, namely,

$$p_i = (T_s/T)_i . \quad (4)$$

Therefore, we can write for the entire population of vehicles that

$$\Sigma p_i = \Sigma (T_s/T)_i , \quad i = 1, 2, \dots, N. \quad (5)$$

Dividing both sides of Eq 5 by the total number of vehicles we obtain

$$\frac{1}{N} \Sigma p_i = \frac{1}{N} \Sigma (T_s/T)_i , \quad i = 1, 2, \dots, N. \quad (6)$$

The left-hand side of Eq 6 is the mean probability of seeing any vehicle of the population stopped, or in other words it is the mean fraction of vehicles stopped. On the other hand, the right-hand side of Eq 6 is the mean fraction of time stopped for the population of the vehicles. Therefore, over the observation period  $\tau$  we can write that

$$\langle f_{s,p} \rangle = \langle T_s/T \rangle_p \quad (7)$$

under any conditions.

In steady state conditions and over a sufficiently long period of time, each of the  $N$  vehicles will have fully sampled the network area. Therefore, the fraction of time stopped for any vehicle,  $(T_s/T)_i$ , will be equal to that of any other vehicle and thus equal to the mean fraction of

time stopped, namely,

$$(T_s/T)_i = \langle T_s/T \rangle, \quad i = 1, 2, \dots, N. \quad (8)$$

Combining Eqs 7 and 8 we will have for the steady state case that,

$$\langle f_{s,p} \rangle = \langle T_s/T \rangle_p = (T_s/T)_i. \quad (9)$$

Equation 9 contains the second assumption of the Two-Fluid Model as expressed in Eq 3.

The ergodic experiments, described in Chapter 3, were designed to examine the extent to which the fraction of the time stopped for a single test vehicle in a real traffic network satisfactorily approaches the mean value of this fraction taken over  $N$  test vehicles for reasonable times, i.e., times short enough so that traffic conditions are not changing too much but at the same time long enough so that a test vehicle can properly sample the test area. On the other hand, if the time period  $\tau$  during which the traffic conditions are reasonably stable is not long enough to allow a test vehicle to properly sample the test area, then daily repetitive observations made by a single test vehicle during the period  $\tau$  should on the average correspond to the averages obtained over the entire population on a typical day during this particular time period. Moreover, by these experiments we also wished to show with actual data that the fraction of test vehicles stopped,  $\langle f_{s,t} \rangle$ , was equal to the mean fraction of time stopped taken over all the test vehicles,  $\langle T_s/T \rangle_t$ . If the traffic conditions do not change significantly over the test period, then the mean fraction of time stopped for the test vehicles is a good estimator of the mean fraction of

time stopped for the population of vehicles,  $\langle T_s / T \rangle_p$ . Thus, in an actual system and over a period during which the traffic conditions do not fluctuate significantly, we should have that

$$\langle T_s / T \rangle_{i,t} \rightarrow \langle T_s / T \rangle_t = \langle f_{s,t} \rangle \rightarrow \langle T_s / T \rangle_p = \langle f_{s,p} \rangle . \quad (10)$$

Time-lapse aerial photography of traffic in a network will permit the determination of  $\langle f_{s,p} \rangle$  to verify Eq 10. Aerial photography of the Dallas central traffic network has been recently carried out. These photographs will be analyzed for this and other purposes as will be discussed in the last chapter of this report.

Adopting Eqs 1 and 3, we are now able to derive the theoretical relation between the trip time and the stop time per unit distance predicted by the Two-Fluid Model. Let  $T$  be the trip time per unit distance,  $T_r$  be the running time per unit distance,  $T_s$  be the stop time per unit distance, and  $T_m$  be the average minimum trip time per unit distance or the reciprocal of the average maximum speed,  $V_m$ , in the system. Thus, Eq 1 can be rewritten as

$$T_m = T_r f_r^n . \quad (11)$$

Substituting for  $f_r$  in Eq 11 in terms of  $f_s$  yields

$$T_m = T_r (1 - f_s)^n . \quad (12)$$

Combining Eqs 3 and 12 we have

$$T_m = T_r (1 - T_s/T)^n . \quad (13)$$

Rearranging Eq 13 gives

$$T_m T^n = T_r (T - T_s)^n , \quad (14)$$

and knowing that

$$T_r = T - T_s . \quad (15)$$

Eq 14 can be rewritten as

$$T_r^{n+1} = T_m T^n \quad (16a)$$

or

$$T_r = T_m^{\frac{1}{n+1}} T^{\frac{n}{n+1}} . \quad (16b)$$

Combining Eqs 14 and 16b, we have,

$$T - T_s = T_m^{\frac{1}{n+1}} T^{\frac{n}{n+1}} \quad (17a)$$

or finally

$$T_s = T - T_m \frac{1}{n+1} T^{\frac{n}{n+1}} \quad (17b)$$

Equation 17b is the theoretical relation between the trip time and the stop time per unit distance. Figure 1 shows the  $T$  versus  $T_s$  curves of Eq 17b for values of  $T_m$  of 1.5 and 3.0 minutes per mile and for  $n$  values of 1, 2, 3 and 4. Note that  $T_m$  is the intercept of Eq 17b with the T-axis. Figure 2 is a family of  $T$ ,  $T_s$  curves (Eq 17b) for an  $n$  value of 2 and for  $T_m$  values of 1.0 through 5.0 minutes per mile in increments of half a minute per mile. We will now use Figs 1 and 2 to illustrate the significance of the slope  $dT/dT_s$ ,  $n$ , and  $T_m$  in connection with the quality of traffic service in an urban street network.

Let us first discuss the slope  $dT/dT_s$ . The slope of the theoretical  $T$ ,  $T_s$  curve represented by Eq 17b can be written as

$$dT/dT_s = \left[ 1 - \frac{n}{n+1} (T_m/T)^{\frac{1}{n+1}} \right]^{-1} \quad (18)$$

Consider two traffic networks, both having a  $T_m$  of 1.5 minutes per mile but one with an  $n$  of 1 and the other with an  $n$  of 2 (Fig 1). As can be seen analytically from Eq 18 or graphically from Fig 1, for a given value of  $T_s$  the network with a larger value of  $n$  will have a larger slope at, of course, different values of  $T$ ; likewise for a given value of  $T$  the network with a larger  $n$  will have the larger slope. Therefore, for a given change in the stop time per unit distance,  $\Delta T_s$  at  $T_s$ , the change in trip time per unit distance,  $\Delta T$ , will be smaller for the network with the smaller value of  $n$  or with a smaller slope. As a result, a network with a

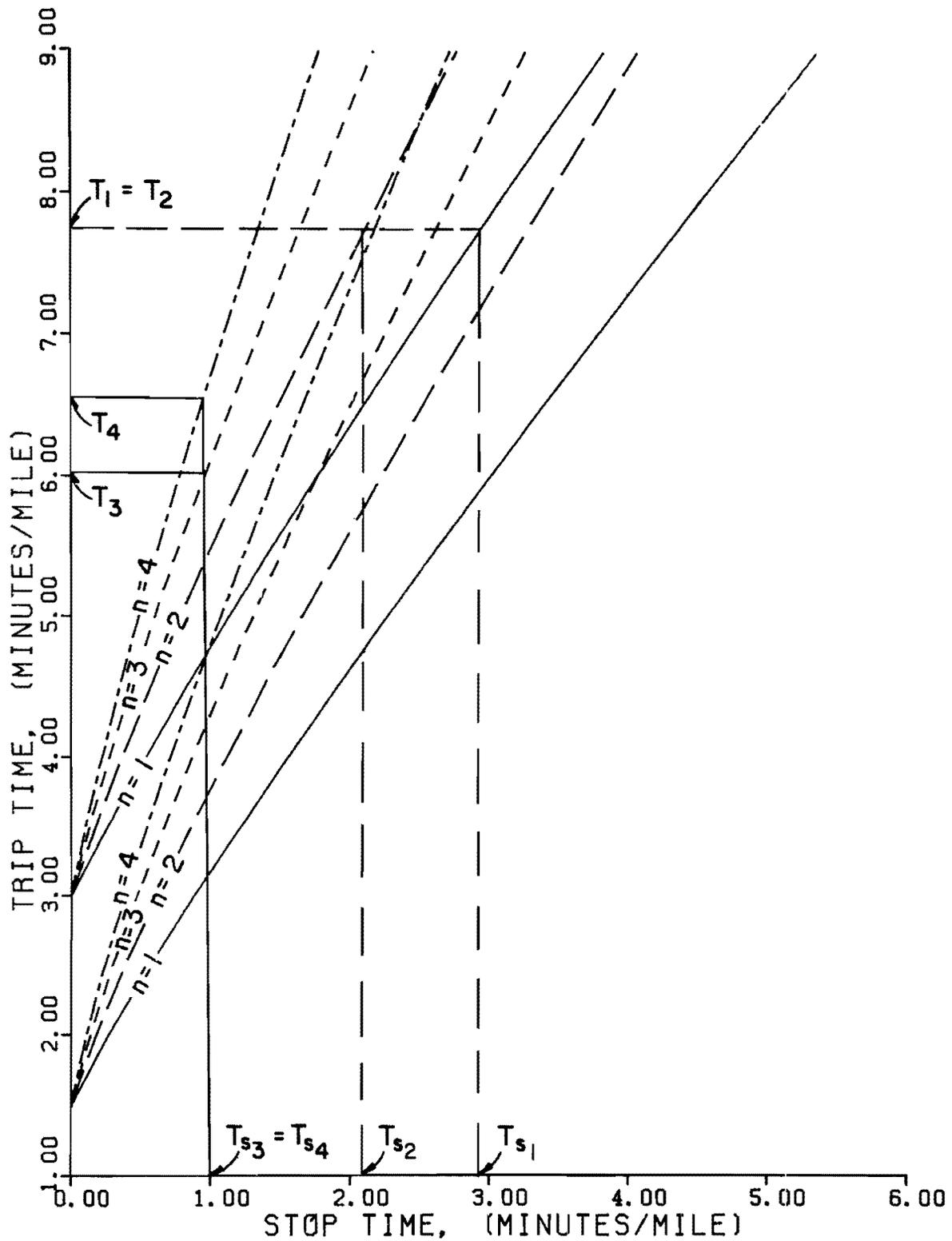


Fig 1. Curvilinear relation between trip time and stop time, as predicted by the Two-Fluid Model, for  $T_m$ 's of 1.5 and 3.0 minutes per mile and  $n$  values of 1, 2, 3, and 4.

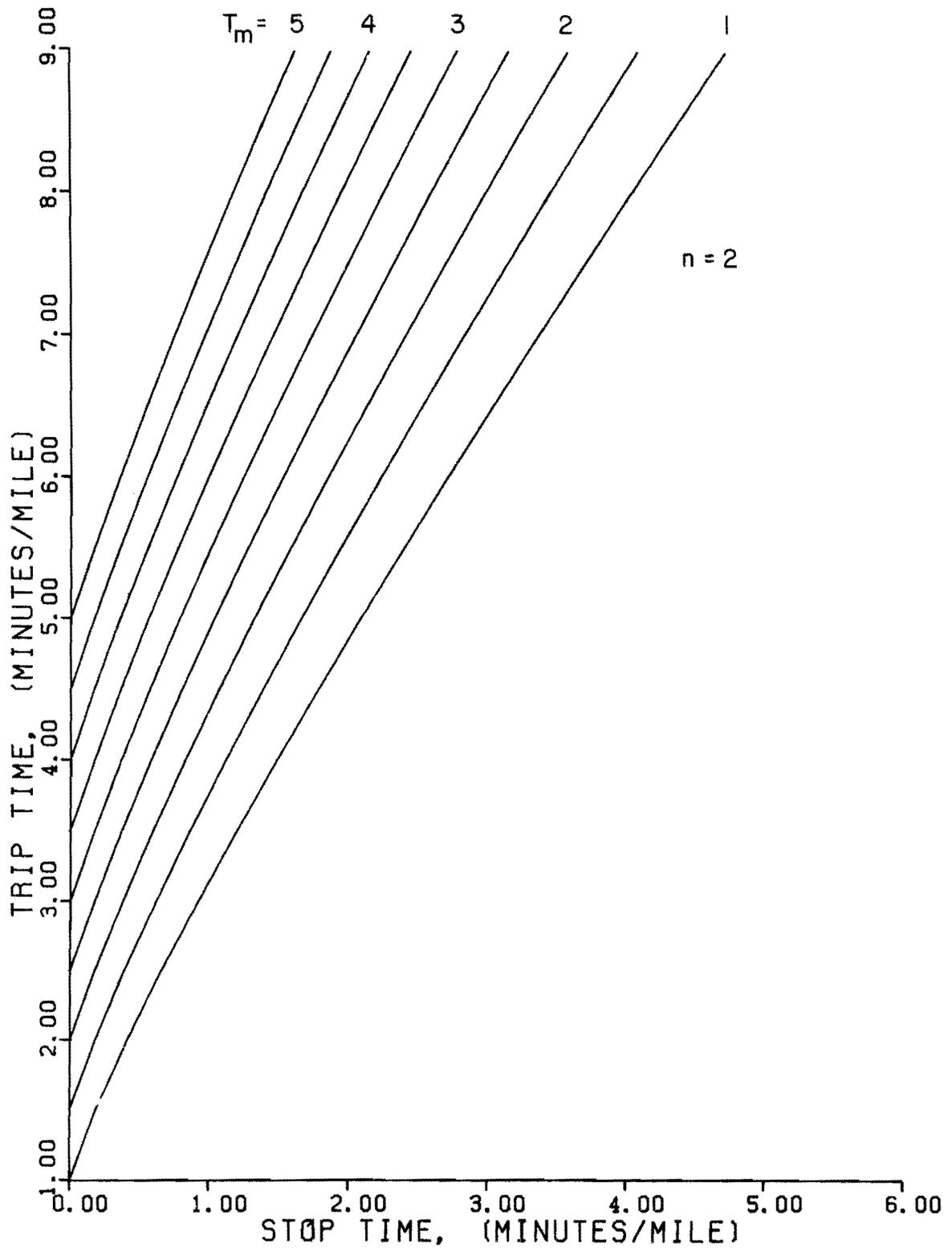


Fig 2. Curvilinear relation between trip time and stop time, as predicted by the Two-Fluid Model, for an  $n$  of 2 and  $T_m$ 's of 1.0 through 5.0 minutes per mile.

smaller  $n$  or a smaller slope is operationally more efficient and more desirable.

Furthermore, according to Eq 18, as the value of  $T_m$  increases while the value of  $n$  remains constant, the slope of the corresponding curve at a given  $T$  or  $T_s$  becomes steeper. In other words, a family of curves with the same  $n$  but different  $T_m$  values are not parallel to one another; and the greater the  $T_m$  value, the steeper its corresponding curve (Fig 2).

To further illustrate the role of  $n$  as a traffic characterizing parameter, let us consider a family of curves with a  $T_m$  of 3.0 minutes per mile and  $n$  values of 1, 2, 3 and 4 (Fig 1). These curves are referred to as curves 1, 2, 3 and 4, respectively. If curves 1 and 2 are accessed with a given value of  $T$ , the following relations will hold true

$$T_1 = T_2 \quad (19a)$$

$$T_{s1} > T_{s2} \quad (19b)$$

$$f_{s1} > f_{s2} \quad (19c)$$

$$T_{r1} < T_{r2} \quad (19d)$$

The relations in Eq 19 reflect the superiority of the network represented by curve 1 over that represented by curve 2. In this case the hypothetical traffic conditions show  $T_{s(1)}$  and  $f_{s(1)}$  to be greater than  $T_{s(2)}$  and  $f_{s(2)}$ , while the mean speeds in these networks are equal and the mean running speed in the network 1 ( $V_{r(1)} = T_{r(1)}^{-1}$ ) is greater than that in network 2 ( $V_{r(2)} = T_{r(2)}^{-1}$ ).

Let us now access curves 3 and 4 of Fig 1 with a given value of  $T_s$  .  
Then we can write

$$T_{s3} = T_{s4} \quad (20a)$$

$$T_3 < T_4 \quad (20b)$$

$$f_{s3} > f_{s4} \quad (20c)$$

$$T_{r3} < T_{r4} \quad (20d)$$

Again, the above relations indicate that the network with the smaller  $n$  value, i.e., the network represented by curve 3, has a better quality of traffic service than the network represented by curve 4, with the larger  $n$  value.

Finally, the significance of  $T_m$  is in representing the average minimum trip time per unit distance or the reciprocal of the average maximum speed in a network. The average maximum speed is the mean speed a vehicle can achieve in a network under very light traffic conditions while obeying the traffic controls and regulations. Therefore, the larger the average maximum speed or the smaller  $T_m$ , the more efficient a traffic network will be. In short, a desirable traffic system is one with small  $T_m$ , small  $n$ , and thus small  $dT/dT_s$ .

Furthermore, the Two-Fluid Model predicts a linear relation between the logarithms of the running time per unit distance and the trip time per unit distance. This relation can be derived by performing a logarithmic

transformation of Eq 16b, which yields

$$\log T_r = \left( \frac{1}{n+1} \right) \log T_m + \frac{n}{n+1} \log T \quad (21)$$

or

$$\log T_r = A + B \log T \quad (22)$$

with

$$n = \frac{B}{1-B} \quad (23)$$

$$\log T_m = \frac{A}{1-B} \quad (24)$$

Therefore the parameters  $n$  and  $T_m$  associated with a traffic network can be obtained from Eqs 22-24 by collecting trip time versus stop time data for a test vehicle injected into the traffic of that network and performing a linear regression between  $\log T_r$  and  $\log T$ .

However, we believe that the value of  $T_m$  obtained from the Two-Fluid Model is underestimated. Thus, the average maximum speed of a traffic network as predicted by the model is undoubtedly larger than the observational value of  $V_m$ . A theoretical discussion of this subject is presented in Chapter 5.

The Two-Fluid Model is not merely an abstract characterizer of the traffic quality through parameters such as  $T_m$  and  $n$ . On the contrary, it is closely interrelated with a simple macro fuel utilization model

developed from urban fuel consumption studies (Refs 1, 7, 15 and 16). The connecting link between these two models is the trip time per unit distance. In 1973 a study was conducted in the Detroit metropolitan area to determine some of the main variables capable of explaining the fuel consumption rate of automobiles in urban traffic networks (Ref 7). The preliminary analysis involved 48 variables, from which 17 were selected for the final multivariate statistical analysis (Ref 15). For urban areas in which average speeds are lower than  $\sim 40$  miles per hour, it was shown that three variables, namely, the trip time per unit distance, the energy per unit distance used while accelerating, and the fraction of the distance travelled while braking or coasting explained approximately 80 percent of the variability in the fuel consumption per unit distance. However, among these three variables, the trip time per unit distance alone accounted for 73 percent of the variability. Therefore, the fuel consumed per unit distance,  $\phi$ , can be expressed as a linear function of the trip time per unit distance, namely,

$$\phi = k_1 + k_2 T, \quad V < 40 \text{ mph} . \quad (25)$$

In the above relation,  $k_1$  can be interpreted as the fuel consumed per unit distance to overcome the rolling resistance and thus is proportional to the vehicle mass. The parameter  $k_2$  is the fuel consumed to overcome the various time dependent fuel losses and is approximated by the idle fuel flow rate (Ref 1).

Parameters  $k_1$  and  $k_2$  have been calibrated for various classes of vehicles (Ref 16). For example, data for a 1974 standard size car driven in the Detroit metropolitan area indicated a  $k_1$  of 0.0474 gallons per mile and a  $k_2$  of 0.994 gallons per hour. The corresponding average values for

$k_1$  and  $k_2$  taken over eight vehicle classes were 0.0362 and 0.746, respectively (Ref 16). On the average it was shown that

$$k_1 = 9.01 \times 10^{-6} W \quad (26)$$

and

$$k_2 = 1.25 I \quad (27)$$

where  $W$  is vehicle weight in pounds and  $I$  is the idle fuel flow rate in gallons per hour (Ref 16).

The fuel consumption relation of Eq 25 together with the Two-Fluid Model predictions relates the fuel consumption characteristics of an individual vehicle to the overall traffic characteristics of the urban traffic network in which the vehicle is operated. While the Two-Fluid Model characterizes the quality of traffic in an urban network, the fuel consumption relation indicates the effect of this traffic quality on the rate of fuel consumption of the vehicles in the traffic system.

It is possible to use the Two-Fluid Model and the fuel consumption parameters to establish a multi-dimensional traffic map of a city traffic network. This, however, requires a knowledge of the distribution of trip time per unit distance (or the mean speed) over a city traffic network. Hutchinson (Ref 17), for example, suggests that the mean speed increases approximately as the cubic root of distance from a city center,  $r$ , namely,

$$v = k \sqrt[3]{r} \quad (28)$$

Vaughan, et al (Ref 2) describe the traffic intensity also as a function of the distance from the city center, in the following form:

$$I = A \exp( -\sqrt{r/a} ) \quad (29)$$

where  $a$  and  $A$  are parameters and  $I$  is the traffic intensity or the total distance traveled by all vehicles on major roads per unit area of road per unit time. In turn, the fraction of the area which is covered by major roads,  $\gamma$ , is given by the following relation:

$$\gamma = B \exp( -\sqrt{r/b} ) \quad (30)$$

where  $b$  and  $B$  are parameters. Combining Eqs 29 and 30 yields  $L$  the total distance traveled by all vehicles on major roads per unit of land per unit time, in the form

$$L = AB \exp(-\sqrt{r/a} - \sqrt{r/b} ) . \quad (31)$$

Thus, the fuel per unit distance used by all the vehicles on major roads per unit of land per unit time,  $\phi^*$ , can be derived by combining Eqs 25, 28 and 31, as follows:

$$\phi^* = L \phi(r) = AB (k_1 + k_2 \sqrt[3]{k_r}) \exp( -\sqrt{r/a} - \sqrt{r/b} ) . \quad (32)$$

Time lapse aerial photography can be used to determine the various parameters discussed above, namely,  $a$ ,  $b$ ,  $A$ ,  $B$ , and  $k$ , for any given city. Thus, a fuel consumption spatial distribution function can be established for

that city. The city map may be divided into small zones; and for each zone the Two-Fluid Model parameters, namely,  $T_m$  and  $n$ , can be determined. Furthermore, the fuel consumption  $\phi^*$  for any zone  $i$  can be calculated from Eq 32 by using for  $r_i$  the distance from the center of zone  $i$  to the city center.

In principle, contour lines for  $T_m$ ,  $n$  and  $\phi^*$  could be drawn on an ordinary city map. Such a contour map would provide an overall picture of the quality of traffic service on a city-wide basis and would be an invaluable tool in transportation planning and traffic engineering.

It should be pointed out that considerable work along these lines must be carried out to assess the accuracy and sensitivity of such a procedure which we believe can give important results even if only qualitative.

### CHAPTER 3. OBSERVATIONAL AND EXPERIMENTAL DETAILS

The observations under consideration in this program consisted of recording the trip time and stop time of automobiles and passenger buses travelling known distances. The data for passenger buses were obtained aboard the CC, IF, and WC shuttle buses of the University of Texas at Austin Shuttle Bus System, whereas three different street networks, namely, shuttle bus routes, Austin's Central Business District, and Dallas' central traffic network, were used to collect the automobile data. The purpose of these observations was to verify the Two-Fluid Model's prediction of a relation between stop time, running time, and trip time, all per unit distance, in urban, non-freeway traffic networks.

The experimental part consisted of two experiments, similar in design, carried out in the Austin central street network to evaluate the assumptions underlying the Two-Fluid theory of traffic flow. In this report, these experiments will be referred to as the "ergodic experiments" and are explained below.

#### Collection of Automobile Data

As indicated earlier, automobile data were collected on shuttle bus routes as well as in Austin's Central Business District and Dallas' central

traffic network. The test automobile driven on these routes was monitored by an observer equipped with two stopwatches. The stop time and trip time of this test vehicle were accumulated and recorded by the observer. To obtain the length of the test vehicle's route, the odometer reading at the beginning and end of each trip was also recorded. See Appendix A, Table A.1 for a typical field data sheet.

To collect the automobile data in the Austin and Dallas central traffic networks, a technique different from that used on the shuttle bus route was employed. First, a trip was defined as a 2-mile segment of travel. Each test vehicle carried a driver and an observer. The driver was responsible for the following: informing the observer of the odometer readings at the beginning and end of each trip, driving along with the local traffic, obeying all traffic regulations, and remaining within the boundaries of the designated street network as much as possible. The observer, on the other hand, was responsible for recording the odometer readings and the absolute times corresponding to the beginning and end of each 2-mile trip and for noting the absolute times associated with each stop made by the test vehicle and the subsequent resumption of motion. In these cases, time was measured with Casio Digital watches, Model No. 79. Appendix A, Table A.2 shows a typical data sheet.

In Austin, experiments of this type were conducted in a preselected area during the noon and evening rush hours as well as at midnight and during the early morning hours. Data for the Dallas experiment were collected on February 6 and April 28 of 1981 during the morning, noon, and evening rush hours as well as the morning, afternoon, and nighttime off-peak hours. While the Chase-Car technique was occasionally used in Austin, it was widely applied in the Dallas area. In the Chase-Car technique, the driver of a test

vehicle follows a random car until the car leaves the test area or parks and then follows the next nearest vehicle. The "chase" is conducted in such a manner that the speed-time history of the followed car is essentially reproduced (Refs 4 and 10). This technique randomizes the route taken by the drivers of the test vehicles. In the long time scale the test vehicle will travel over the area of streets in essentially the manner in which the population of vehicles travels in that area.

The street network employed for the observations in Austin was bounded by 38th Street on the north, the Colorado River on the south, Red River Street on the east and Lamar Boulevard on the west. The Dallas observations were made in three one-mile wide corridors centered by three arterials, namely Elm Street, Ross Avenue, and Hall Street, respectively. The Elm and Ross corridors chosen are each 3 miles long, both starting from Stemmons Freeway and stretching eastward and northeastward, respectively. The Hall corridor is 4.5 miles long, beginning at Wycliff Street and running southeastward. Preliminary aerial photographs of the traffic in these corridors have been obtained and will be analyzed later in this research activity.

#### Collection of Shuttle Bus Data

The University of Texas shuttle buses operate on fixed routes and fixed schedules. For the purposes of our research effort, data were collected on the CC, IF, and WC bus routes since they run through non-freeway street networks including low-speed-limit campus streets and residential non-arterial streets. The round-trip lengths were 2.64, 4.66, and 2.77 miles for the CC, IF, and WC bus routes, respectively.

The shuttle bus data were collected during an eleven-month period from December 1979 to October 1980. A typical field data sheet is shown in Appendix A, Table A.3.

To collect the bus data, an observer, equipped with three stopwatches, boarded a bus at a terminal station. The total trip time, traffic stop time, and loading/unloading time were accumulated and recorded for each round trip, and the stopwatches were reset for the following trip. Experience has shown that the chances were quite small of an overlap occurring between the traffic stop time and the loading/unloading time. Therefore, the overlap time was neglected in the analysis.

Throughout the observational and experimental stages of the project, the beginning of a stop period was defined as that time at which a vehicle was no longer in motion. To account for the slack time occurring at the IF terminal stations, a round trip run on this particular route was divided into inbound and outbound trip-lengths of 2.35 and 2.31 miles, respectively.

#### The Ergodic Experiments

In an "ergodic" system the performance of a single test particle averaged over a long period of time is identical to the mean performance of all the particles in that system. Thus, in the Two-Fluid Model we assume that the average trip time per unit distance, the average stop time per unit distance, etc., of a test vehicle in the long time scale are good estimators of these quantities averaged over the entire system at a given time. Moreover, the Two-Fluid Model assumes that over a long period of time, the fraction of time a single vehicle circulating in a traffic network is stopped is equal to the mean fraction of vehicles stopped in that network over the

same time period. The model assumes that a non-freeway traffic network is "ergodic." While realizing that such a traffic network can never be a perfect ergodic system, two experiments were performed in Austin to investigate the rationale behind this assumption in the Two-Fluid Model.

The first ergodic experiment was conducted during the evening rush hour (5 - 6 pm) of January 15, 1981, in an area of downtown Austin approximately 1.5 miles wide and 3 miles long. The boundaries of the test area are described in the previous section. The experiment involved eight automobiles, each carrying a driver and an observer with a digital watch. Prior to performing the experiment, the odometer of each test vehicle was calibrated, and all the watches were synchronized with time signals from Fort Collins, to the nearest tenth of a second. The duties of the observers and the drivers were similar to those also described in the previous section. To randomize the routes taken by each driver, the Chase-Car technique was again applied. However, operators were instructed not to follow aggressive or unreasonable drivers nor other test vehicles. Each driver was requested to drive continuously for one hour. The one-hour trip of each test vehicle was divided into 2-mile segments to obtain average values of trip time, stop time, and running time, all per unit distance. The typical data sheets for the first 2-mile trip of two of the test vehicles are shown in Tables A.4 and A.5 of Appendix A.

A similar experiment, also in Austin, was conducted with six vehicles during the noon rush hour (12 - 1 pm) of February 24, 1981. In this case, the test area was bounded by 11th Street on the north, Colorado River on the south, Red River Street on the east, and Lamar Boulevard from the west. This street network is approximately 0.7 mile wide and 1.0 mile long and falls within the boundaries of the previous test area. Since the test area was

rather small in size, the Chase-Car technique was difficult to apply by the volunteer drivers because it was necessary to switch the chased cars too frequently. Thus, the drivers were not instructed to follow other vehicles.

In the following chapter the analysis and results of the aforementioned observations and experiments are presented.

## CHAPTER 4. RESULTS AND ANALYSIS

The raw data from various observations were analyzed to obtain the trip time, stop time, and running time per unit distance. The trip time per unit distance,  $T$ , was calculated by dividing the minutes of travel time by the miles of travelled distance for every trip. By a similar procedure the stop time per unit distance,  $T_s$ , and the running time per unit distance,  $T_r$ , were calculated. In the case of shuttle bus data, the loading-unloading time was subtracted from both the trip time and the stop time before carrying out the calculations were carried out. It is readily seen from all the data in the  $T$  versus  $T_s$  plots, e.g., Fig 3, that  $T$  and  $T_s$  are approximately linearly related. For this reason we have determined the least square fits to this type of data to establish the linear trends. The Two-Fluid Model, however, predicts a curvilinear relation between  $T$  and  $T_s$  (see Eq 17b, Chapter 2) but this is in most cases rather close to the linear approximation. A plot of  $T$  versus  $T_s$  was prepared for each separate observational case.

The model predicts a linear relationship between the logarithm of  $T_r$  and the logarithm of  $T$  (Eq 21). Therefore, the logarithm of  $T_r$  was linearly regressed against the logarithm of  $T$  for each case and the corresponding plots were prepared. Using Eqs 23 and 24, the values of the pair of parameters  $T_m$  and  $n$  which characterize the quality of traffic in an urban network were calculated for each case. Finally, the results of

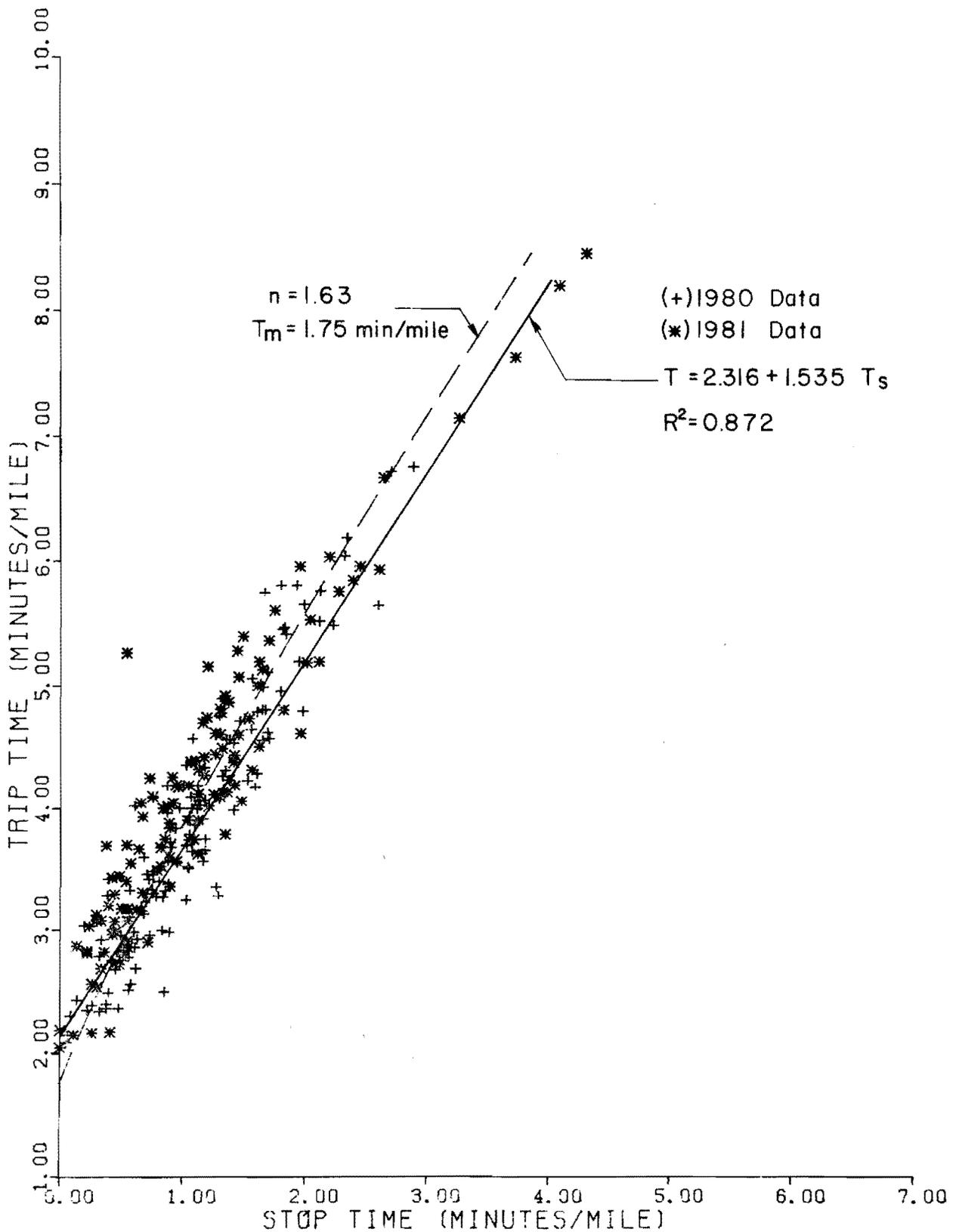


Fig 3. Trip time versus stop time for automobile data in Austin central traffic network.

these observations were compared to the previously available results of similar observations in other metropolitan areas around the world.

#### Results of the Trip Time versus Stop Time Observations

Figure 3 is a plot of the trip time versus stop time per unit distance in the central business district of Austin. The dashed curve shows the theoretical relation between the trip time and the stop time per unit distance. The linear approximation to this curve is a best-fit regression line to the plotted data points. This best-fit is shown as a solid line and has a slope of 1.54. Similarly, Figs 4 through 9 are the trip time - stop time plots for Dallas, Melbourne, Sydney, Milwaukee, Brussels and London, respectively. It must be emphasized that the trip time - stop time data used in Figs 3 through 9 are taken at different times of the day and in specific street networks of each city. Thus, they do not necessarily represent the traffic conditions corresponding to any specific time period nor the traffic conditions in the entire street network of the city under study. As a means of comparison, the best-fit lines of Figs 3 through 9 are shown together in Fig 10 but without the data points. The corresponding curvilinear relations for the Two-Fluid Model are shown in Fig 11. The slope of a trip time - stop time best-fit line is a measure of the ability of a traffic network to handle a given traffic load in terms of the effectiveness of the geometric configuration of the network and the traffic control system. It should be noted that the slope,  $dT/dT_s$ , represents the increase in the trip time per unit distance per unit increase in the stop time per unit distance. Thus, the street systems of Austin, Dallas, Melbourne and Milwaukee appear in a

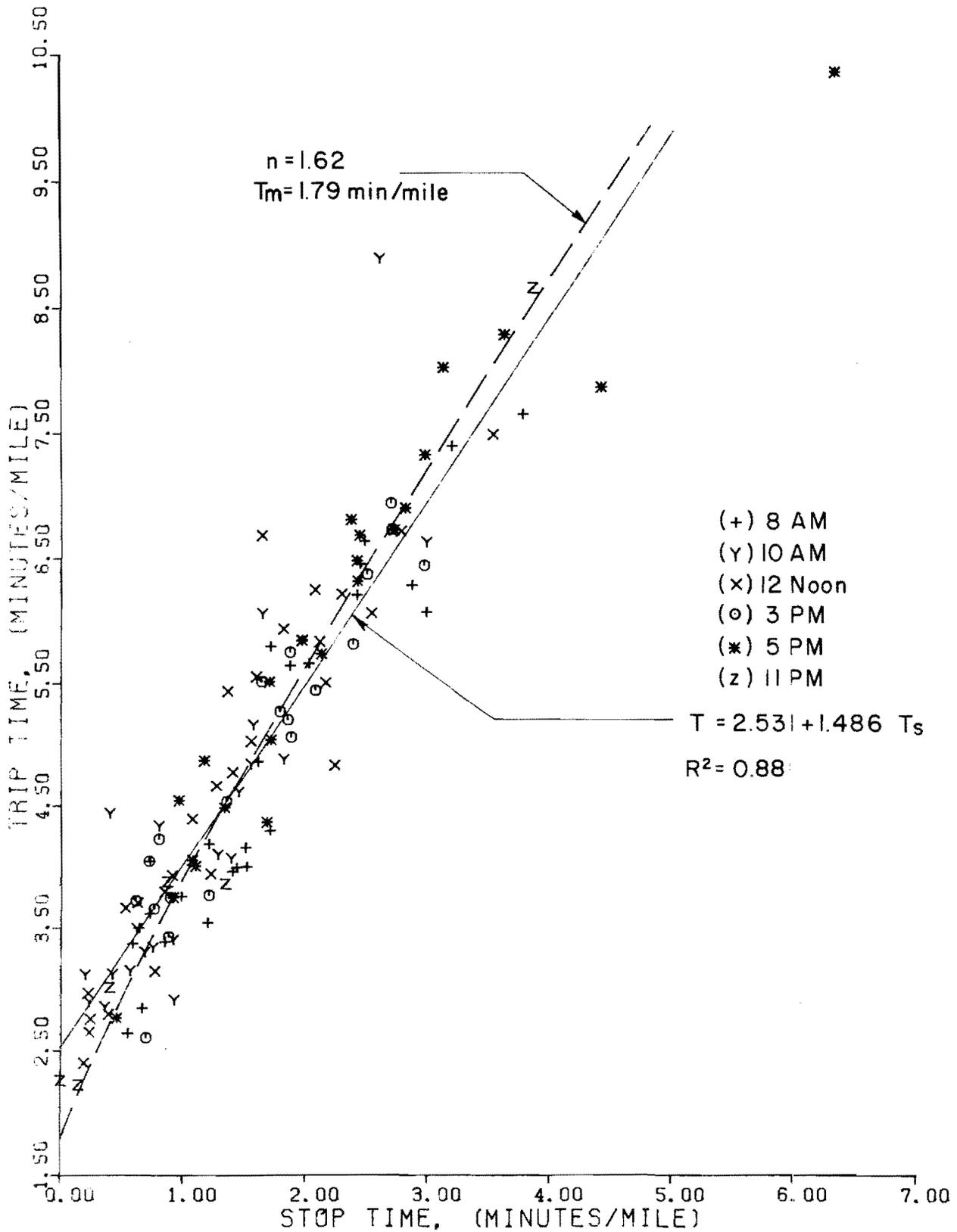


Fig 4. Trip time versus stop time for 1981 automobile data in the Dallas central traffic network.

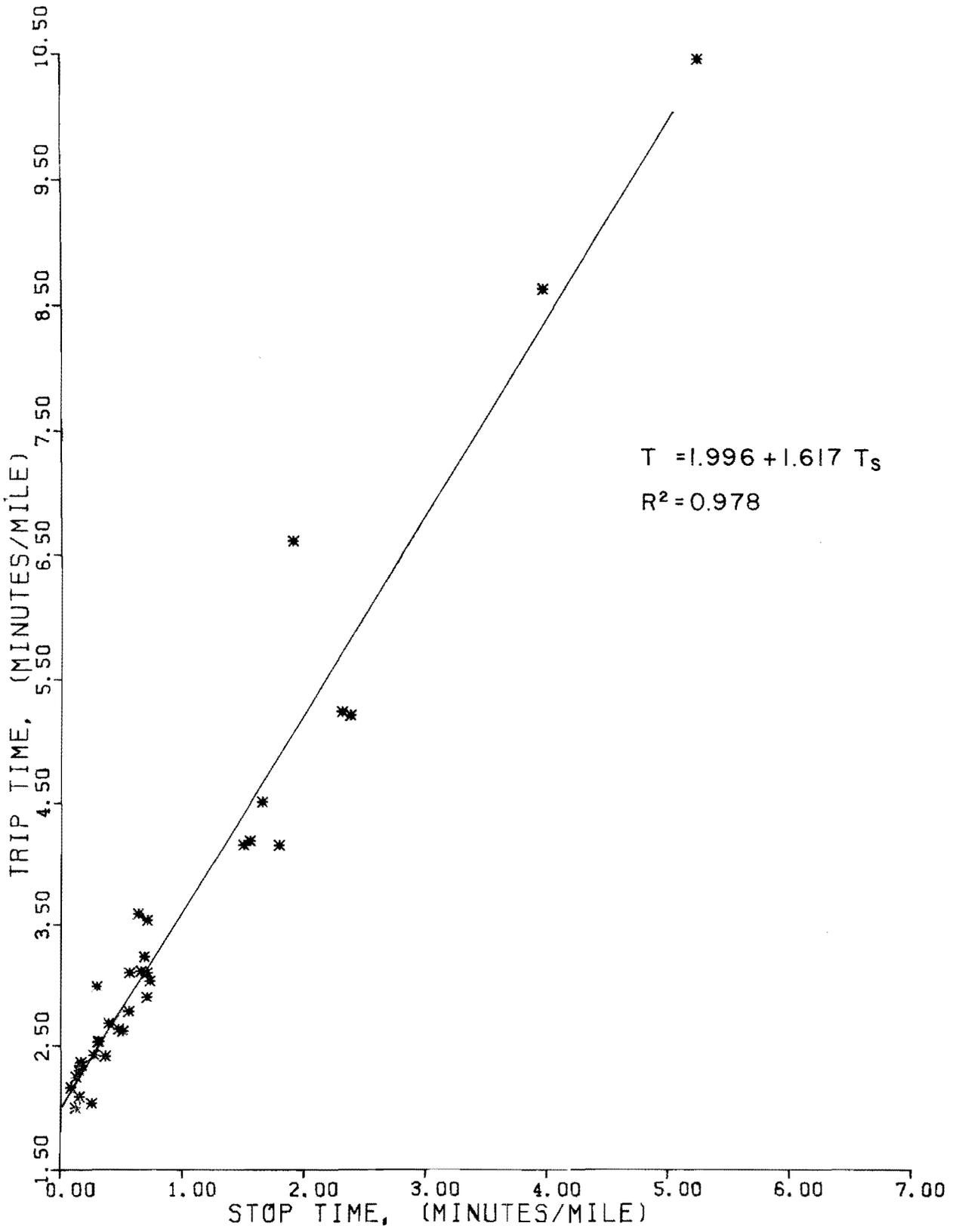


Fig 5. Trip time versus stop time for automobile data from Melbourne, Australia (Refs 3 and 4).

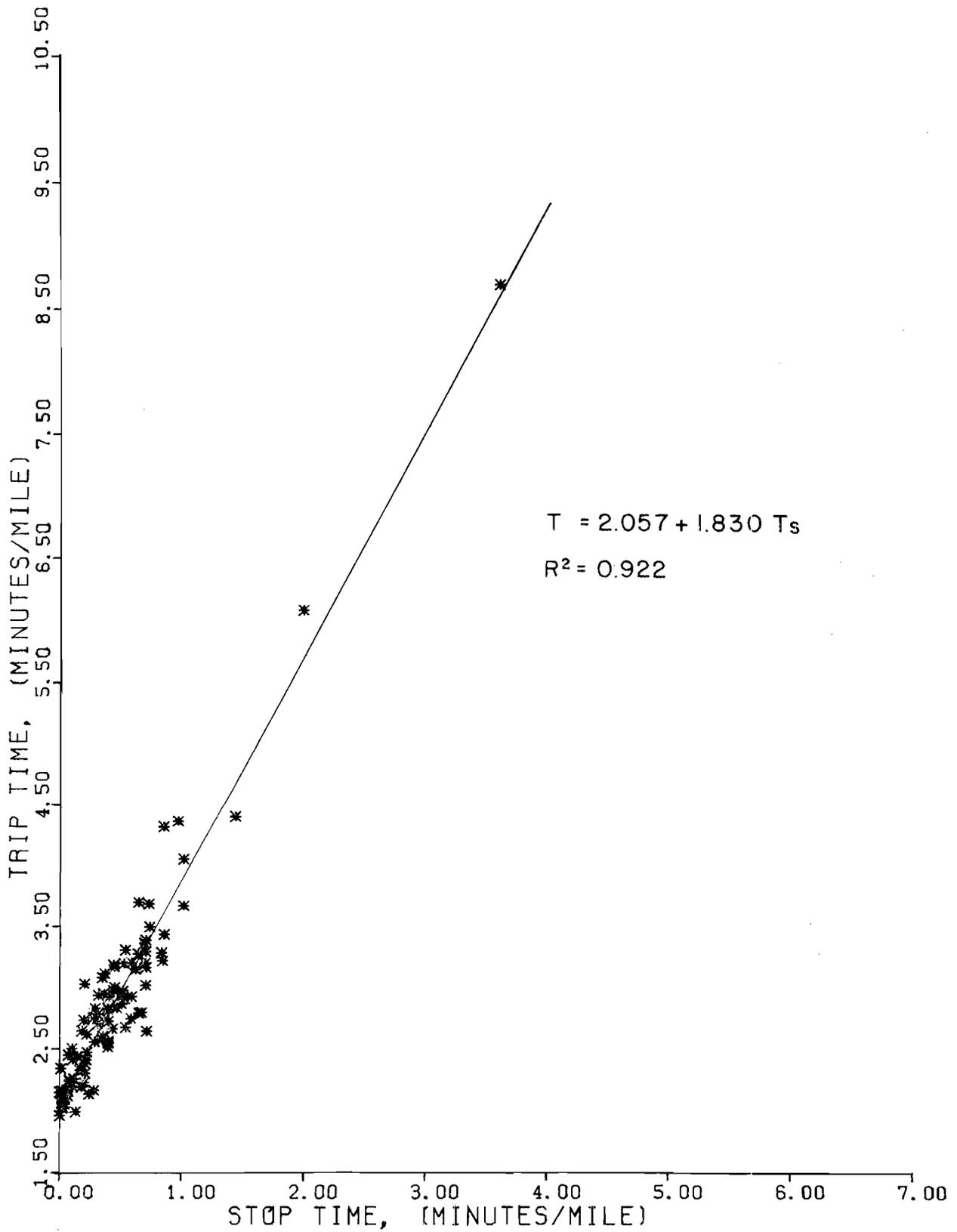


Fig 6. Trip time versus stop time for 1966 automobile data from Sydney, Australia (Refs 4 and 5).

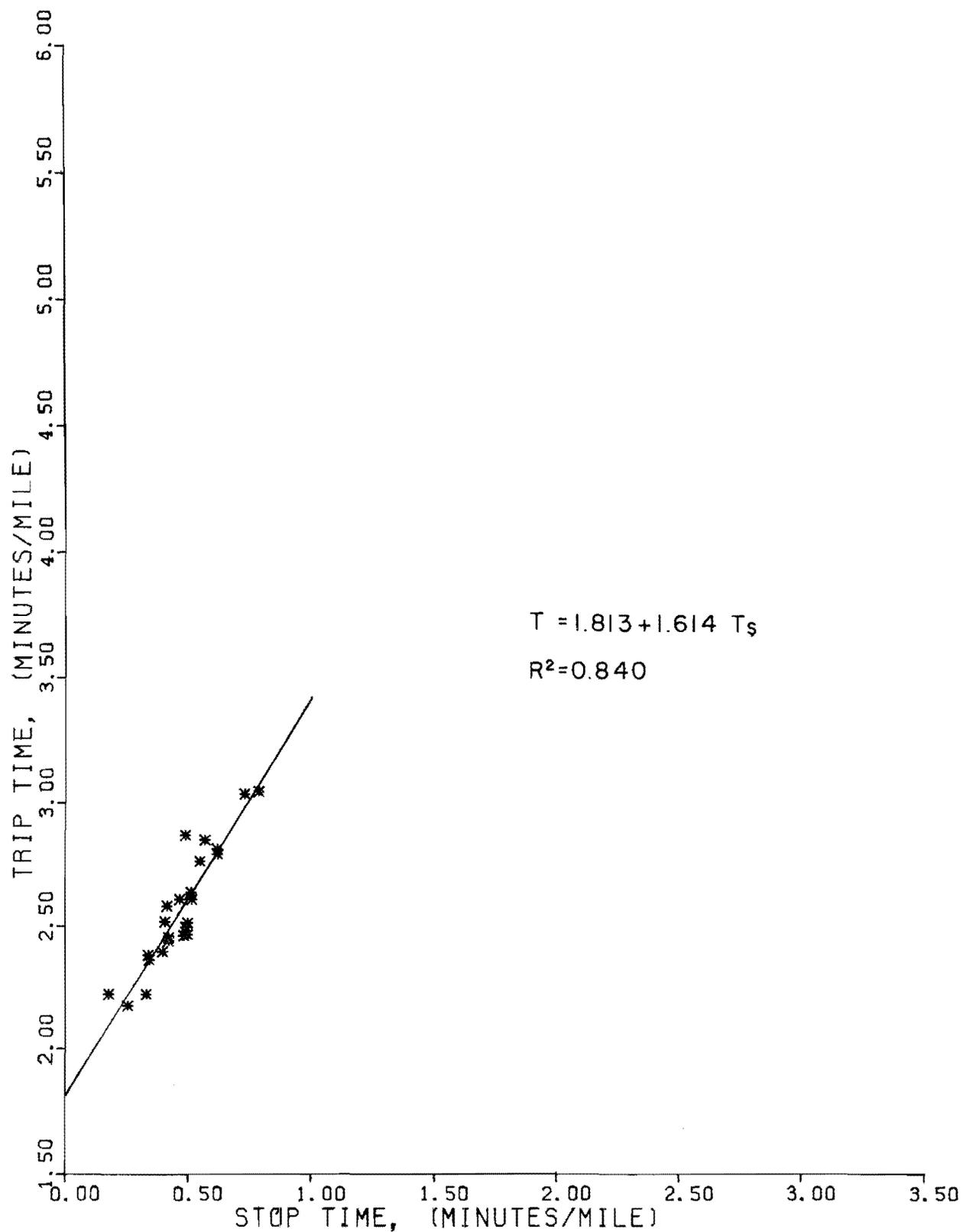


Fig 7. Trip time versus stop time for automobile data from Milwaukee (Ref 6).

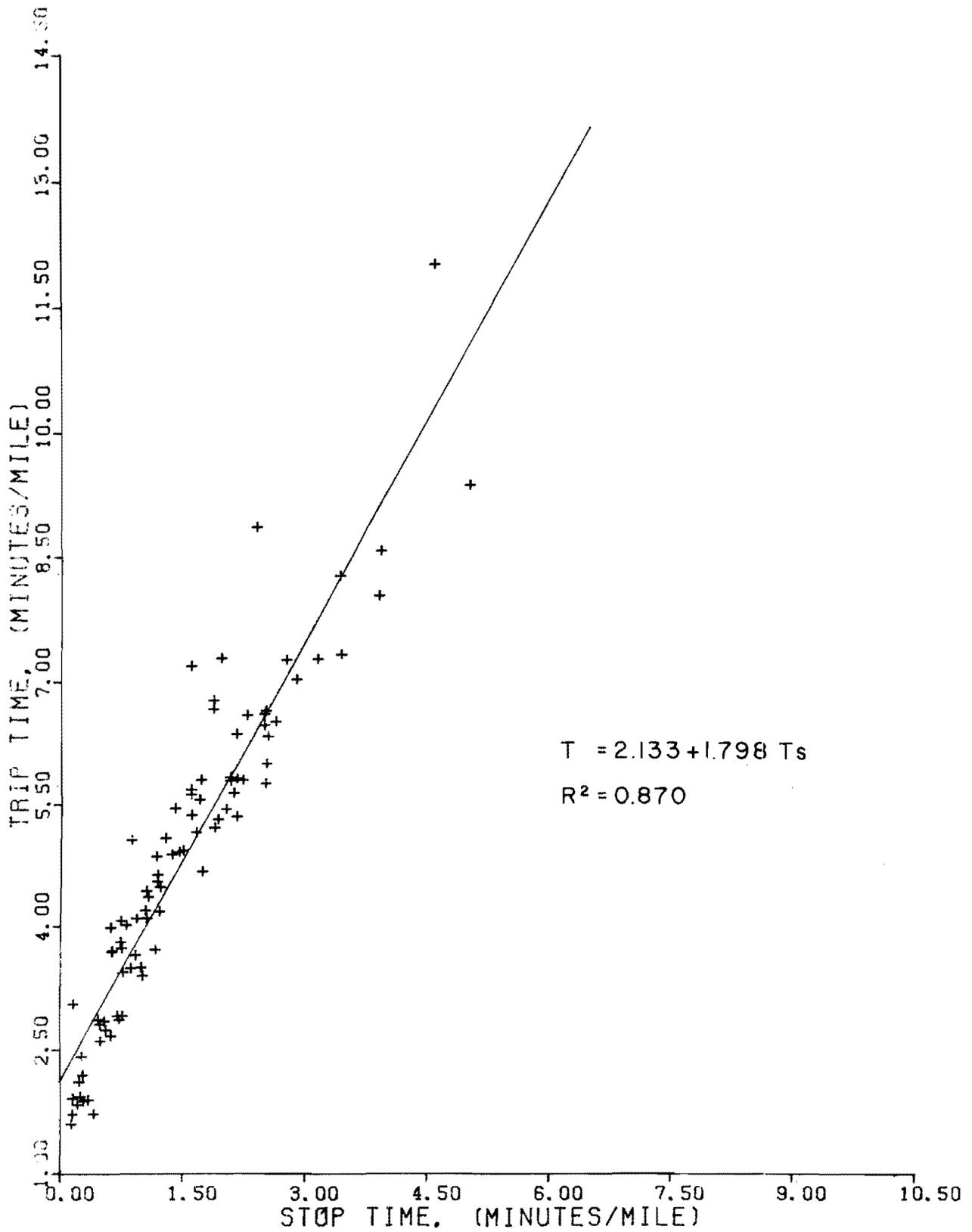


Fig 8. Trip time versus stop time for automobile data in the central traffic network of Brussels, Belgium (Ref 8).

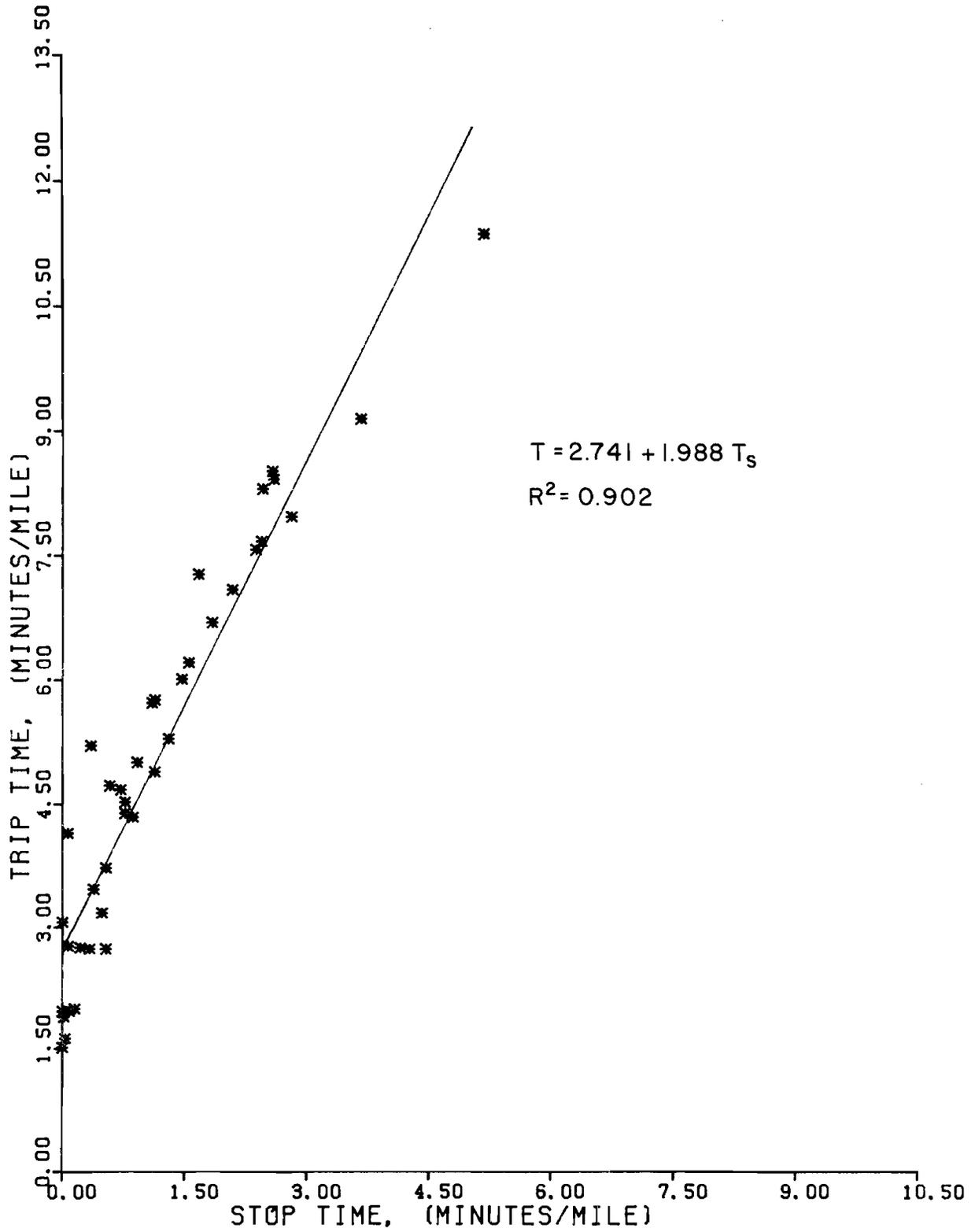


Fig 9. Trip time versus stop time for automobile data from London (Ref 7).

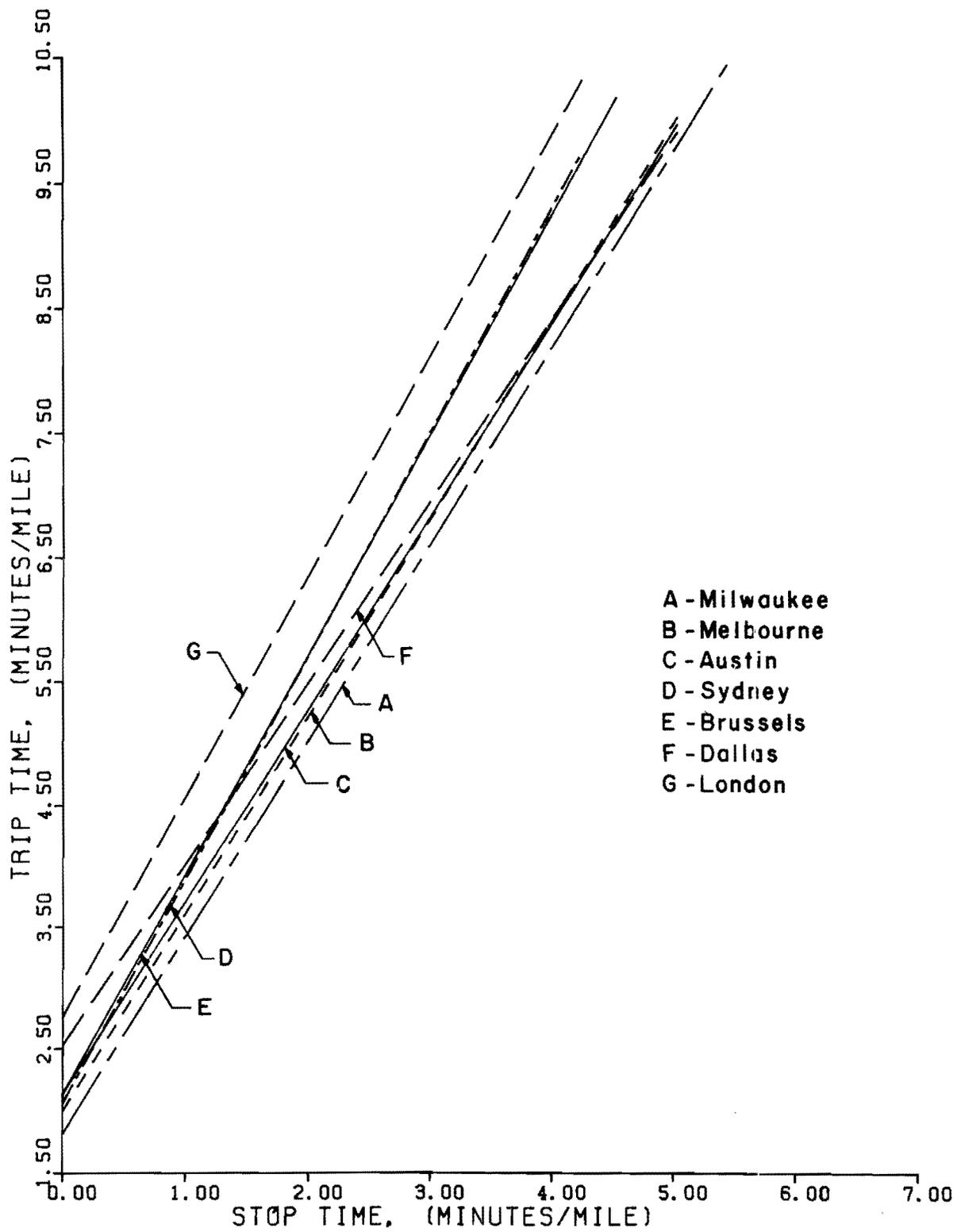


Fig 10. Linear trip time - stop time relations for various metropolitan areas around the world.

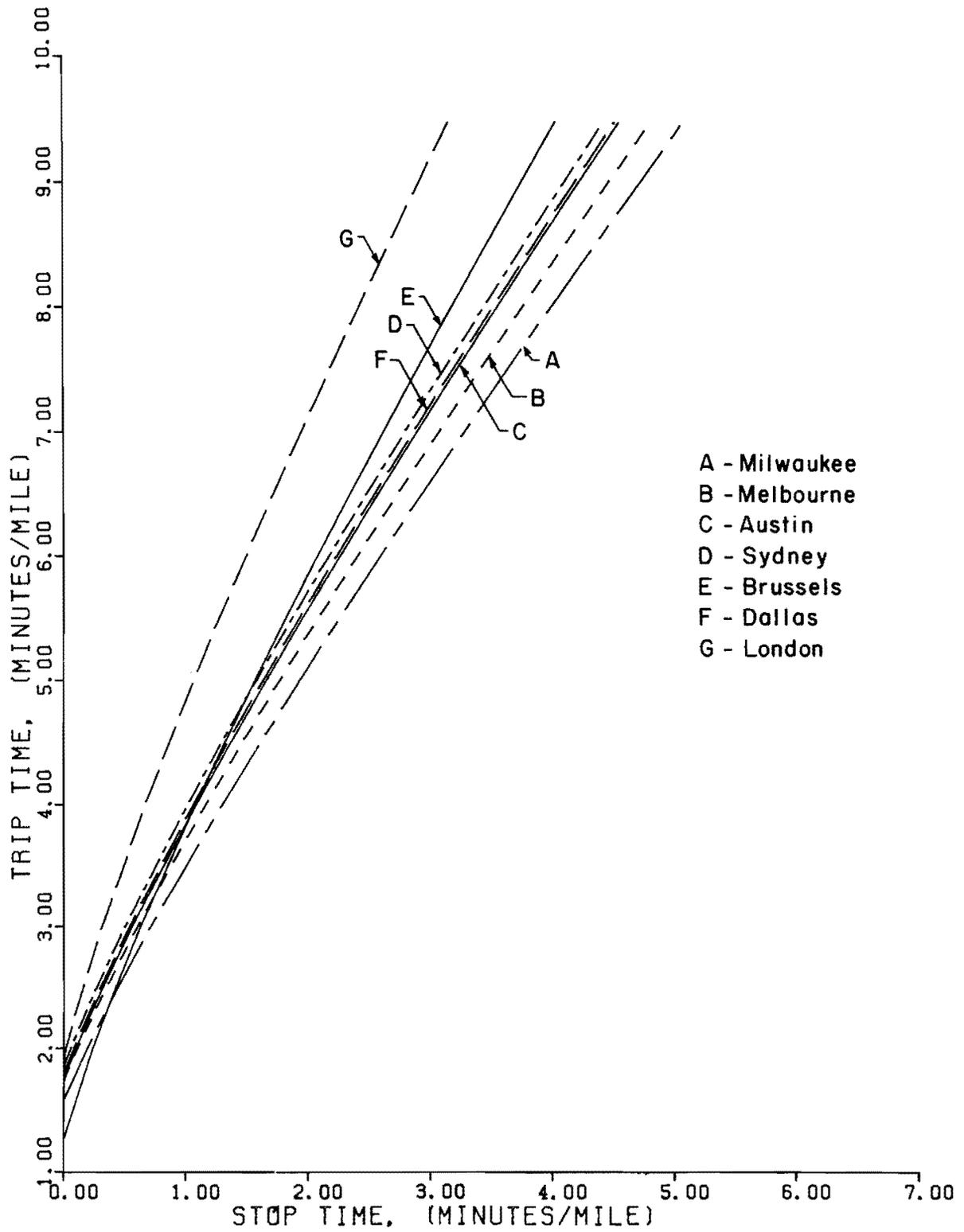


Fig 11. Curvilinear trip time - stop time relations for various metropolitan areas around the world.

general sense to have better traffic engineering and geometric features than those of Sydney, Brussels, and London (Fig 10). For example, the traffic network of London, with many narrow two-way streets, frequent long-cycled uncoordinated traffic signals, heavy pedestrian crossings with pedestrian actuated controls, etc., has a slope of 1.80 while the Dallas network, with wide one-way streets, short-cycled traffic signals, moderate pedestrian crossings, etc., shows a slope of 1.45.

In terms of the Two-Fluid Model the slope of the  $T$  ,  $T_s$  curve is given by

$$dT/dT_s = \left[ 1 - \frac{n}{n+1} (T_m/T)^{\frac{1}{n+1}} \right]^{-1} \quad (33)$$

and depends on  $T$  or  $T_s$  . For the case  $T = 3.0$  min/mi the slopes  $dT/dT_s$  for London and Dallas become 3.07 and 2.03, respectively. For example for London when  $T = 3$  min/mi or 20 mi/hr a change  $\Delta T_s$  in  $T_s$  would lead to a 50 percent larger change in trip time per unit distance.

Apart from the relative value of its slope as a comparison criterion, the  $T$  ,  $T_s$  characteristic curve has another significant property. As the traffic loading on a street network increases, the characteristic curve of that particular network will remain constant while the trip time - stop time data points will move upward along the curve. This property is best depicted in Fig 4, in which, as the data collection proceeded from the offpeak hours to the peak hours, the corresponding data points began to climb upward along the line. The results for Austin and Dallas shown in Figs 3 and 4 agree with the earlier results for various metropolitan areas around the world (Refs 10 and 11), suggesting that in urban traffic the trip time per

unit distance is highly correlated to the stop time per unit distance and that this correlation includes the variation of the traffic density.

The intercept of the characteristic curve for a network with the T-axis represents the average minimum trip time per unit distance (reciprocal of the average maximum speed) achievable in that network. The estimate of this intercept by the Two-Fluid Model is the parameter  $T_m$  (Eq 24) given in Figs 3 and 4. We believe that this estimated value of the average minimum trip time per unit distance is underestimated by the model. In other words, the model predicts a higher average maximum speed than the average maximum speed in the physical street network. The discussion of this issue is taken up in the next chapter.

Nonetheless, the average minimum trip time per unit distance,  $T_m$ , is a quantity that can be used to characterize the traffic network and can be measured independently. It is a quantitative measure of the effect of all the traffic control devices and the geometric characteristics of a network on the average maximum speed in the network.

Clearly, a smaller average minimum trip time per unit distance,  $T_m$ , as given in Figs 12 thru 17, signifies a more efficient system of traffic control devices, a better street network capacity, and a smoother geometric configuration. On the contrary, a large value of  $T_m$  as shown in Fig 18 represents less efficient control devices and street network.

Another available observational value for different data sets is the parameter  $n$  (Eq 23). In the Two-Fluid model  $n$  is a second parameter also capable of characterizing the quality of traffic in an urban network. For a given fraction of the vehicles stopped, the network with the larger value of  $n$  is the one with lower average speed. On the other hand, since the average speed is directly related to the average delay and the fuel

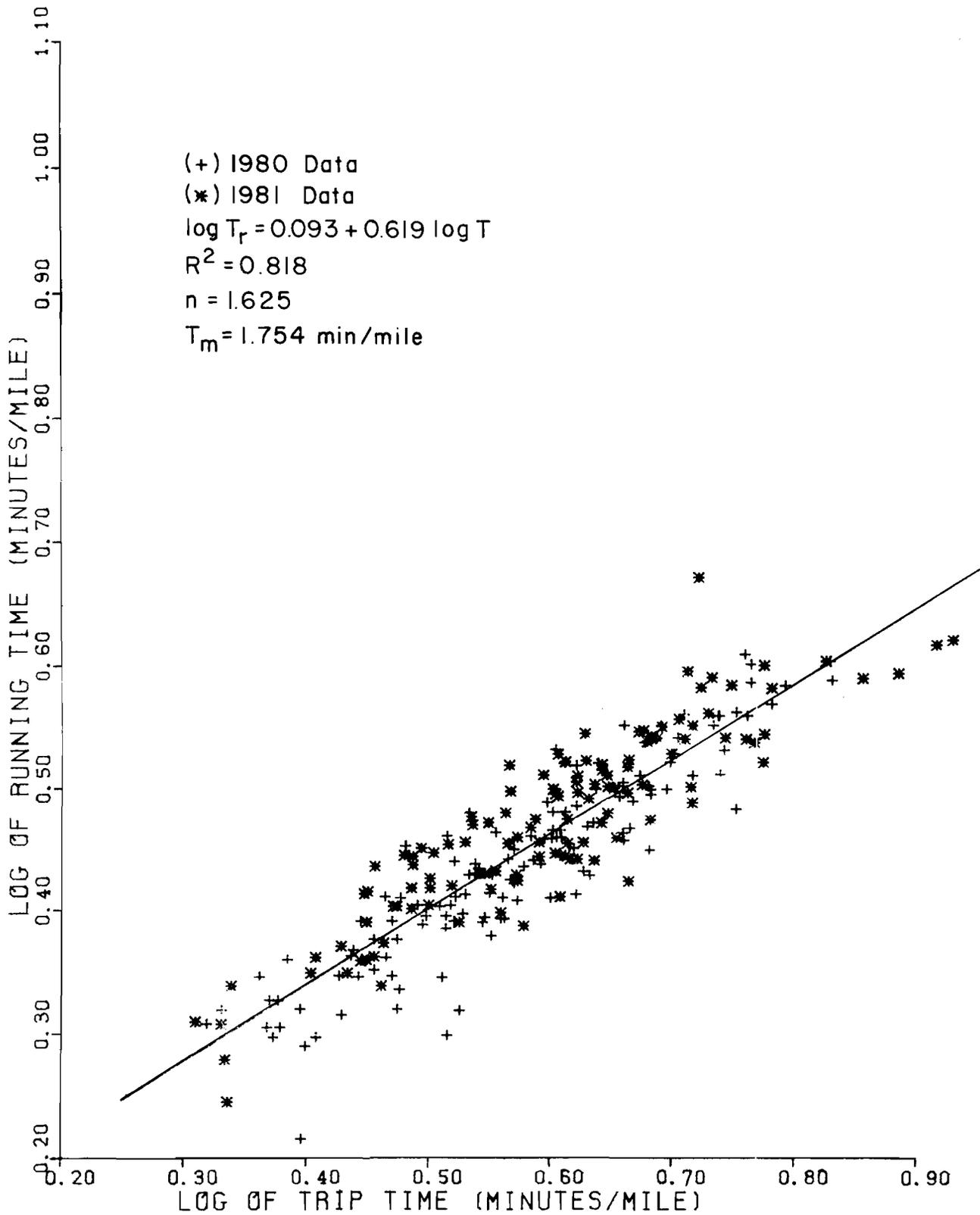


Fig 12. Log of running time versus log of trip time for automobile data in Austin central traffic network.

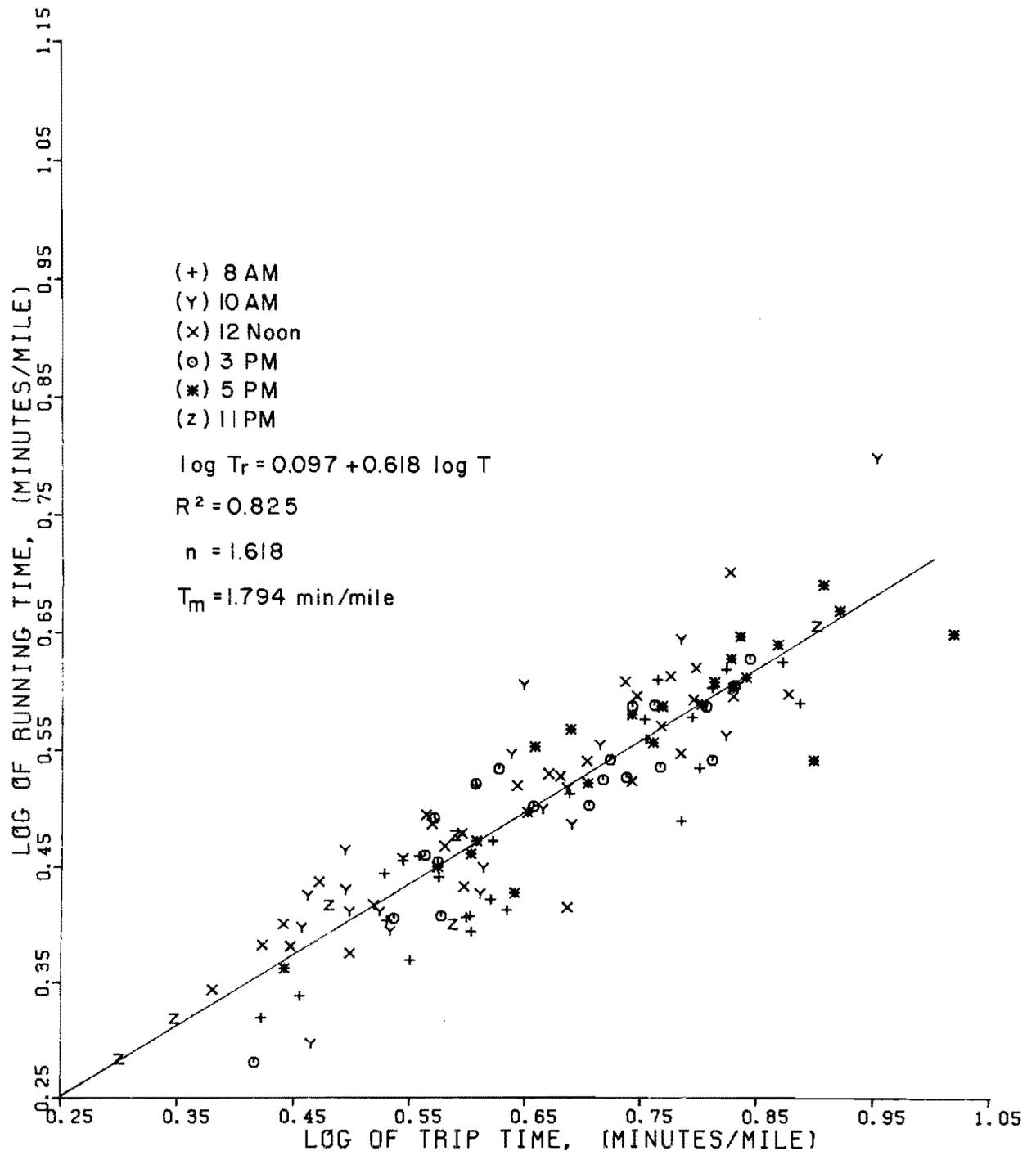


Fig 13. Log of running time versus log of trip time for 1981 automobile data in Dallas central traffic network.

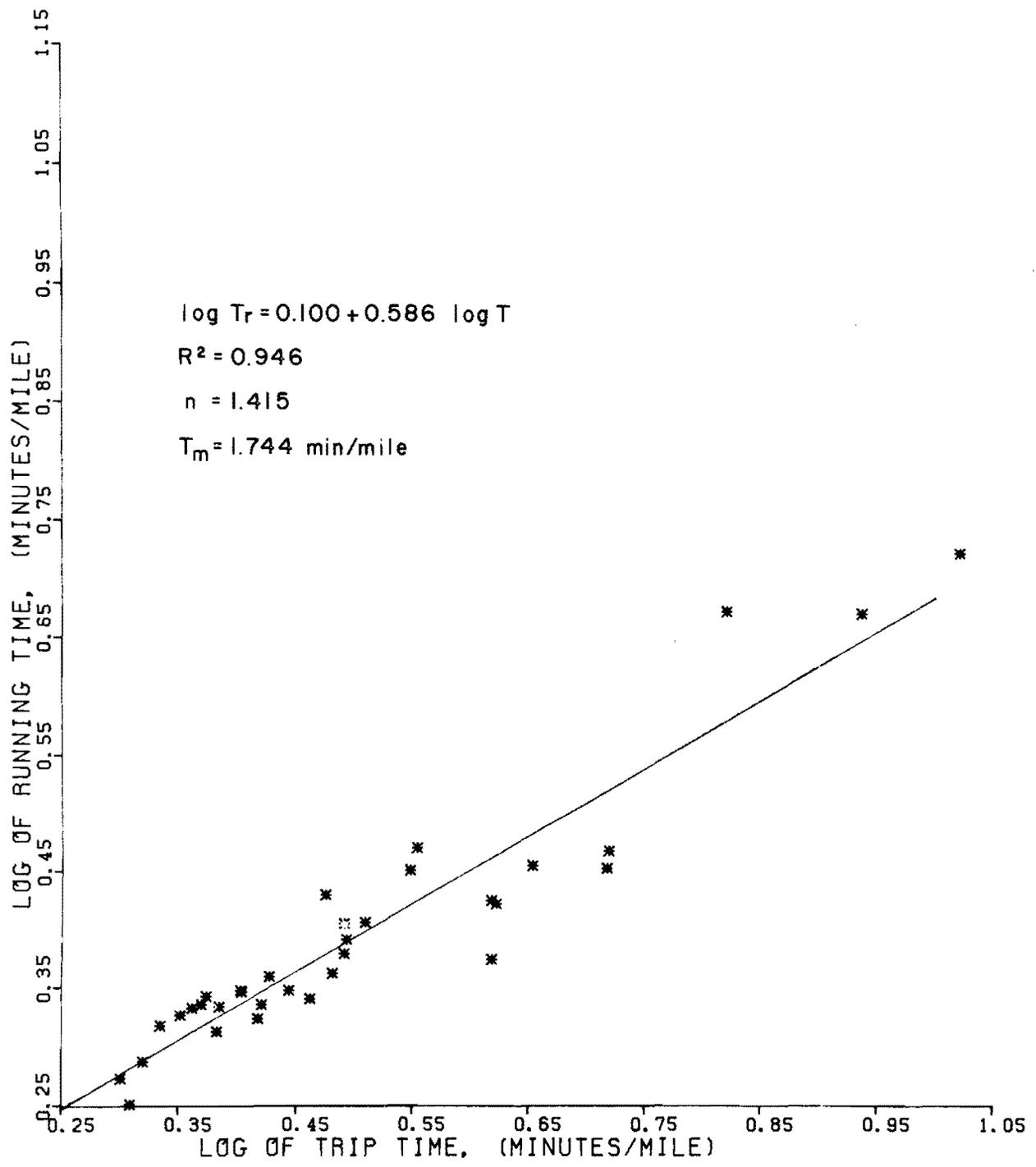


Fig 14. Log of running time versus log of trip time for automobile data from Melbourne, Australia (Refs 3 and 4).

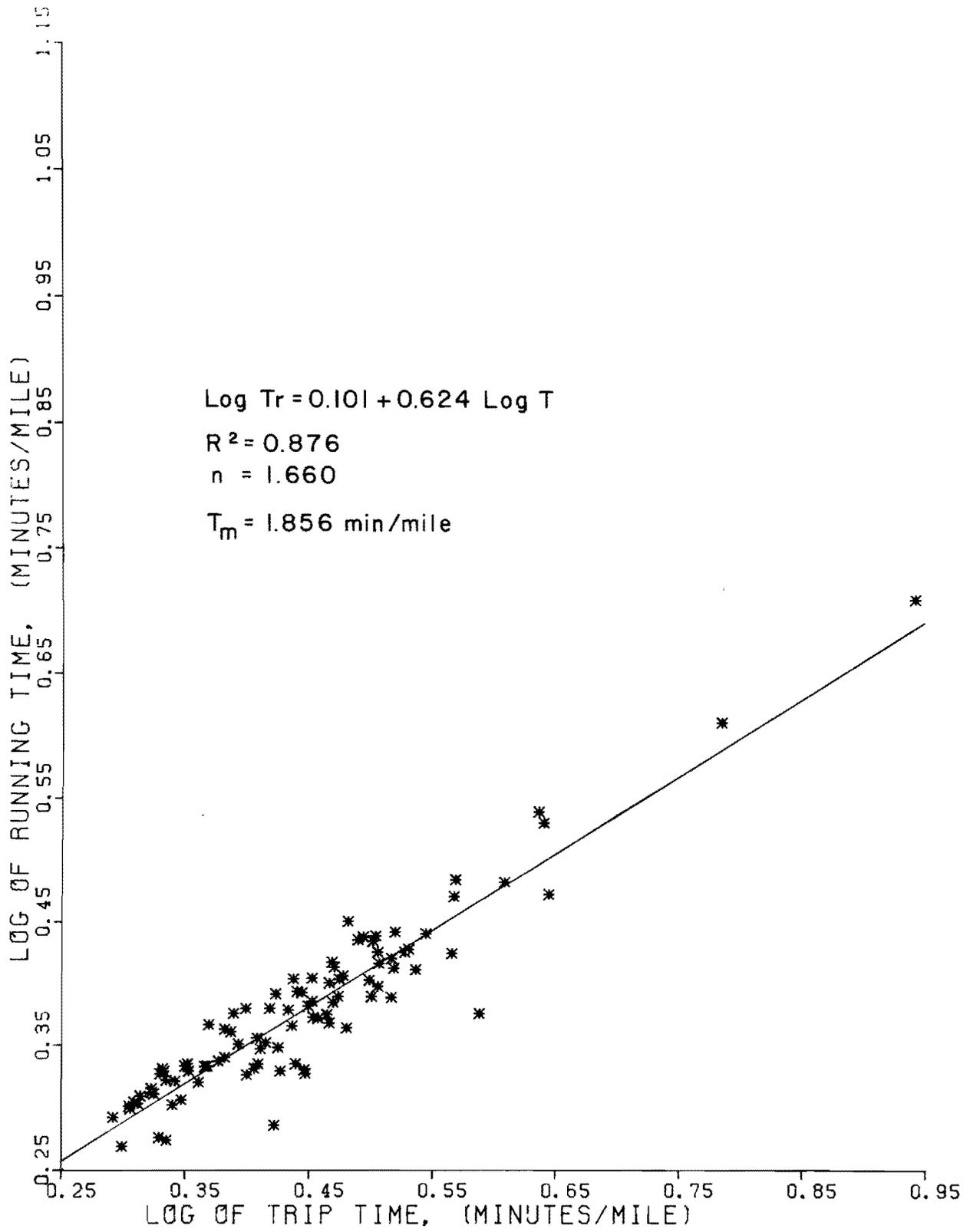


Fig 15. Log of running time versus log of trip time for 1966 automobile data from Sydney, Australia (Refs 4 and 5).

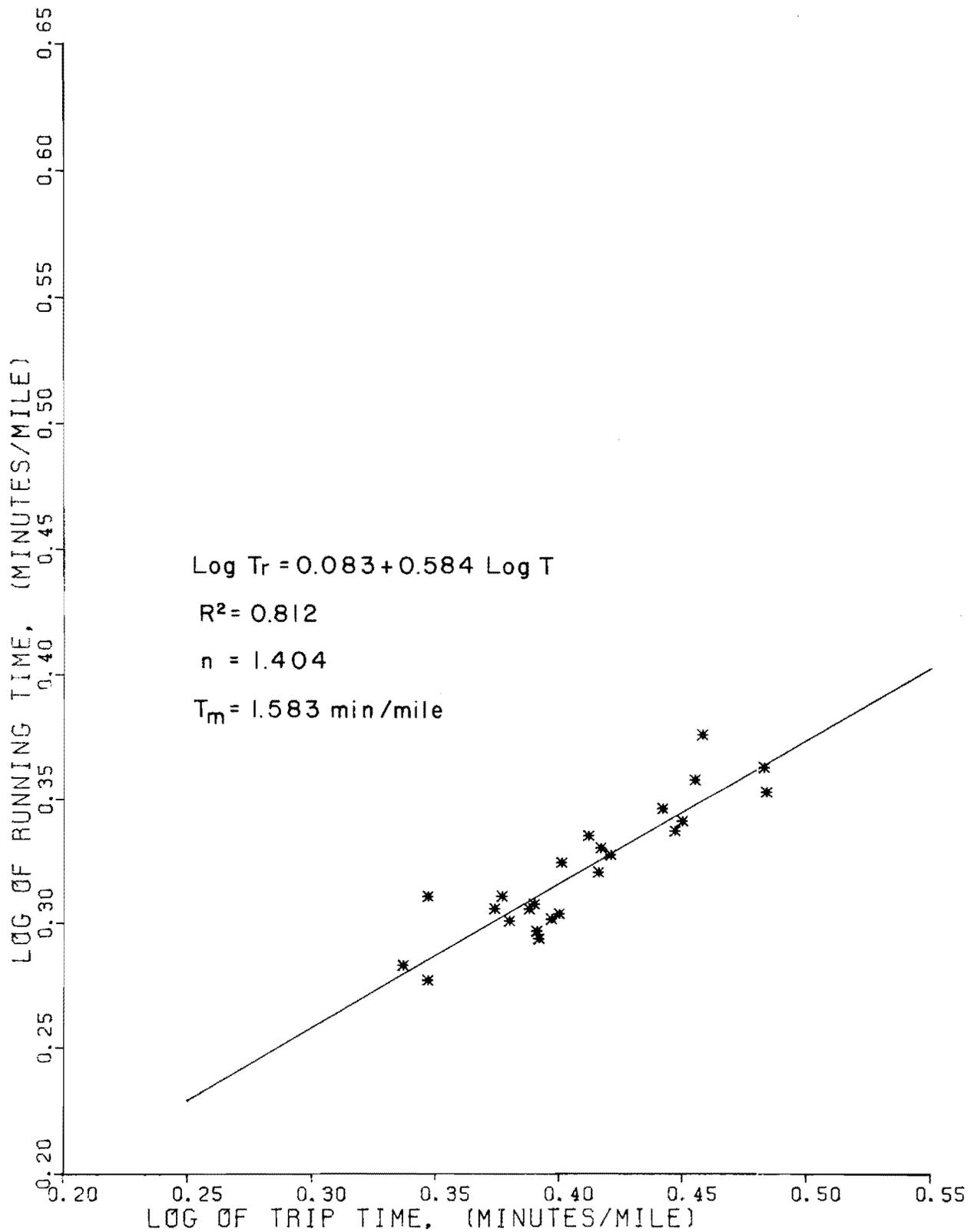


Fig 16. Log of running time versus log of trip time for automobile data from Milwaukee (Ref 6).

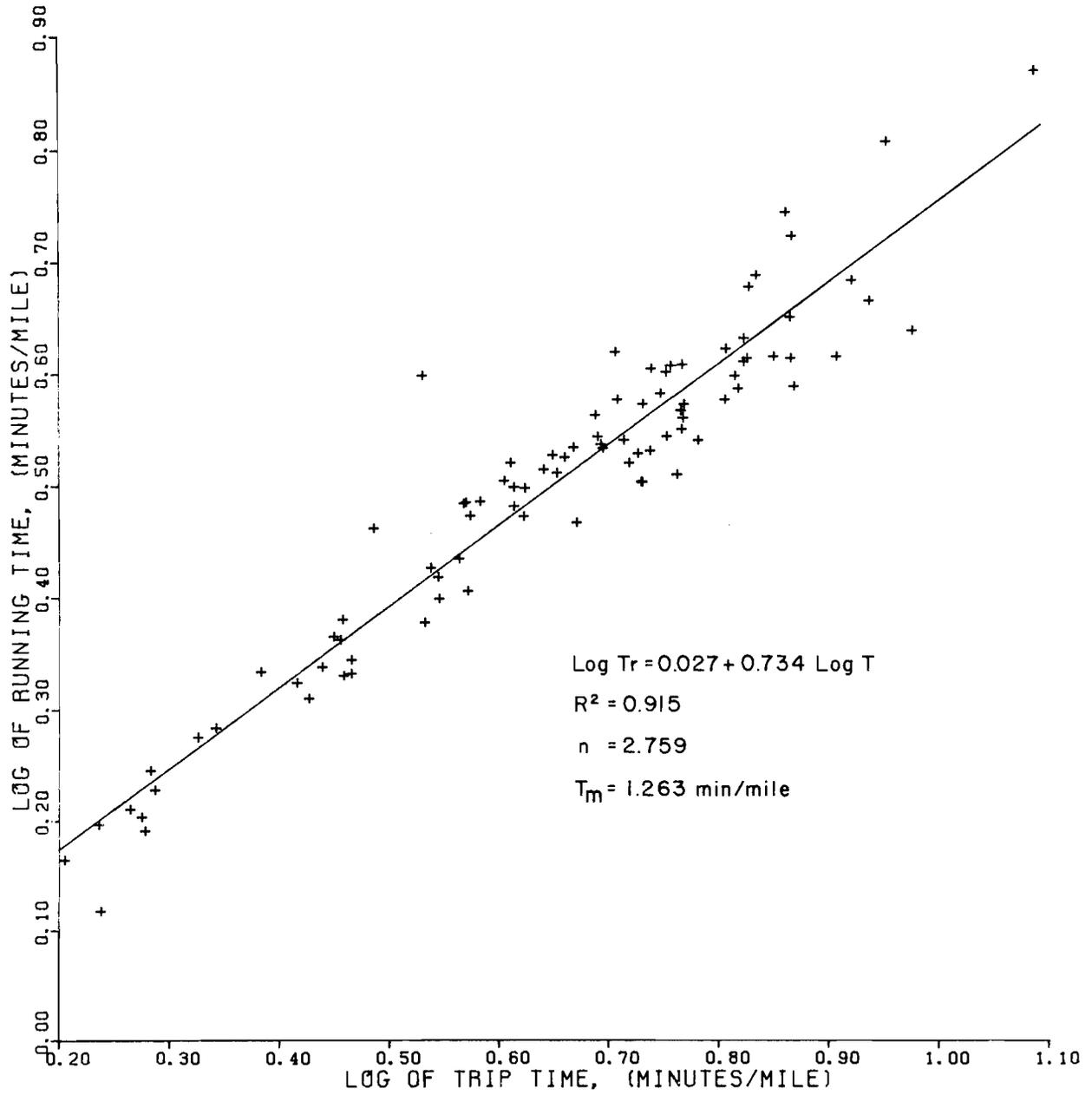


Fig 17. Log of running time versus log of trip time for automobile data in central traffic network of Brussels, Belgium (Ref 8).

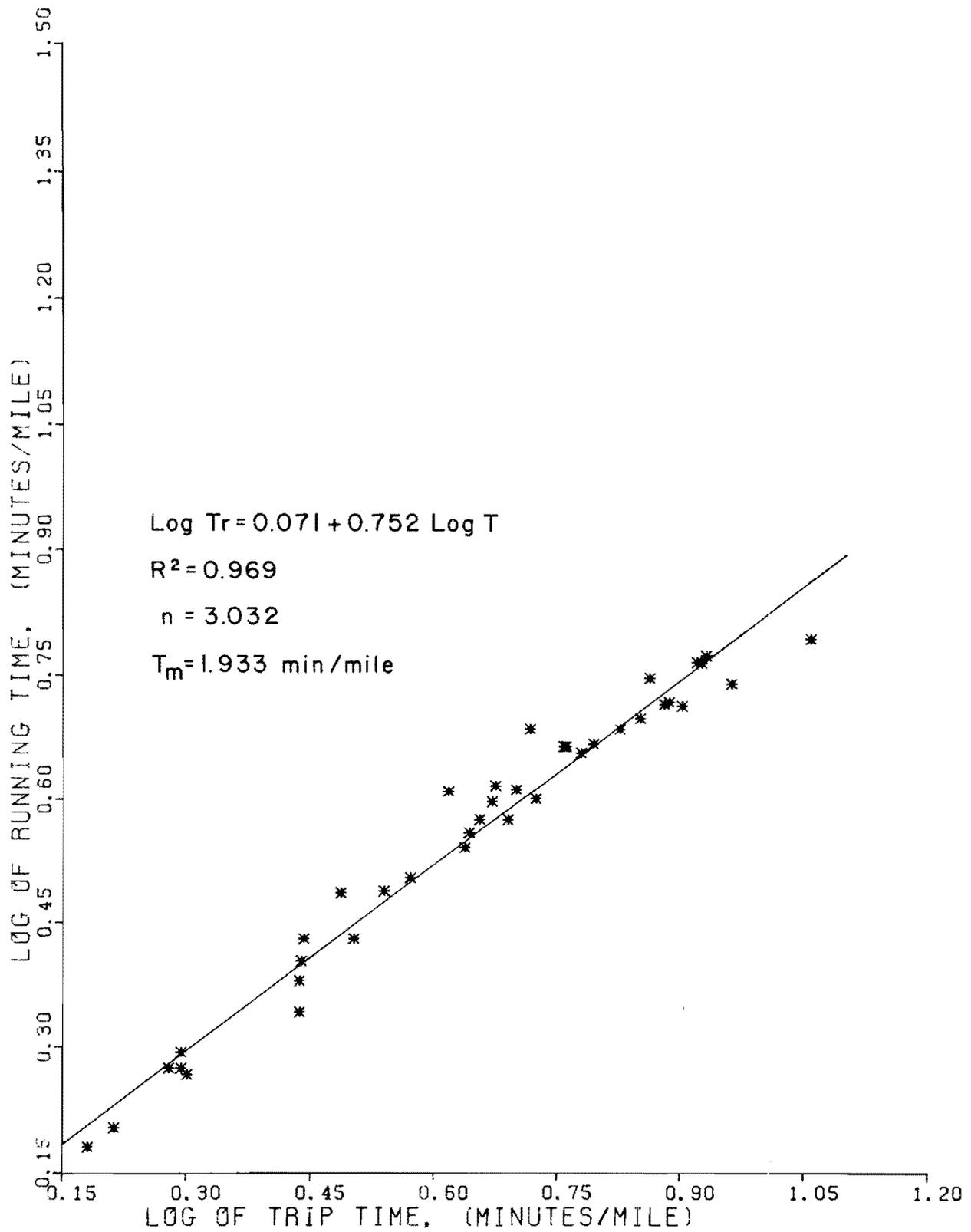


Fig 18. Log of running time versus log of trip time for automobile data from London (Ref 7).

utilization, a lower average speed indicates a poorer quality of traffic service. Therefore the  $n$  values of 3.03 and 2.76 for London and Brussels, respectively, represent less desirable traffic qualities than those of Austin, Dallas, Melbourne, Sydney, and Milwaukee with the respective  $n$  values of 1.63, 1.62, 1.42, 1.66 and 1.40. Table 1 includes the Two-Fluid Model parameters  $T_m$  and  $n$  as well as the intercepts and slopes of both the linear and the logarithmic best-fit regression lines for the traffic networks discussed in this section. Moreover, the table includes the various model parameters obtained from the average trip times, stop times, and running times over nine major U.S. cities, as shown in Figs 19 and 20. In Figs 19 and 20 the data points corresponding to Los Angeles, New York, Chicago, Salt Lake City, and Detroit are the averages of the data collected in the Central Business Districts of these cities for various traffic density conditions. For the remaining four areas, each point is the average of data collected in the Central Business District independent of the traffic density.

Figures 21 and 22 show the linear and logarithmic plots obtained from the observations made aboard the shuttle buses on routes CC, IF, and WC. The low correlation coefficient for the linear case indicates that the trip time per unit distance is not defined sufficiently by the stop time per unit distance alone. Buses are vehicles with low acceleration and deceleration characteristics and slow maneuverability. Although the loading-unloading time is subtracted from the trip time of the shuttle bus, the effect of these loading-unloading stops on the remaining trip time (the automobile-equivalent trip time) is not completely removed. This is so because every stop made for the purpose of passenger loading and unloading will introduce an additional deceleration-acceleration cycle to the trip history of a bus. Thus, the

TABLE 1. MODEL PARAMETERS

City	Linear Representation		Logarithmic Representation		Two-Fluid Model Parameters	
	Intercept (minutes/mile)	Slope	A	B	n	$T_m$ (minutes/mile)
Austin (present study)	2.32	1.54	0.09	0.62	1.63	1.75
Dallas (present study)	2.53	1.45	0.10	0.62	1.62	1.79
Melbourne (Refs 5, 18)	2.00	1.62	0.10	0.59	1.42	1.74
Sydney (Refs 5, 19)	2.06	1.83	0.10	0.62	1.66	1.86
Milwaukee (Ref 20)	1.81	1.61	0.08	0.58	1.40	1.58
London (Ref 22)	2.74	1.99	0.07	0.75	3.03	1.93
Brussels (Ref 22)	2.13	1.80	0.03	0.73	2.76	1.26
Average over nine major U.S. cities (Ref 10)	2.17	2.15	0.06	0.74	2.83	1.74

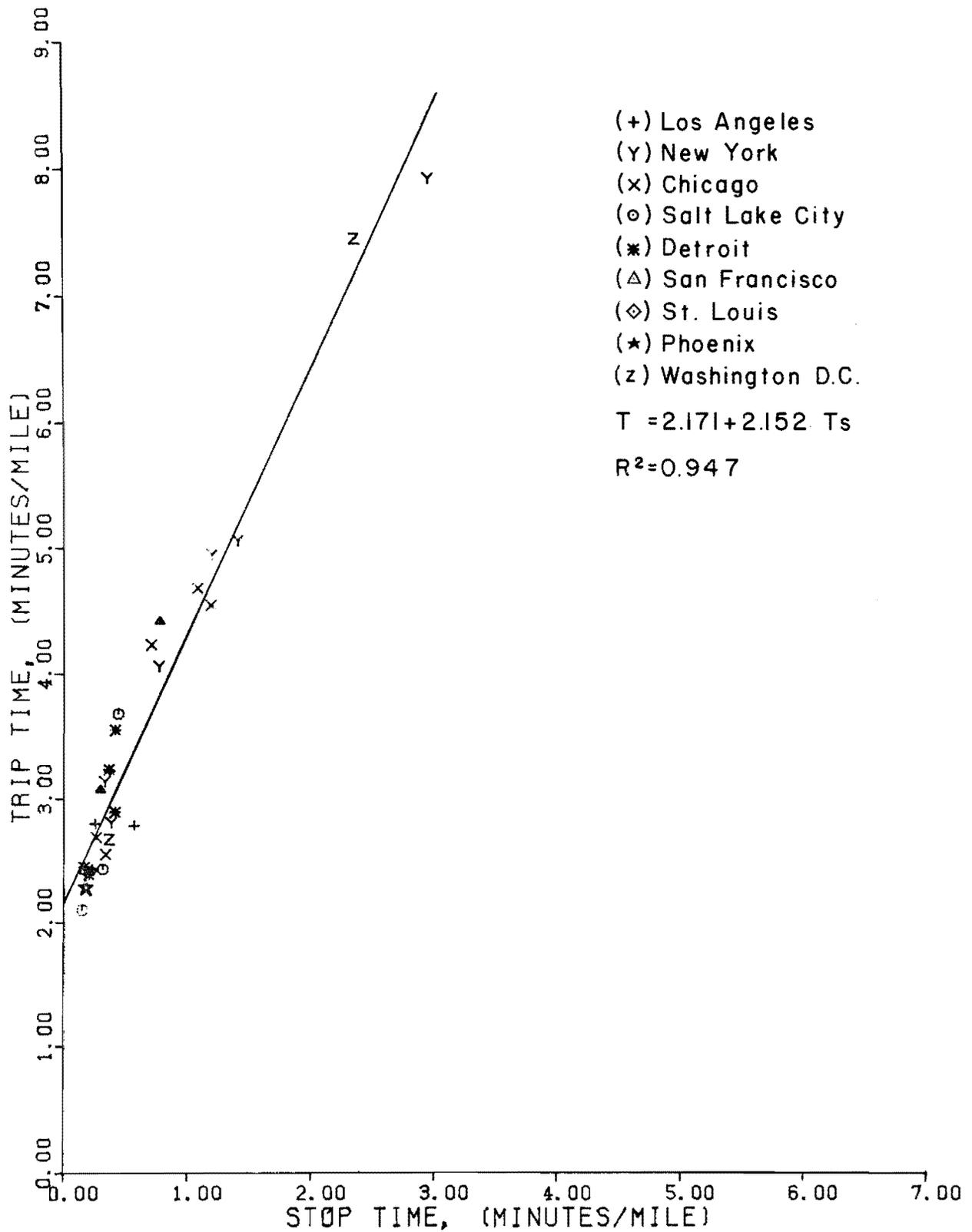


Fig 1). Trip time versus stop time for automobile data from major U. S. cities (Ref 9).

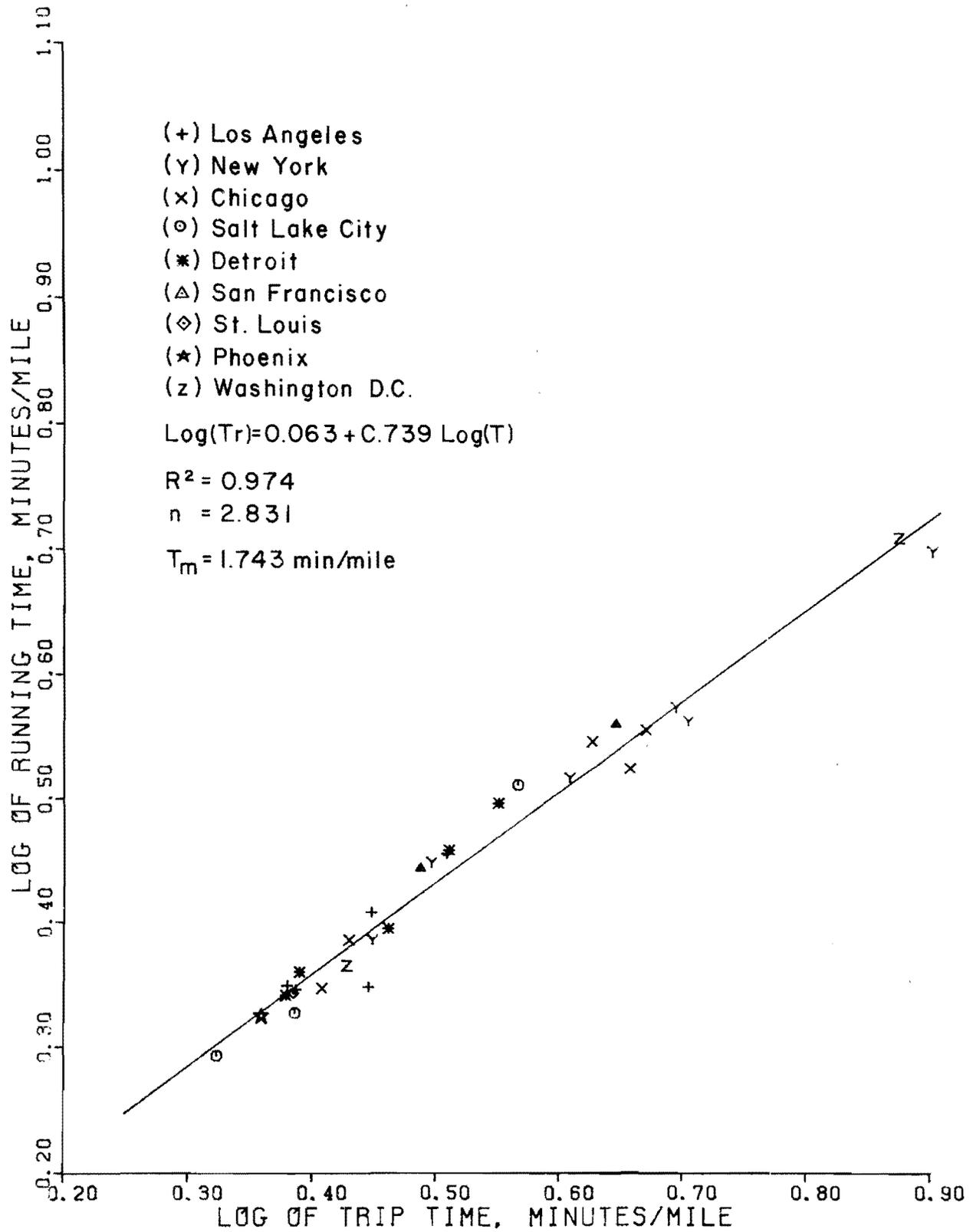


Fig 20. Log of running time versus log of trip time for automobile data from major U. S. cities (Ref 9).

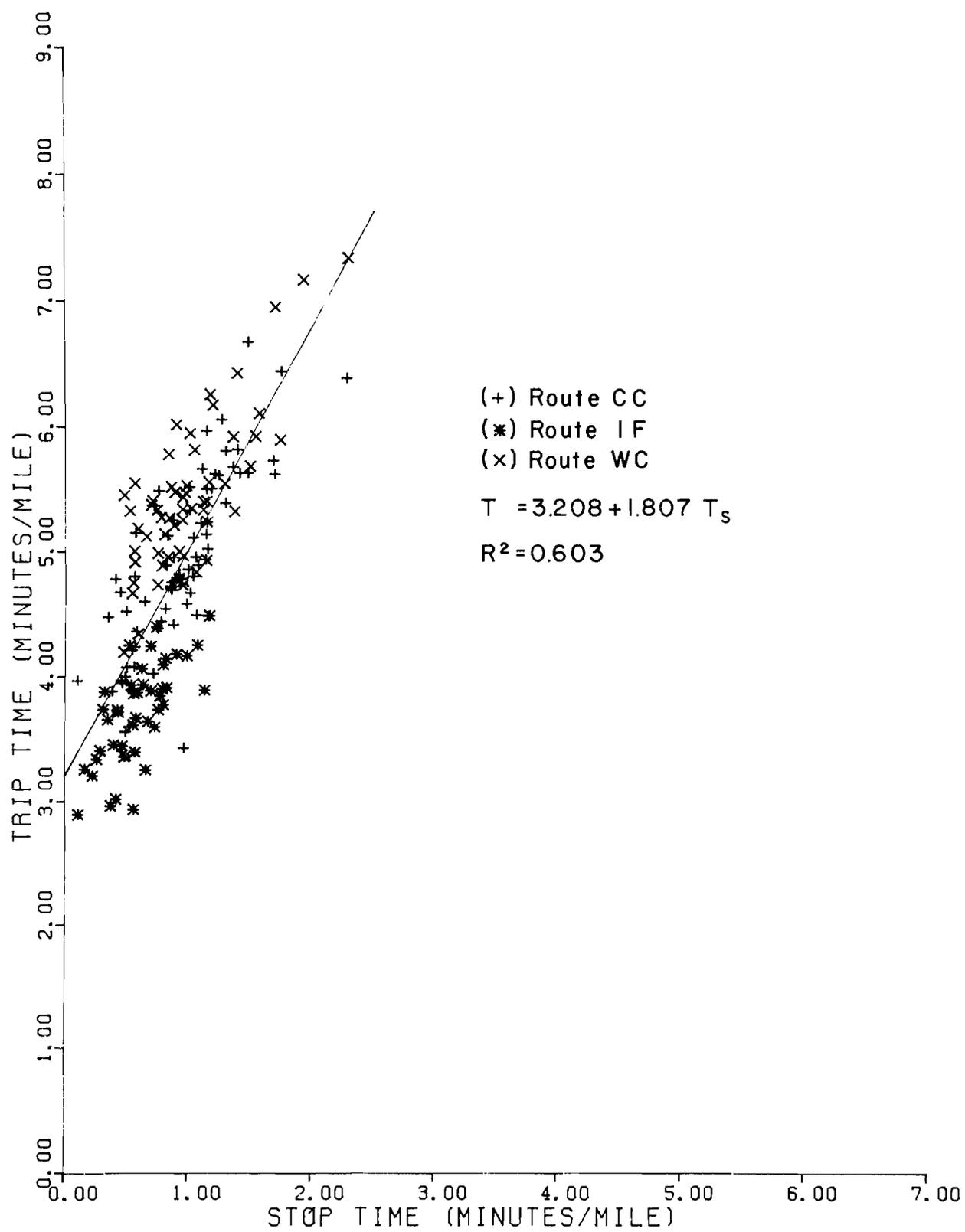


Fig 21. Trip time versus stop time for the Shuttle Bus system, University of Texas at Austin.

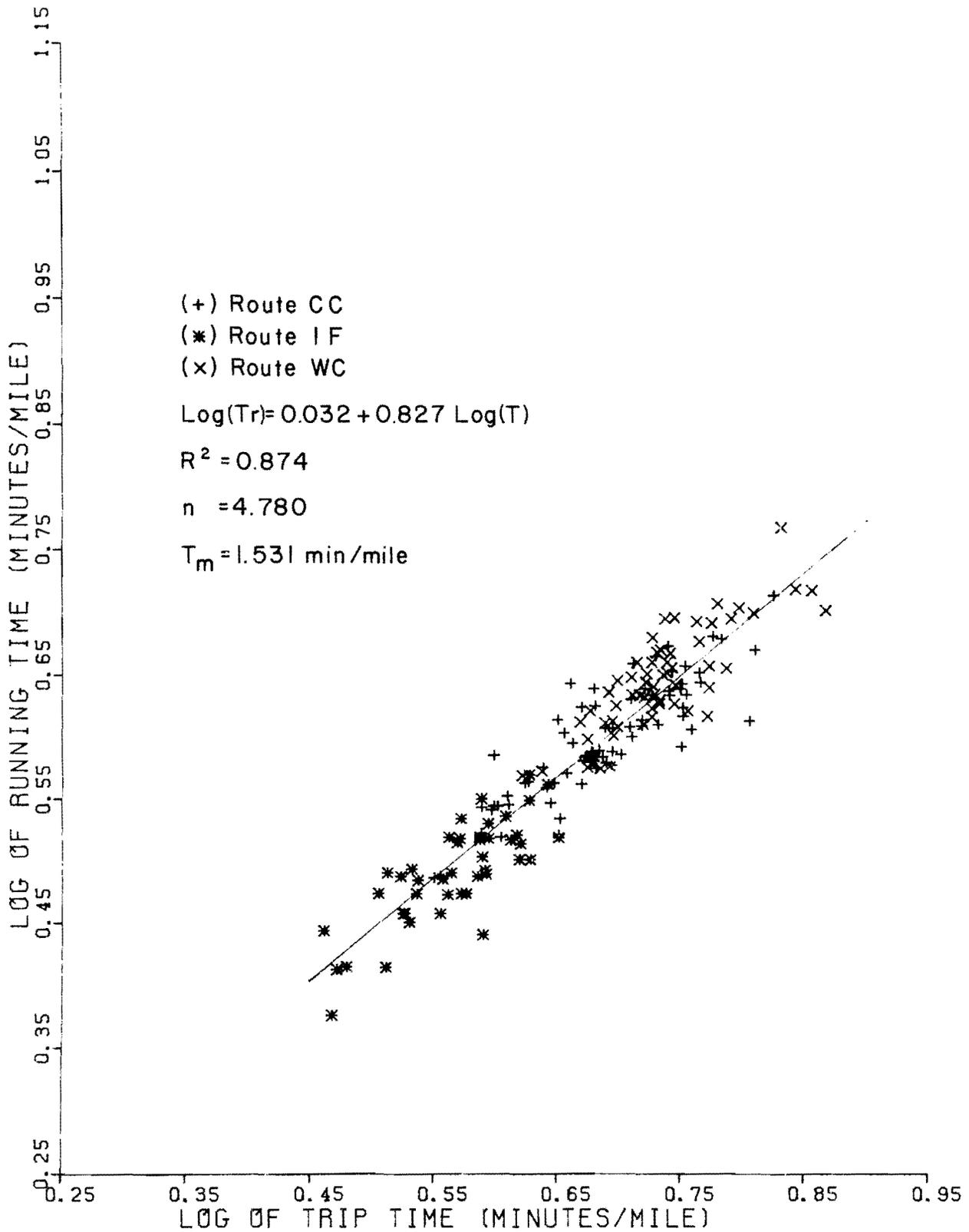


Fig 22. Log of running time versus log of trip time for Shuttle Bus system, University of Texas at Austin.

automobile-equivalent trip time per unit distance for a bus is considerably longer than that for an automobile driven on the same route and subject to identical traffic conditions. In other words the running time per unit distance for the bus is greater; however, the traffic stop time per unit distance for the bus and automobile will be identical. Consequently, the trip time-stop time best-fit line for a bus will be steeper than that for an automobile driven along the same route. A comparison of Figs 21 and 23 illustrates the above point.

Observations indicate that the logarithmic best-fit line ( $\log T_r = A + B \log T$ ) for the shuttle bus data (Fig 22) has a higher value of  $B$  and a lower value of  $A$  than the logarithmic line for the automobiles driven on the same shuttle bus routes (Fig 24). This is consistent with the Two-Fluid theory.

In order to show this, Eqs 23 and 24 are rewritten in the following form:

$$B = \frac{n}{n + 1} \quad (34)$$

and

$$A = (1 - B) \log T_m \quad (35)$$

According to Eq 34, the higher the  $n$  value, the greater is the value of  $B$ . In addition, the value of the parameter  $n$  determined from the shuttle bus data is greater than the value of  $n$  obtained from the automobile data (Figs 23 and 24). Therefore, the value of  $B$  for buses would be greater than the value of  $B$  for automobiles driven on the bus

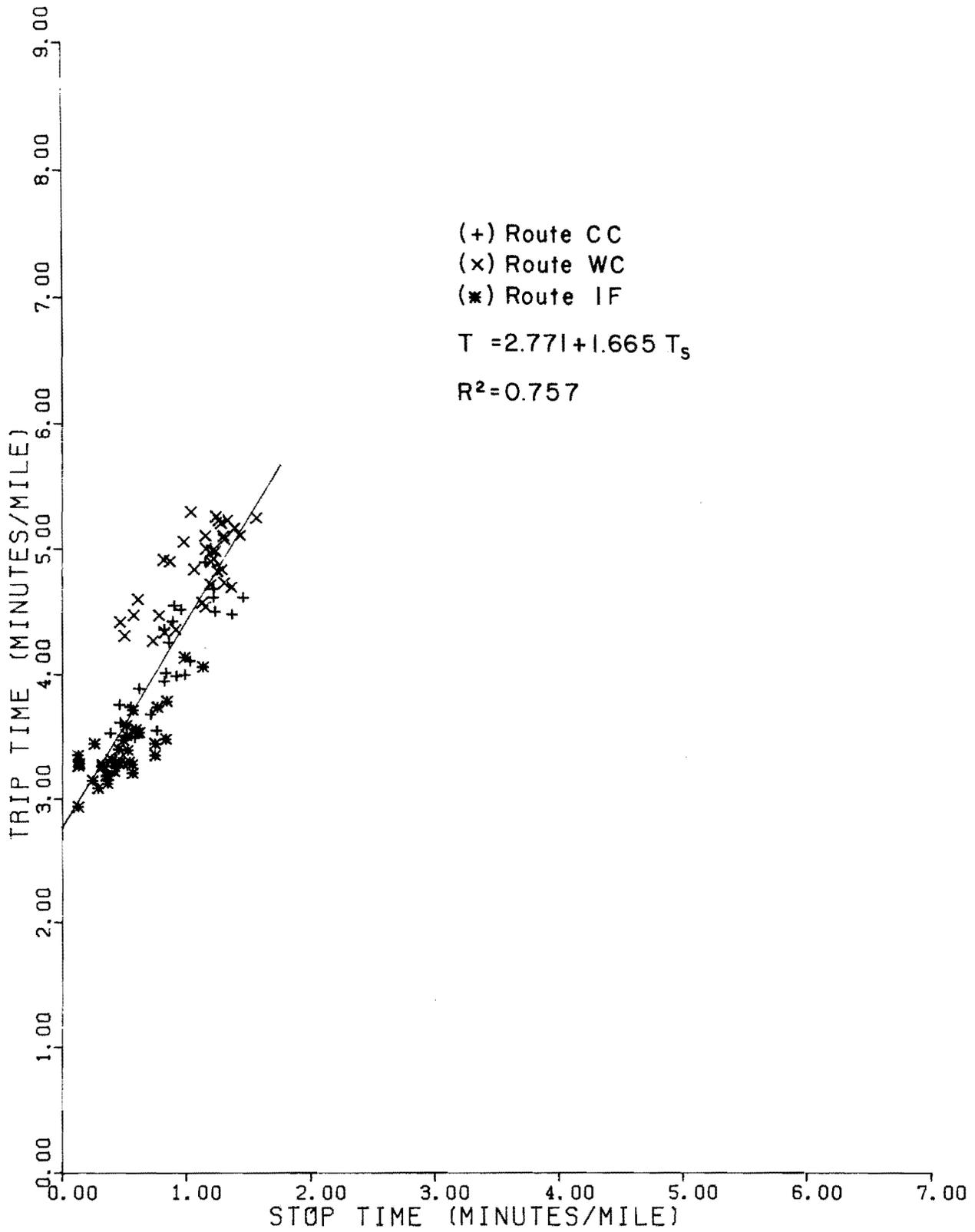


Fig 23. Trip time versus stop time for automobile data on Shuttle Bus routes.

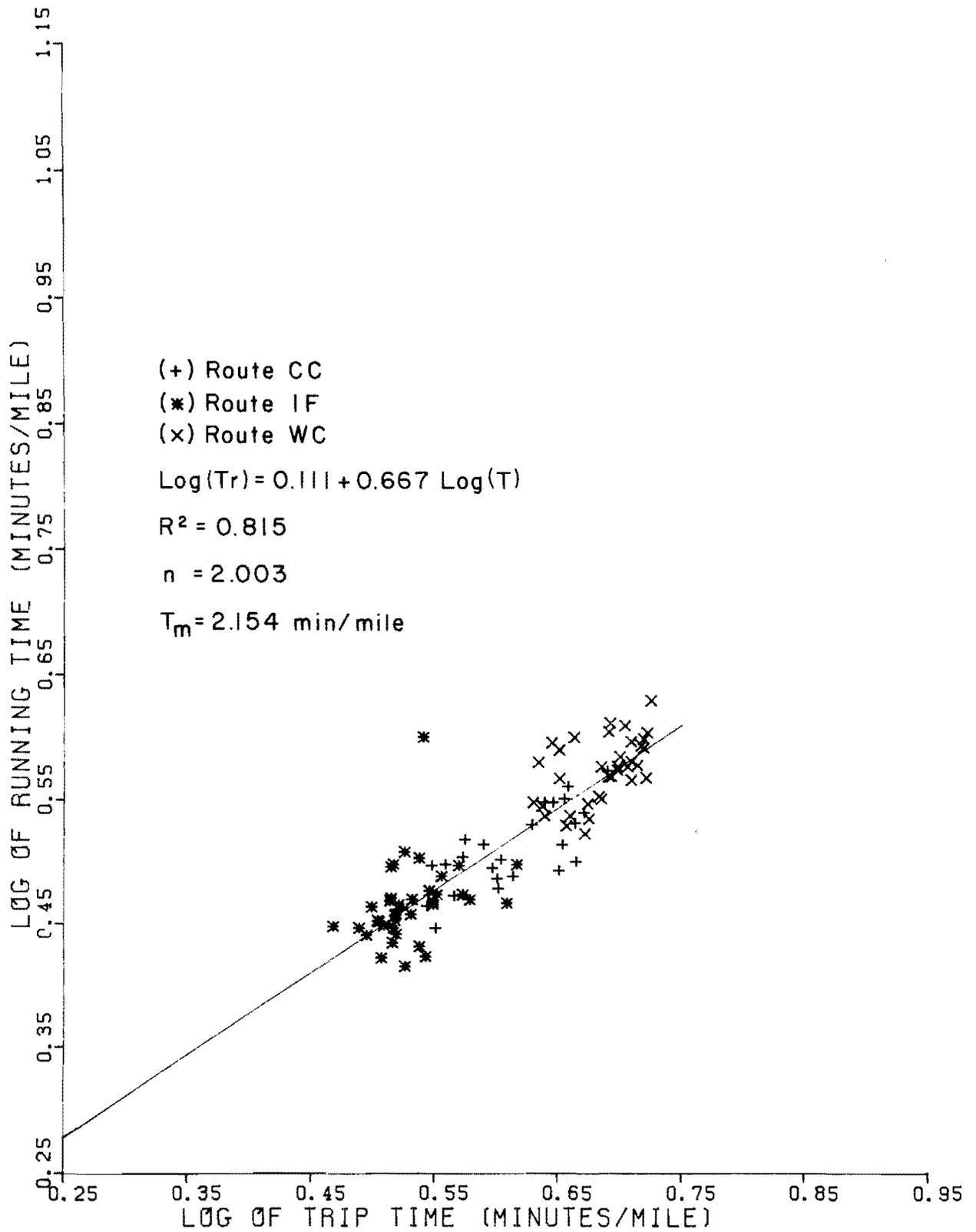


Fig 24. Log of running time versus log of trip time for automobile data on Shuttle Bus routes in Austin.

routes. Furthermore, for a given value of  $T_m$ , as  $B$  increases  $A$  becomes smaller (Eq 35). Therefore, the logarithmic representation of the shuttle bus data would have a greater  $B$  and a smaller  $A$  than its corresponding automobile representation.

#### Analysis of the Data from the Ergodic Experiments

In the Two-Fluid model, the mean fraction of vehicles stopped in a traffic network (excluding parked vehicles) is assumed to be identical to the fraction of time a single vehicle will be stopped while circulating in that network over a long period of time.

To evaluate this assumption, two ergodic traffic experiments were performed in the Central Business District of Austin. The first step toward this evaluation was the determination of the mean fraction of test vehicles stopped,  $f_s$ . To obtain this variable, the absolute time data from all the test vehicles were normalized to a single origin taken as zero time. Next, a computer program was developed to determine, for any given instant of time, the number of test vehicles not moving. The program calculated the ratio of the number of motionless test vehicles,  $N_s$ , to the total number of vehicles involved in the experiment,  $N$ . This ratio is the fraction of the vehicles stopped for that instant of time (i.e., for that entry). Therefore, for a number of entries,  $m$ , the mean fraction of vehicles stopped,  $f_s$ , over some chosen time period can be determined from

$$f_s = \frac{1}{m} \sum (N_s/N)_i, \quad i = 1, 2, \dots, m. \quad (36)$$

Whether the trip-time history of the test vehicles should be accessed at random or in uniform time entries was yet to be investigated. Runs of one thousand random entries and one thousand uniform entries were made for the data from each of the two ergodic experiments. For every entry, an individual fraction of vehicles stopped for that entry alone and a mean fraction of vehicles stopped up to and including that entry in time were calculated. Random entries can only be used for a predetermined time interval while the use of uniform entries allows the subdivision of the total time interval studied in any way desired. For example, one thousand uniform entries, which were originally used over the entire test periods of the first and second experiments, were later employed to determine the mean fraction of vehicles stopped over five-minute intervals, as shown in Figs 25 and 26. This allowed the study of changes in traffic conditions with time. However, as shown in Figs 27 and 28, random accessing converges much more rapidly to the mean of vehicles stopped over the entire test period than uniform accessing. This is shown very clearly in Table 2. In the uniform accessing case the mean is achieved only after all the entries in the entire time period are made. In short, while both uniform and random entries eventually converge on the same value of  $\langle f_s \rangle$ , accessing by uniform time entries also allows the subdivision of the total time interval being studied and therefore is more desirable.

Next, the number of uniform time entries which would provide a reasonably stable value for the mean fraction of vehicles stopped had to be determined. Several trial runs showed that good stability of  $f_s$  was obtained for three-second entries over various test time periods. This stability was not significantly improved by using one-second entries as shown in Table 3. The possibility of using entry intervals longer than three

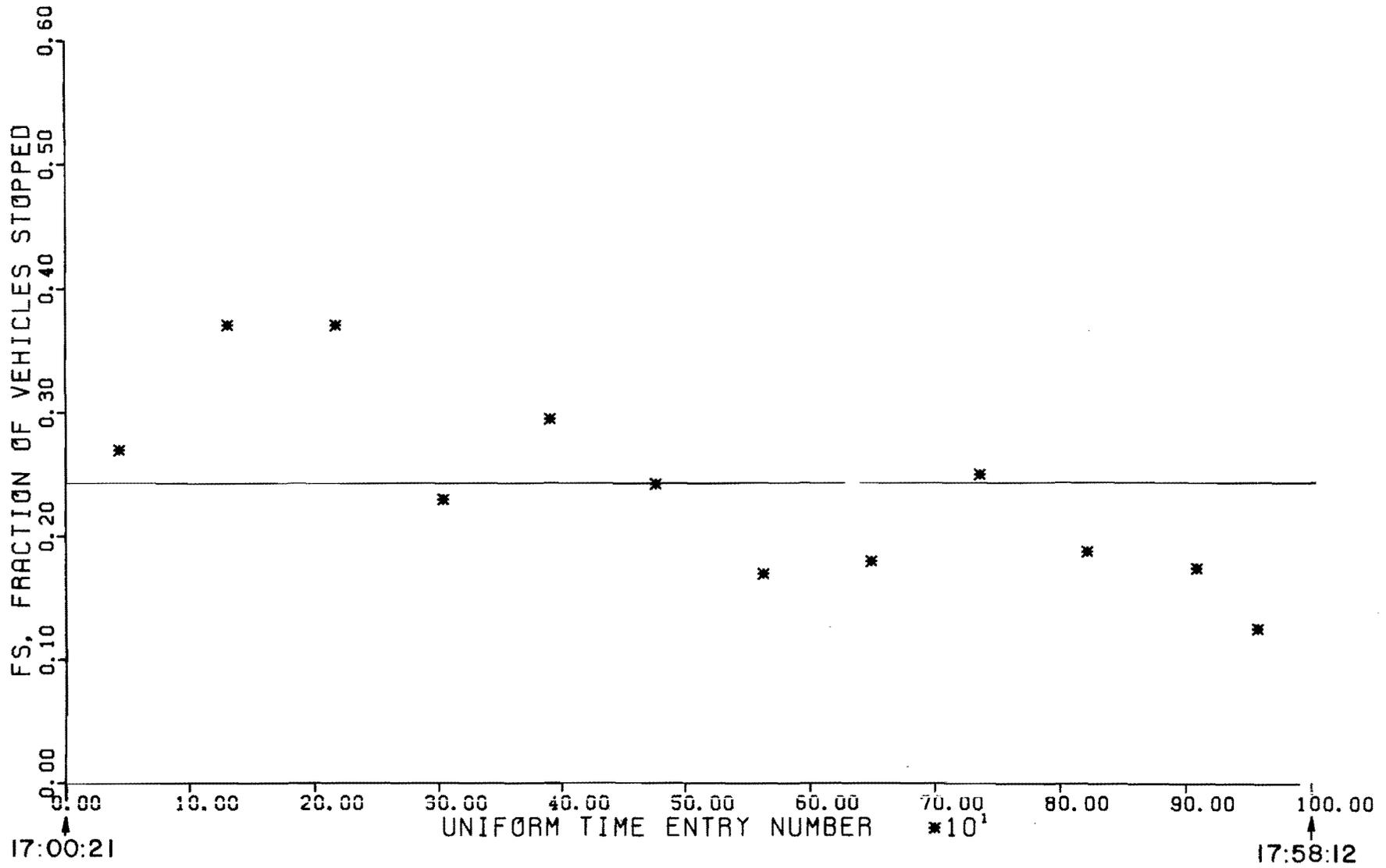


Fig 25. Mean fraction of vehicles stopped for 5-minute periods of the first ergodic experiment in Austin. The total time period of 57'51" was analyzed with 1000 uniform time entries. The last point is for the residual 2'51".

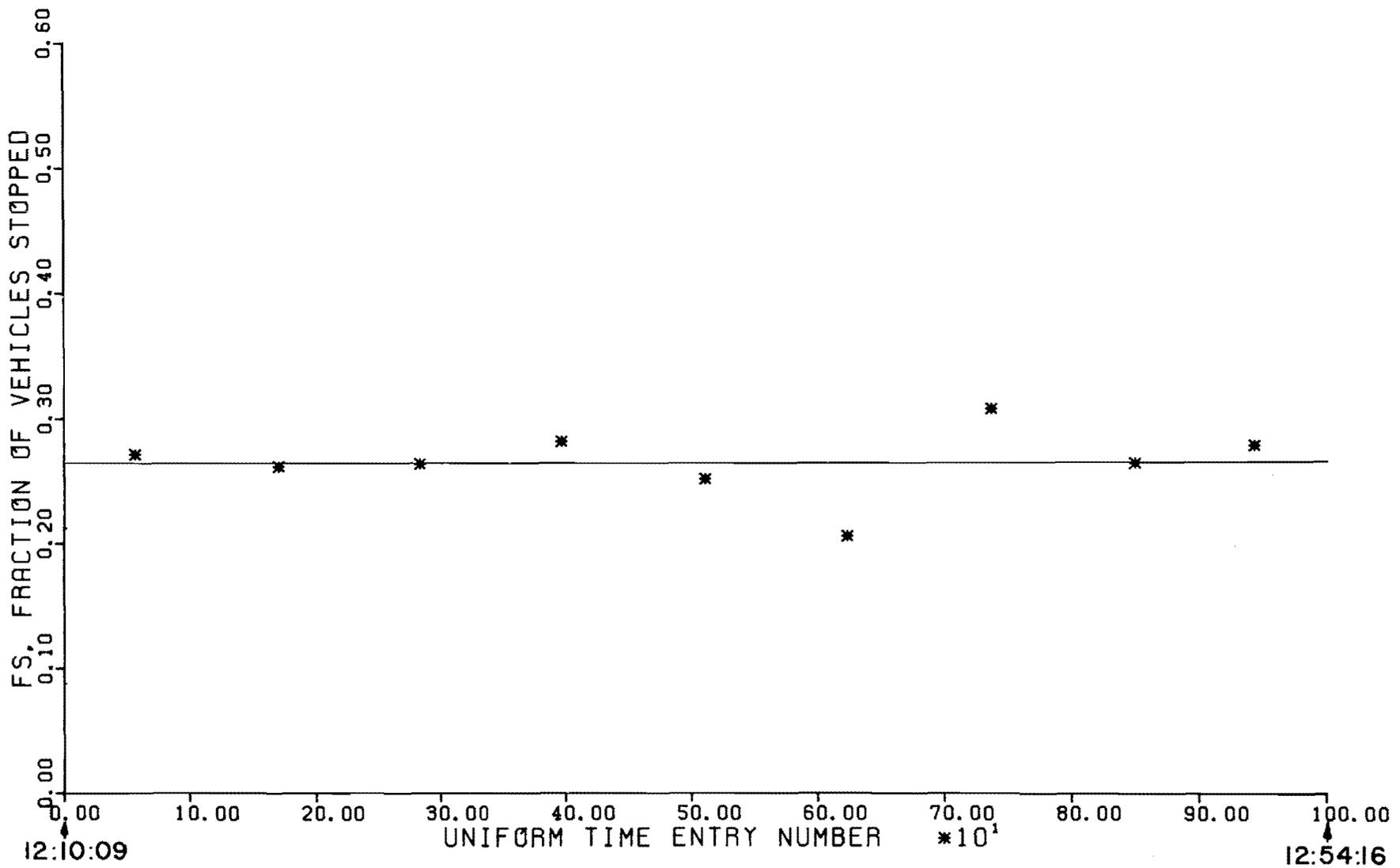


Fig 26. Mean fraction of vehicles stopped for 5-minute periods of the second ergodic experiment in Austin. The total time period of 44'7" was analyzed with 1000 uniform time entries. The last point is for the residual 4'7".

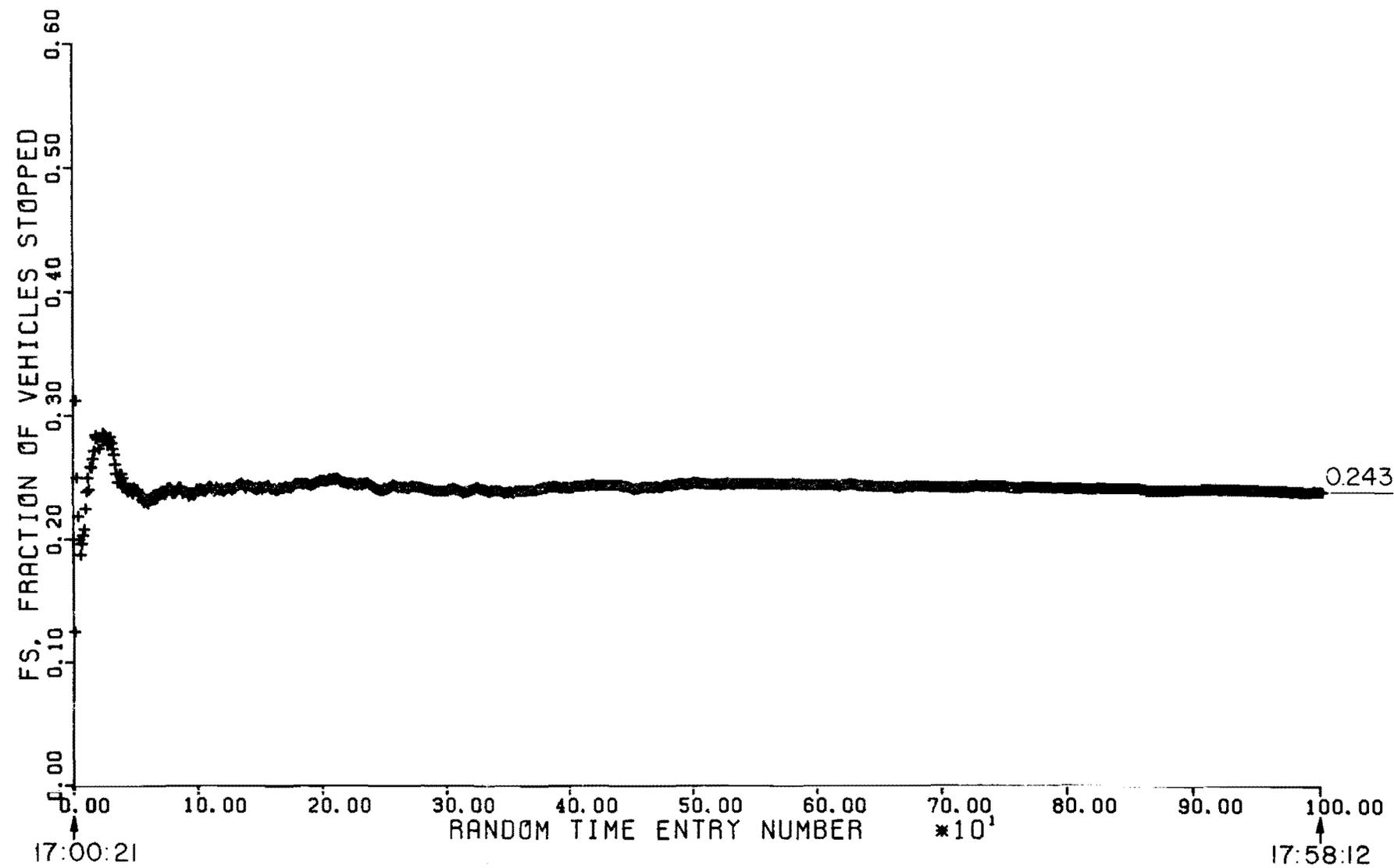


Fig 27. Variation of mean fraction of vehicles stopped with the number of random time entries for the first ergodic experiment in Austin.

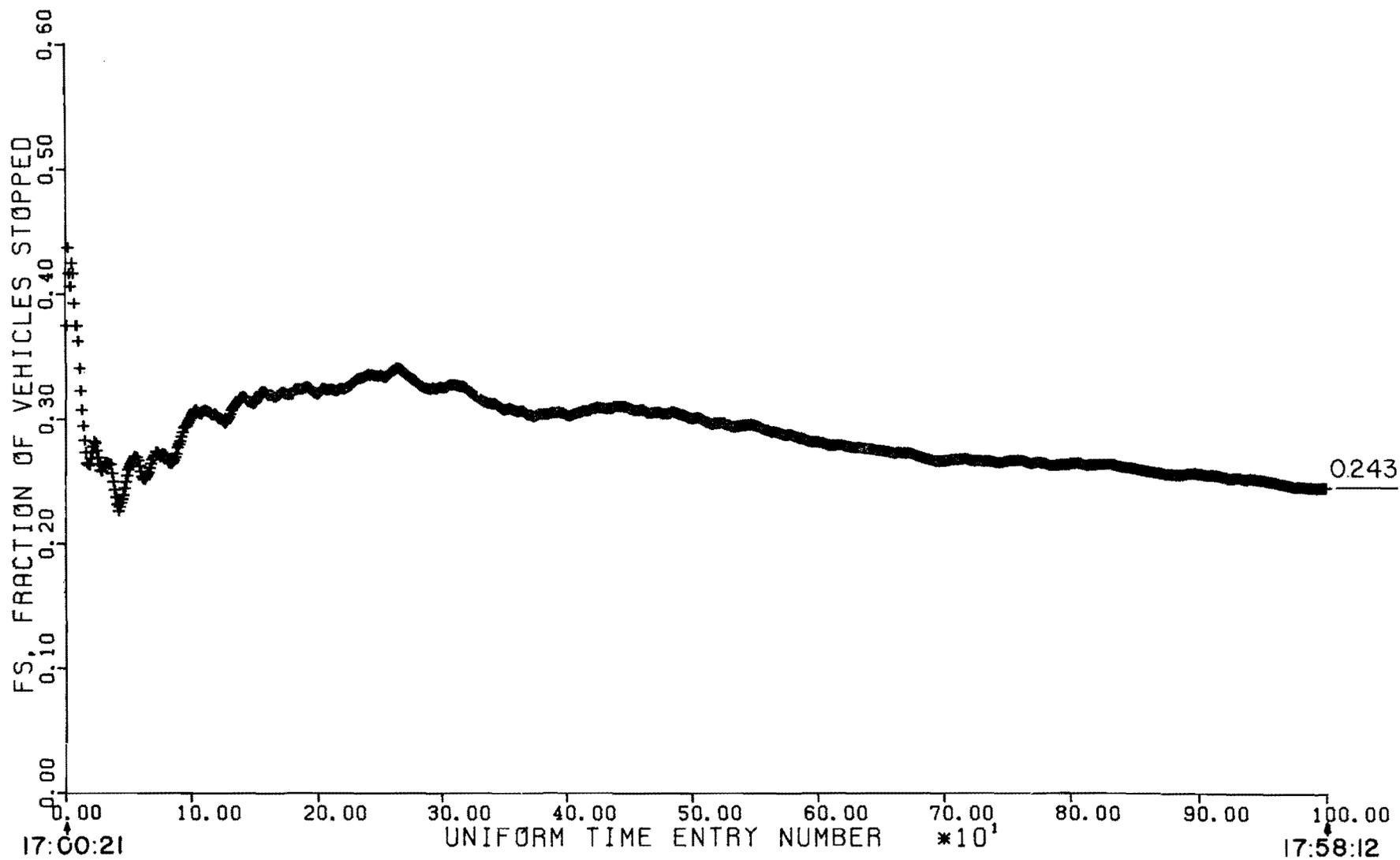


Fig 28. Variation of mean fraction of vehicles stopped with the number of uniform time entries for the first ergodic experiment in Austin.

TABLE 2. FREQUENCY DISTRIBUTION OF THE CUMMULATIVE MEAN  $f_s$  FOR 1000  
RANDOM ENTRIES.

Mean		$f_s$ Frequency
$f_s$ Interval		
Less than .120		0
.120 to .125		1
.125 to .180		0
.180 to .185		1
.185 to .190		0
.190 to .195		2
.195 to .200		1
.200 to .205		1
.205 to .210		0
.210 to .215		1
.215 to .220		1
.220 to .225		1
.225 to .230		10
.230 to .235		256
.235 to .240		582
.240 to .245		118
.245 to .250		3
.250 to .255		2
.255 to .260		1
.260 to .265		2
.265 to .270		3
.270 to .275		3
.275 to .280		9
.280 to .285		1
.285 to .305		0
.305 to .310		1
.310 and Higher		0

TABLE 3. COMPARISON OF THE RESULTS FOR 3-SECOND VERSUS 1-SECOND ENTRIES, FIRST ERGODIC EXPERIMENT

Period	3-Second Entry		1-Second Entry	
	$f_s$		$f_s$	
	Mean	S.D.	Mean	S.D.
17:00:21-05:21	.27000	.14797	.26667	.15096
17:05:21-10:21	.37125	.16469	.37375	.16735
17:10:21-15:21	.37125	.14212	.36958	.14360
17:00:21-58:21	.24299	.16091	.24168	.26296

TABLE 4. MEAN FRACTION OF VEHICLES STOPPED FOR ENTRY INTERVALS OF 3-SECOND AND LONGER

Entry Interval (seconds)	First Experiment		Second Experiment	
	$f_s$		$f_s$	
	Mean	S.D.	Mean	S.D.
3	.24299	.16081	.26440	.20398
4	.24265	.16324	.26082	.20506
5	.24334	.16489	.26087	.20112
6	.24308	.16082	.26259	.20598
7	.24343	.16343	.26190	.19992
8	.23990	.16193	.25879	.20640
10	.24316	.16554	.25379	.20979

seconds was also addressed. Table 4 indicates that the mean fraction of vehicles stopped shows a great insensitivity to the size of the entry intervals. However, as the time intervals become longer, the probability of a short-duration stop-start cycle not being sampled increases rapidly. As a result, many short-duration events will be ignored in a sampling process involving a large uniform time entry interval. Therefore, for the purpose of the ergodic experiments, a uniform 3-second entry interval was used. This was both practical and sufficiently informative. Nevertheless, there is a need of further effort for a better determination of a proper entry interval.

In the next step of the data analysis, the mean fraction of time stopped was calculated for each experiment. Equation 37 was used for this purpose, namely,

$$\langle T_s/T \rangle = \frac{1}{k} \sum (T_s/T)_j, \quad j = 1, 2, \dots, k \quad (37)$$

where  $k$  is the number of test vehicles involved in each experiment. Then the mean fraction of vehicles stopped and the fraction of time stopped for each individual vehicle were compared. The comparison had to be made for a time period sufficiently long to allow each individual test vehicle to properly sample the test area and thereby obtain stable average values of the fractions of time stopped. For each experiment several time periods were selected and for each selection the mean and the standard deviation of the fractions of time stopped were calculated as shown in Tables 5 and 6. As anticipated, the standard deviations decreased with a decrease in the size of the observational network area and an increase in the duration of the analysis period. The reader is reminded that the test areas for the first and second ergodic experiments were about 1.5 x 3.0 miles and 0.7 x 1.0

TABLE 5. MEAN AND STANDARD DEVIATION OF  $T_s/T$  FOR VARIOUS ANALYSIS PERIODS FOR THE FIRST ERGODIC EXPERIMENT

Period No.		Period Duration					
		5 Min	10 Min	15 Min	20 Min	30 Min	57.9 Min
1	Mean	.26626	.31941	.33681	.30886	.29515	.24201
	S.D.	.22071	.15061	.13118	.09196	.06075	.03010
2	Mean	.37256	.29830	.25348	.22190	.18478	
	S.D.	.12864	.06359	.06857	.06043	.03447	
3	Mean	.37160	.26772	.19933	.18966		
	S.D.	.17179	.08179	.03536	.06283		
4	Mean	.22500	.17608	.16780			
	S.D.	.09558	.07683	.04572			
5	Mean	.29874	.21689				
	S.D.	.11683	.12433				
6	Mean	.23669	.15497				
	S.D.	.14650	.04413				
7	Mean	.17545					
	S.D.	.08194					
8	Mean	.17670					
	S.D.	.14065					
9	Mean	.24584					
	S.D.	.14501					
10	Mean	.18793					
	S.D.	.12528					
11	Mean	.17166					
	S.D.	.07119					
12	Mean	.12569					
	S.D.	.09265					
Average of Means		.23784	.23890	.23936	.24014	.23997	.24201
Average S.D.		.12806	.09021	.07021	.07174	.04761	.03010

TABLE 6. MEAN AND STANDARD DEVIATION OF  $T_s/T$  FOR VARIOUS ANALYSIS PERIODS FOR THE SECOND ERGODIC EXPERIMENT

Period No.		Duration			
		5 Min	10 Min	15 Min	44.1 Min
1	Mean	.27397	.27066	.26887	.26533
	S.D.	.11986	.08777	.06892	.03026
2	Mean	.26734	.27131	.24640	
	S.D.	.06742	.06617	.02737	
3	Mean	.26529	.23094	.28163	
	S.D.	.10947	.04609	.03108	
4	Mean	.27732	.28258		
	S.D.	.03045	.02272		
5	Mean	.25269	.27933		
	S.D.	.05082	.08948		
6	Mean	.20919			
	S.D.	.07315			
7	Mean	.30187			
	S.D.	.02462			
8	Mean	.26328			
	S.D.	.05194			
9	Mean	.27933			
	S.D.	.08948			
Average of Means		.26559	.26696	.26563	.26533
Average S. D.		.06858	.06245	.04246	.03026

miles, respectively (see Chapter 3).

For both the first and the second ergodic experiments, the variation in the fractions of time stopped of the test vehicles was rather low for the 15-minute analysis periods (Tables 5 and 6). For example, the means of the standard deviations for the 5, 10 and 15-minute intervals in the first experiment were 0.13, 0.09, and 0.07, respectively; while the corresponding values for the second experiment were 0.07, 0.06, and 0.04.

#### Results of the Ergodic Experiments

The mean fraction of test vehicles stopped is identical to the mean fraction of time stopped for both experiments as shown in Tables 7 and 8. Furthermore, the values of the fractions of time stopped for individual vehicles are within 1.5 to 2.0 standard deviations from the mean value over all the vehicles for the 15-minute periods of the two experiments as shown in Table 9. These variations around the mean decrease considerably as the duration of the analysis period increases. Consequently, the variations of the individual fractions of time stopped for the entire test period fall within 1.4 standard deviations of their mean value as shown in Table 10. Therefore, over a long period of time, the dispersion of the fractions of time stopped around their mean can be fairly assumed to be small. Thus, again over a long period of time, the fraction of time stopped for each individual test vehicle is assumed to converge to the mean fraction of time stopped for all the vehicles and again be identical to the mean fraction of vehicles stopped. These results are in agreement with the ergodic assumption of the Two-Fluid Model (Eq 3).

TABLE 7. MEAN FRACTION OF VEHICLES STOPPED AND MEAN FRACTION OF TIME STOPPED FOR 5-MINUTE PERIODS OF THE FIRST ERGODIC EXPERIMENT

Period	$f_s$		$T_s / T$	
	Mean	S.D.	Mean	S.D.
17:00:21-05:21	.27000	.14797	.26626	.22071
17:05:21-10:21	.37125	.16469	.37256	.12864
17:10:21-15:21	.37125	.14212	.37160	.17171
17:15:21-20:21	.23000	.16513	.22500	.09558
17:20:21-25:21	.29500	.14057	.29874	.11683
17:25:21-30:21	.24250	.16879	.23669	.14650
17:30:21-35:21	.17000	.13180	.17545	.08194
17:35:21-40:21	.18000	.10993	.7670	.14065
17:40:21-45:21	.25000	.14918	.24584	.14501
17:45:21-50:21	.18750	.12980	.18793	.12528
17:50:21-55:21	.17375	.14193	.17166	.07119
17:55:21-58:12	.12500	.11811	.12569	.09265
17:00:21-58:12	.24299	.16091	.24201	.03010

TABLE 8. MEAN FRACTION OF VEHICLES STOPPED AND MEAN FRACTION OF TIME STOPPED FOR 5-MINUTE PERIODS OF THE SECOND ERGODIC EXPERIMENT

Period	$f_s$		$T_s / T$	
	Mean	S.D.	Mean	S.D.
12:10:09-15:09	.27200	.19583	.27397	.11986
12:15:09-20:09	.26200	.20154	.26734	.06742
12:20:09-25:09	.26400	.22565	.26529	.10947
12:25:09-30:09	.28200	.20519	.27732	.03045
12:30:09-35:09	.25200	.17831	.25269	.05082
12:35:09-40:09	.20600	.15703	.20919	.07315
12:40:09-45:09	.30800	.23999	.30187	.02462
12:45:09-50:09	.26400	.20591	.26328	.05194
12:50:09-54:16	.27805	.19033	.27933	.08948
12:10:09-54:16	.26440	.20398	.26533	.03026

TABLE 9. COMPARISON OF THE INDIVIDUAL FRACTIONS OF TIME STOPPED WITH THE MEAN VALUE FOR 15-MINUTE PERIODS FOR THE FIRST AND SECOND ERGODIC EXPERIMENTS

Mean Fraction of Time Stopped							
Vehicle	Period						
	17:00:21 to 15:21	15:21 to 30:21	30:21 to 45:21	45:21 to 58:12	12:10:09 to 25:09	25:09 to 40:09	40:09 to 54:16
1	.2322	.2479	.1700	.1452	.3378	.2723	.3115
2	.4933	.1455	.1967	.1855	.2800	.2121	.2432
3	.1688	.3212	.2067	.1141	.3311	.2588	.2574
4	.2989	.3589	.2233	.1415	.2055	.2666	.3116
5	.2777	.1900	.2378	.1789	.1899	.2222	.2845
6	.3956	.2834	.2089	.2411			
7	.2789	.2289	.2234	.2167			
8	.5491	.2522	.1279	.1193			
Mean $T_s/T$	.3368	.2535	.1993	.1678	.2689	.2464	.2816
Std. Dev.	.1312	.0686	.0354	.0457	.0698	.0274	.0311
Mean $f_s$	.3367	.2508	.2012	.1685	.2660	.2513	.2617
Std. Dev.	.1620	.1597	.1378	.1332	.2076	.1906	.2168

TABLE 10. COMPARISON OF THE INDIVIDUAL FRACTIONS OF TIME STOPPED WITH THE MEAN VALUE FOR THE ENTIRE DURATION OF THE FIRST AND SECOND ERGODIC EXPERIMENTS

Mean Fraction of Time Stopped		
Vehicle	Period	
	17:00:21 TO 17:58:12	12:10:09 TO 12:54:16
1	0.20083	0.30715
2	0.25785	0.24515
3	0.20600	0.28296
4	0.25985	0.26023
5	0.22266	0.23114
6	0.28377	
7	0.23770	
8	0.26741	
Mean $T_s / T$	0.24201	0.26533
Std. Dev.	0.03010	0.03026
Mean $f_s$	0.24299	0.26550
Std. Dev.	0.16091	0.20398

The above mentioned results also suggest that the mean fraction of vehicles stopped and the mean fraction of time stopped are independent and identical variables by which the quality of traffic service in a network can be expressed (Figs 29 to 32). Moreover, even for short test periods, the fraction of time a single test vehicle is stopped is a reasonable estimator of the mean fraction of time stopped over all the test vehicles and therefore of the mean fraction of vehicles stopped. Thus, the data taken by a single test vehicle circulating in a traffic network for as short as an hour can be used to characterize the quality of traffic service in that network during that time period. Table 11 compares the mean fraction of time stopped for Austin to those for some other U.S. cities. These values were obtained during peak traffic conditions in the Central Business Districts of their respective cities (Ref 10). It would be of great interest to obtain the data required for the expansion of Table 11 to include other major metropolitan areas around the world.

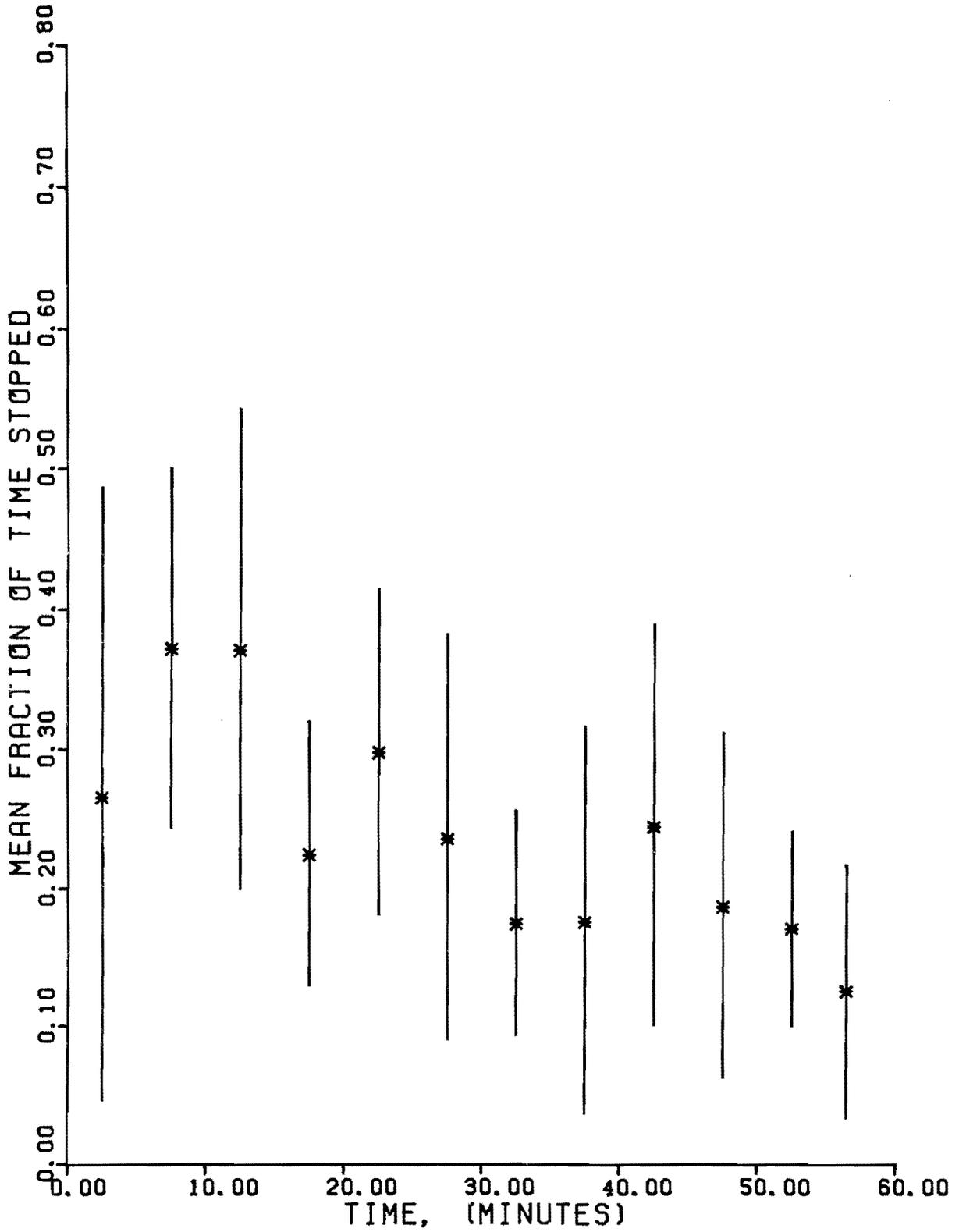


Fig 29. Mean fraction of time stopped versus time for the first ergodic experiment in the Austin central traffic network.

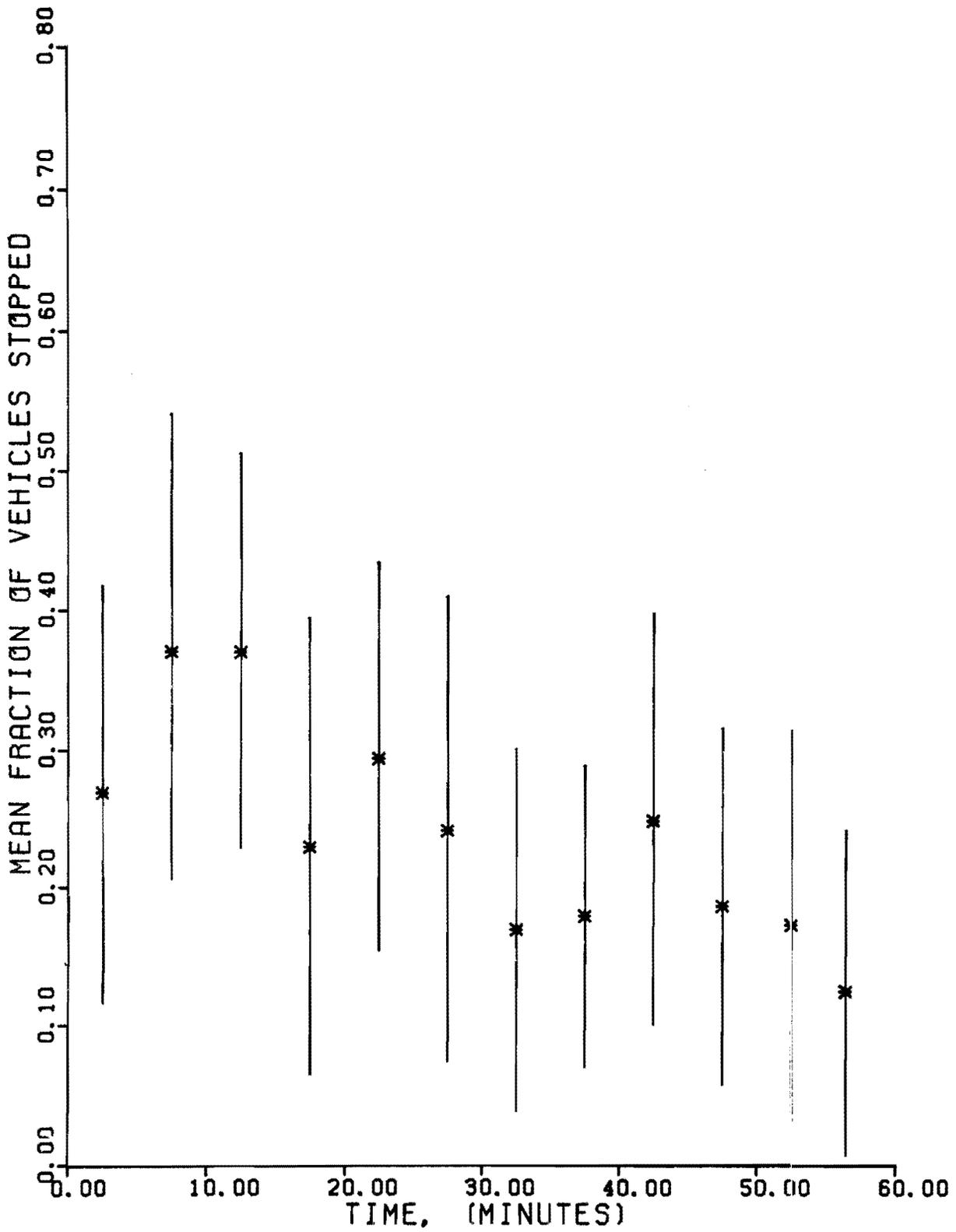


Fig 30. Mean fraction of vehicles stopped versus time for the first ergodic experiment in the Austin central traffic network.

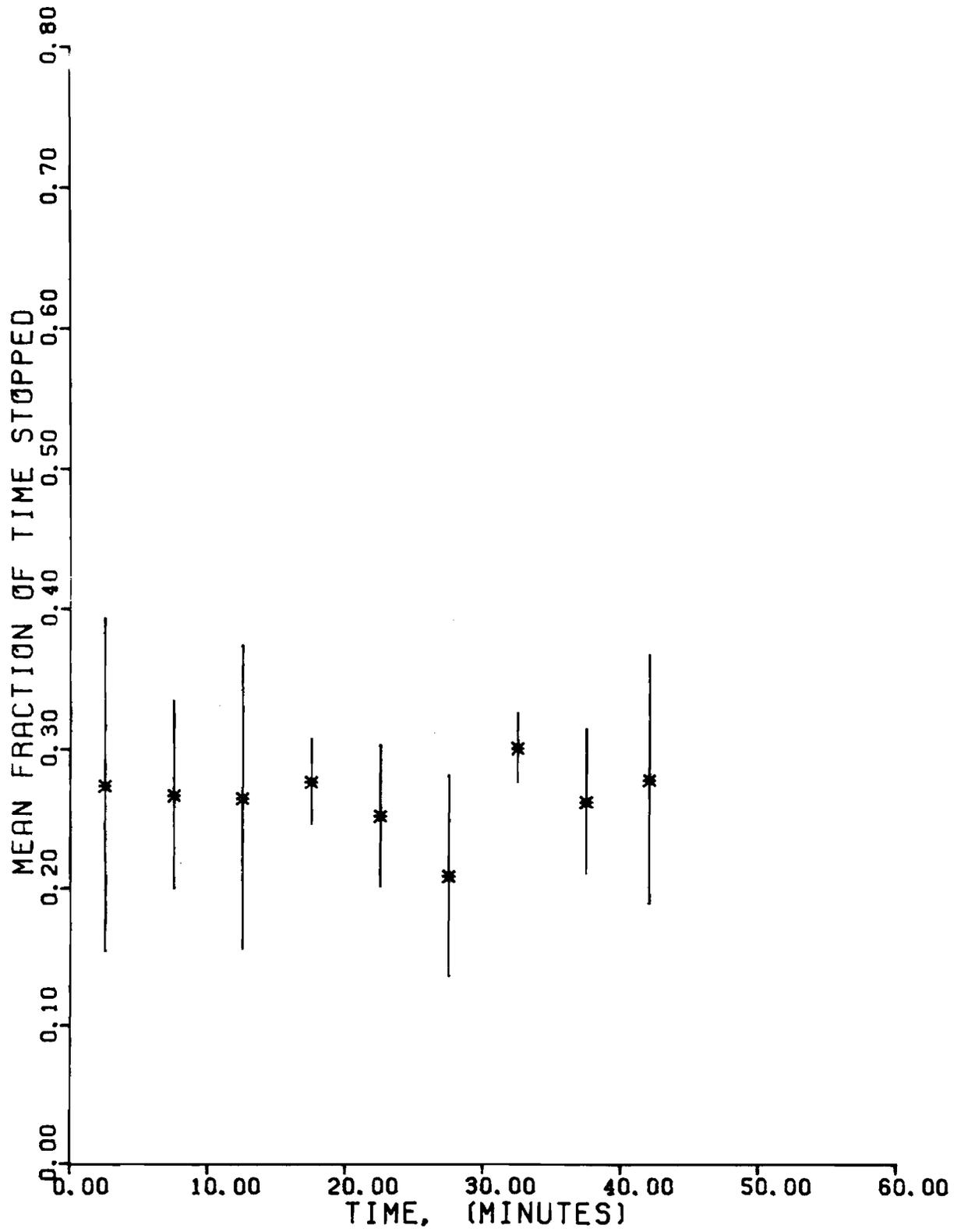


Fig 31. Mean fraction of time stopped versus time for the second ergodic experiment in the Austin central traffic network.

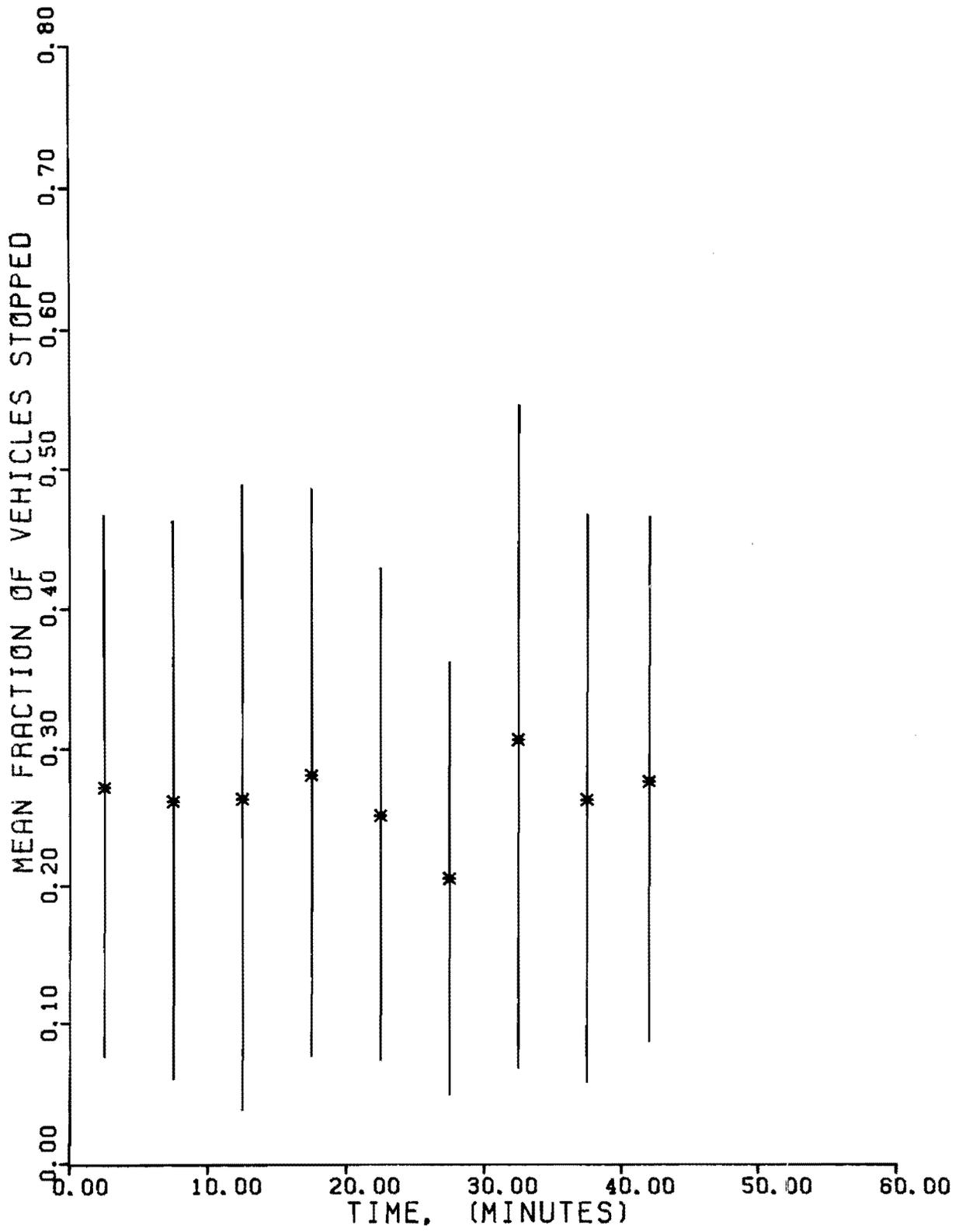


Fig 32. Mean fraction of vehicles stopped versus time for the second ergodic experiment in the Austin central traffic network.

TABLE 11. MEAN FRACTION OF TIME STOPPED IN BUSINESS DISTRICTS OF AUSTIN, DALLAS, LOS ANGELES, AND NEW YORK CITY/NEWARK

City CBD	Traffic Condition	Fraction of Time Stopped
Austin	Peak	0.242
Dallas	Peak	0.381
Los Angeles	Peak	0.217
N. Y. City/Newark	Peak	0.368



## CHAPTER 5. DISCUSSION

In this report the Two-Fluid Model of Town Traffic has been applied to the traffic networks in Austin and Dallas and the results have been compared to those of similar studies in various other metropolitan areas around the world. During the course of determining the parameters of the Two-Fluid Model for these two city networks new questions were raised concerning the detailed structure of this model, questions which possess a potential for improving the model and insuring more realistic traffic-related predictions.

First, it was discovered that the Two-Fluid Model parameters, as anticipated, showed a great sensitivity to the transportation mode used for their determination. The values of the parameters  $T_m$  and  $n$  for buses were found to be quite different from the corresponding values for automobiles operating on the same routes.

Furthermore, it is suspected that the value of parameter  $T_m$  for a traffic network as determined by the Two-Fluid Model would be smaller than the true minimum average trip time per unit distance in that network. To show this we first re-examine the physical interpretation of the parameter  $T_m$ . This parameter is the intercept on the T-axis of the Two-Fluid Model curve (Eq 17b) fitted to the observed trip time - stop time data obtained in a traffic network. For example, the value of  $T_m$  for the Austin central business district is determined from data to be 1.75 minutes per mile. This value according to the model represents the average trip time per unit

distance for trips when there are no stops. However, in a real traffic network, with traffic control devices, such trips hardly ever occur and on the average there is a non-zero average minimum fraction of vehicles stopped,  $f_{s(\min)}$ . By the same token, the average maximum fraction of vehicles running,  $f_{r(\max)}$ , has a value less than one. Therefore, as a consequence of the existence of traffic control devices, any urban traffic network would have an average minimum trip time per unit distance greater than  $T_m$ , an average minimum stop time per unit distance greater than zero, and an average maximum fraction of vehicles running less than one.

In light of the above, an improvement in the Two-Fluid Model can be made in the following manner. Let us first find the point of intersection between the Two-Fluid Model curve of Eq 17b and the linear relation for  $f_s$  in Eq 3, which are repeated below for convenience:

$$T_s = T - T_m \frac{1}{n+1} - T \frac{n}{n+1} \quad (38)$$

and

$$\langle f_{s,p} \rangle = (T_s/T)_i \quad (39)$$

Substituting in Eq 38 for  $T_s$  in terms of  $T$  and  $f_s$  from Eq 39 yields

$$T = T f_s + T_m \frac{1}{n+1} - T \frac{n}{n+1} \quad (40)$$

Dividing both sides of Eq 40 by  $T$  gives

$$1 = f_s + T_m \frac{1}{n+1} T^{-\frac{1}{n+1}} \quad (41)$$

so that

$$T = \left[ f_r / T_m \frac{1}{n+1} \right]^{-(n+1)} \quad (42)$$

or

$$T = T_m f_r^{-(n+1)} . \quad (43)$$

Combining Eqs 39 and 43 we obtain

$$T_s = T_m f_r^{-(n+1)} f_s = T_m (1 - f_r) f_r^{-(n+1)} . \quad (44)$$

Suppose that for a network in which steady state conditions exist, we have determined the minimum fraction of vehicles stopped,  $f_{s(\min)}$ , from data taken in very light traffic conditions. Let us also suppose that we have determined the parameters  $T_m$  and  $n$  from a large amount of data over all types of traffic conditions. If the observationally determined values of  $f_{s(\min)}$  and  $f_{r(\max)}$  are used in Eqs 43 and 44, then the "true" average minimum trip time per unit distance,  $\langle T_{\min} \rangle$ , and the "true" average minimum stop time per unit distance,  $\langle T_{s(\min)} \rangle$ , will be obtained, i.e.,

$$\langle T_{\min} \rangle = \langle T_{\min}^* \rangle = T_m f_{r(\max)}^{-(n+1)} \quad (45)$$

and

$$\left\langle T_{s_{\min}} \right\rangle = \left\langle T_{s_{\min}}^* \right\rangle = T_m f_{r_{\max}}^{-(n+1)} f_{s_{\min}}, \quad (46)$$

where  $\langle T_{\min}^* \rangle$  and  $\langle T_{s(\min)}^* \rangle$  are the estimates of  $\langle T_{\min} \rangle$  and  $\langle T_{s(\min)} \rangle$  as shown in Fig 33.

Consider now a real network such as the Austin Central Business District with a  $T_m$  value of  $\sim 1.75$  minutes per mile and an  $n$  value of  $\sim 1.63$ . The data gathered in this network under very light traffic conditions during the midnight and early morning hours show a  $\langle T_{\min} \rangle$  value of 3.22 minutes per mile and a  $\langle T_{s(\min)} \rangle$  value of 0.61 minutes per mile, resulting in an  $f_{s(\min)}$  value of 0.19 and an  $f_{r(\max)}$  value of 0.81.

Considering the very light traffic conditions, the above mentioned values are our best estimates of the "true"  $\langle T_{\min} \rangle$ ,  $\langle T_{s(\min)} \rangle$ ,  $f_{s(\min)}$  and  $f_{r(\max)}$  values in this particular Austin network. Using Eqs 45 and 46 and assuming that 0.19 and 0.81 or the "true" values of  $f_{s(\min)}$  and  $f_{r(\max)}$ , we can calculate  $\langle T_{\min}^* \rangle$  and  $\langle T_{s(\min)}^* \rangle$ , namely the theoretical estimates of the "true"  $\langle T_{\min} \rangle$  and  $\langle T_{s(\min)} \rangle$  for the Austin network. Therefore, it can be written that

$$\left\langle T_{\min}^* \right\rangle = (1.75)(0.81)^{-(1.63+1)} = 3.05 \text{ minutes per mile} \quad (47)$$

and

$$\left\langle T_{s_{\min}}^* \right\rangle = (1.75)(0.81)^{-(1.63+1)} (0.19) = 0.58 \text{ minutes per mile} \cdot (48)$$

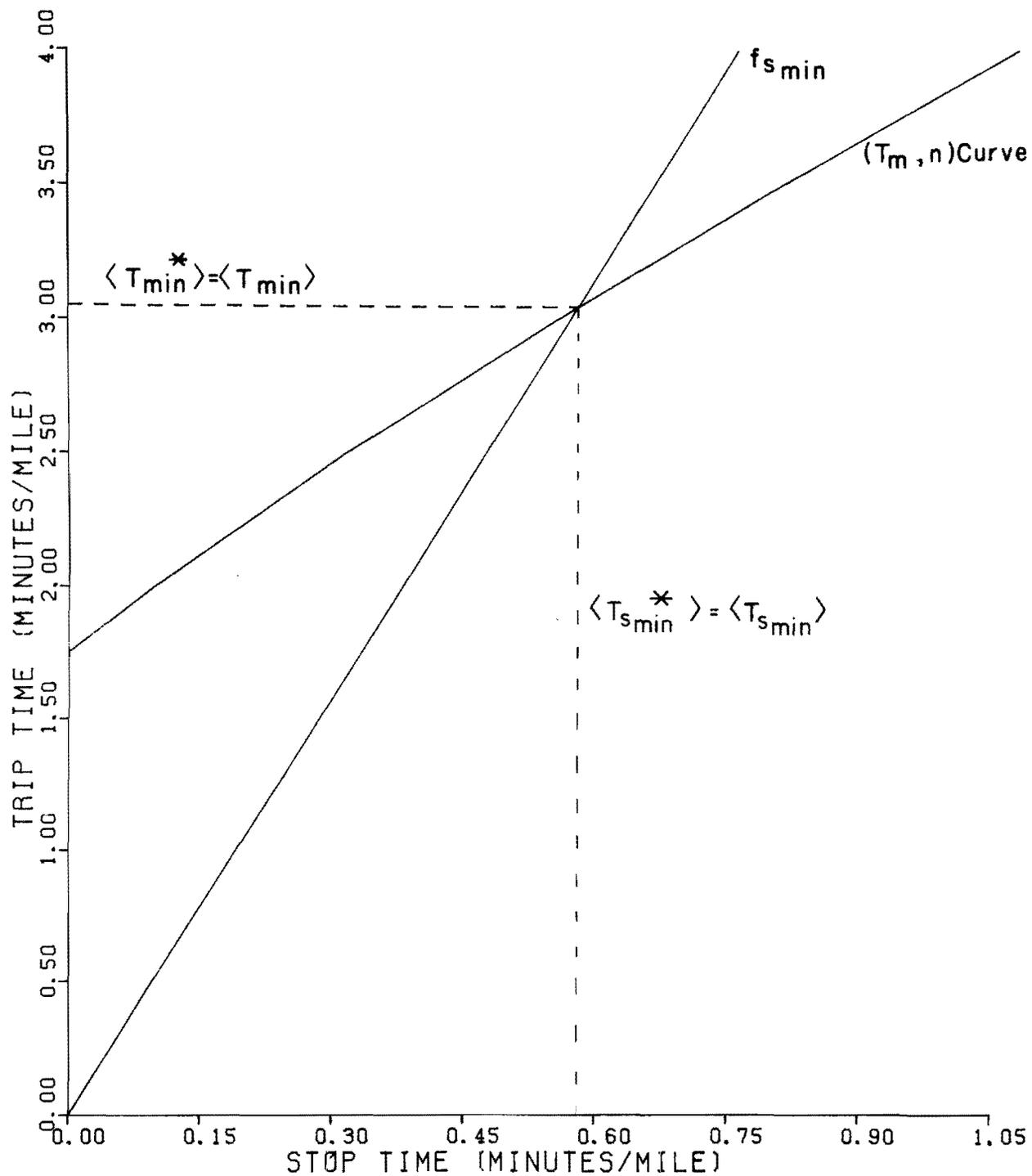


Fig 33. The Two-Fluid Model curve and the line of average minimum fractional vehicles stopped for a hypothetical steady state case.

If the observational value of 3.22 minutes per mile for  $\langle T_{\min} \rangle$  were indeed the "true" value of the average minimum trip time per unit distance for the Austin Central Business District network, then the corresponding theoretical parameter  $\langle T_{\min}^* \rangle$ , with a value of 3.05 minutes per mile is a better estimate than the value of the parameter  $T_m$ , namely 1.75 minutes per mile. However, as the traffic concentration becomes very small and the traffic signals are converted to the flashing amber and red mode, the value of  $\langle T_{\min}^* \rangle$  is expected to approach the value of  $T_m$ .

Figure 34 illustrates the Two-Fluid Model curve and the  $f_{s(\min)}$  line for the Austin Central Business District network. The intersection of the curve and the straight line defines the point shown by an asterisk with coordinates 0.58 and 3.05 minutes per mile corresponding to  $\langle T_{s(\min)}^* \rangle$  and  $\langle T_{\min}^* \rangle$ , respectively. On the other hand, we have determined the values of  $\langle T_{s(\min)} \rangle$  and  $\langle T_{\min} \rangle$  from data taken under the lightest traffic conditions. This pair of values defines the point indicated by a triangle with coordinates 0.61 and 3.22 minutes per mile. If our Two-Fluid Model is, in fact, a good representation of the overall trip time - stop time data, then as we approach a steady state condition these two points will coalesce. Moreover, when an actual system approaches the limit at which there are no traffic control devices requiring stops, then  $\langle T_{s(\min)} \rangle$  will approach zero and the point defined by  $\langle T_{s(\min)} \rangle$ ,  $\langle T_{\min} \rangle$  on the model curve will coalesce with the point  $T_m$  on the T-axis.

Having determined the values of  $\langle T_{\min} \rangle$ ,  $\langle T_{s(\min)} \rangle$ ,  $f_{r(\max)}$  and  $n$  for the Austin Central Business District, we can investigate the consistency of the first assumption of the Two-Fluid Model (Eq 1) as compared to the observational findings. To do this, let us first

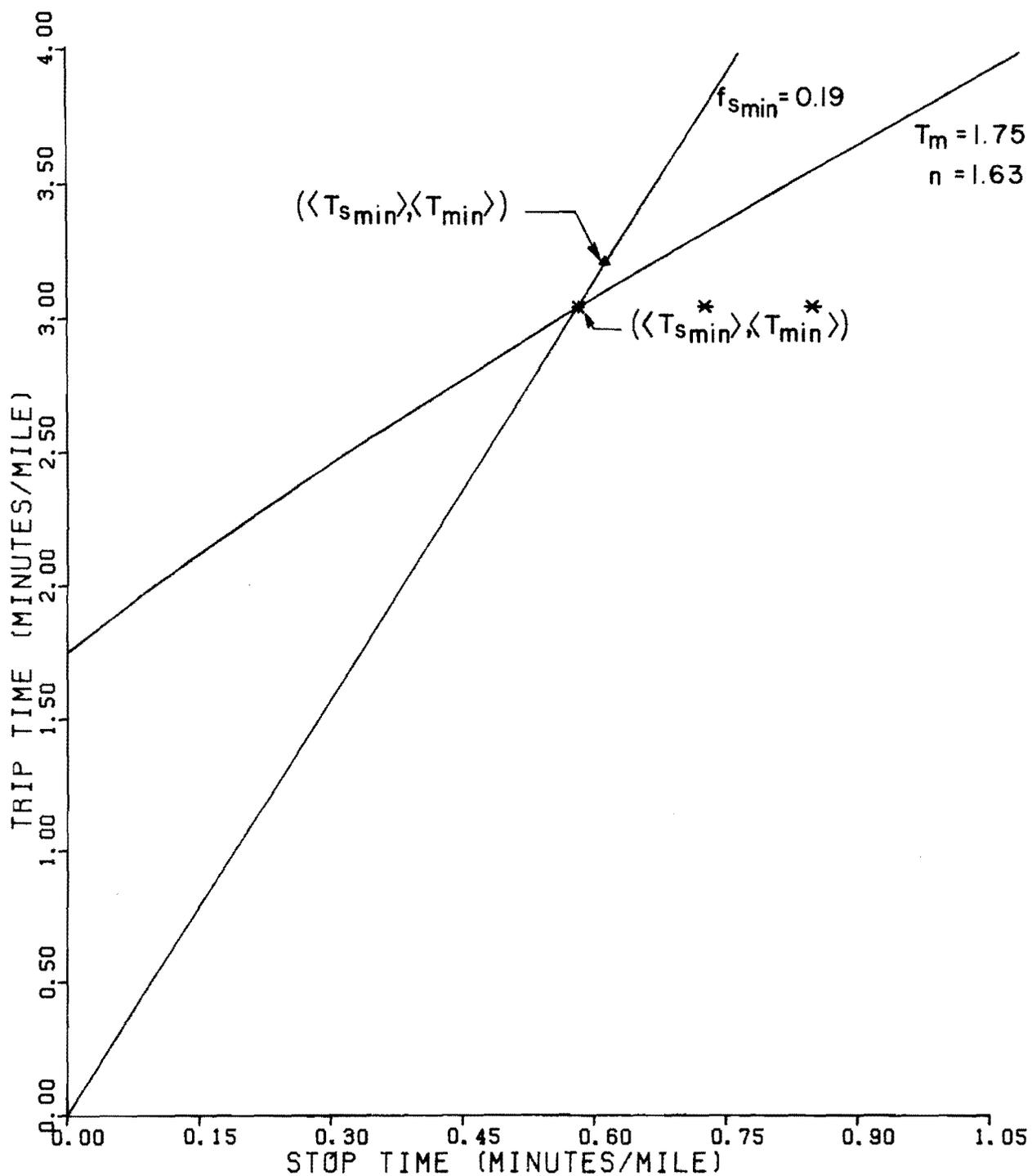


Fig 34. The Two-Fluid Model curve and the line of average minimum fraction of vehicles stopped for the Austin Central Business District network.

calculate the observational value of the running speed, which corresponds to  $\langle T_{\min} \rangle$  and  $\langle T_{s(\min)} \rangle$ , in the following manner:

$$V_r = 60 \left( \langle T_{\min} \rangle - \langle T_{s(\min)} \rangle \right)^{-1} \quad (49)$$

or

$$V_r = 60 (3.22 - 0.61)^{-1} = 22.99 \text{ mph.} \quad (50)$$

Furthermore, let us assume that the value of the average maximum speed which may exist in a network is the weighted average of the posted speed limits in that network. Therefore, a  $V_m$  of 30 miles per hour is assumed for that portion of the Austin Central Business District involved in the observations. Consequently, we can estimate the average running speed in this network according to the first assumption of the Two-Fluid Model, namely,

$$V_r = V_m f_r^n \quad (51)$$

$$V_r = 30 (0.81)^{1.63} = 21.28 \text{ mph} \quad (52)$$

The above value of  $V_r$ , as predicted from the first assumption of the model, is in very close agreement with the empirical average running speed of 22.99 miles per hour (Eq 50). This, in turn, is an indication of the validity of the first assumption upon which the Two-Fluid Model is based.

The fact that the mean fraction of the vehicles stopped in the limit of zero concentration approaches a non-zero  $f_{s(\min)}$  will further require

alteration of the relation

$$f_s = \left( K/K_m \right)^p , \quad (53)$$

where  $K$  is the vehicular concentration,  $K_m$  is the average maximum concentration at which the traffic "jams", and  $p$  is a traffic-related parameter describing the quality of the road facilities and the control system of the traffic network (Ref 12). Equation 53 implies that, as the concentration  $K$  approaches zero, the fraction of vehicles stopped will also approach zero. However, as mentioned earlier, the fraction of vehicles stopped has a non-zero lower bound  $f_{s(\min)}$ . Therefore, Eq 53 can be reformulated, for example, as follows:

$$f_s - f_{s_{\min}} = \left( K/K_m \right)^p . \quad (54)$$

It should be pointed out that in a network where there are few traffic signals and/or stop signs  $f_{s(\min)}$  can approach rather small values.

In addition to what has been learned about the structure, assumptions and limitations of the Two-Fluid Model from the ground traffic observations and experiments, there remains much to be learned about the quality of traffic service in general and the Two-Fluid Model in particular from the analysis of aerial photographs recently taken over the Dallas central traffic network. For example, these photographs will enable determination of the mean fraction of vehicle stopped over the population of vehicles,  $f_{s,p}$ , during the photographing period. We can then compare  $f_{s,p}$  to the mean fraction of time stopped as obtained from the test vehicles circulating in the photographed network during the same general time period. If equality

holds between these two variables, then the second assumption of the Two-Fluid Model (Eq 9) will be directly verified for the sample population of vehicles in the network.

Moreover, the aerial photographs will allow determination of the mean speed  $\langle V \rangle$ , the mean concentration  $\langle K \rangle$ , and the mean flow  $\langle Q \rangle$  for the sample population of vehicles in the network under study. It is of great interest to investigate whether or not simple relations, if any, exist among these space-mean traffic quantities, each measured directly from the aerial photographs. There is no strong reason to believe that the classical relation  $Q = K V$  established from data for an arterial would necessarily be applicable to the traffic in a city network. For example, Zahavi (Ref 3) suggests that the flow per unit length of the road network  $q$ , is inversely proportional to the space-mean speed,  $V$ , in that network, namely,

$$q = \alpha/V, \quad (55)$$

where  $\alpha$  is a parameter describing the quality of traffic service for a specific section or a complete road network. Relations of this general type can be directly investigated by means of the Dallas aerial photographs.

Finally, in Chapter 2 we have discussed a simple fuel consumption relation of the form  $\phi = k_1 + k_2 T$  and the possibility of obtaining a fuel consumption spatial distribution function over a city network (Eq 32). Through the use of fluidyne fuel meters, the fuel consumption relation of Eq 25 can be further verified and the values of the parameters  $k_1$  and  $k_2$  for a specific test vehicle in the networks under study can be determined.

It is further possible to investigate the influence of various traffic and automobile related factors and road features influencing the fuel consumption. Aerodynamic effects as well as the impact of road gradient and road curvature are of special interest.



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APPENDIX

Sample Field Data



TABLE A.1. AUTOMOBILE DATA TAKEN ON CC AND WC ROUTES OF THE UNIVERSITY OF TEXAS AT AUSTIN SHUTTLE BUS SYSTEM

Date: March 5, 1980

Route: WC

Weather: Sunny/Cool

Starting Mileage	Trip Time	Stop Time	Ending Mileage
79761.36	14:09.8	3:11.0	79764.14
79764.14	14:10.6	3:57.4	79766.89
79766.89	14:09.6	3:35.2	79769.65
79769.65	13:35.2	3:18.2	79772.40
79772.40	12:23.4	2:09.2	79775.16

TABLE A.2. A TYPICAL AUTOMOBILE DATA SHEET FOR THE AUSTIN CENTRAL  
TRAFFIC NETWORK

Date: November 11, 1980 (Veterans Day)

Driver: Andrew Eng

Recorder: Siamak Ardekani

Weather: 75° F

Starting Mileage	Starting Trip Time	Time of		Ending Trip Time	Ending Mileage
		Stop	Go		
2401.3	12:09:09	09:44	09:52		
		10:18	10:35		
		11:29	11:31		
		12:15	12:26		
		13:04	13:17		
		13:52	13:58		
		14:16	14:38		
		15:08	15:09		
		15:28	15:29		
		15:45	16:15		
		16:33	16:54		
		17:16	17:50		
		18:20	18:50	12:19:13	2403.3

TABLE A.3. A TYPICAL SHUTTLE BUS DATA SHEET

Date: Tuesday, 4/15/80

Time: 14:10-15:45

Weather: Warm/Sunny

Route: CC

Trip Duration	Loading Related Stop Time	Traffic Related Stop Time
13' 42.6"	1' 21.1"	1' 11.4"
13' 44.4"	1' 06.5"	1' 04.9"
18' 21.7"	3' 46.0"	2' 40.1"
14' 52.8"	2' 12.9"	1' 29.6"

TABLE A.4. DATA FOR THE FIRST 2-MILE TRIP OF TEST VEHICLE NO. 1 IN THE SECOND ERGODIC EXPERIMENT IN AUSTIN

Date: February 24, 1981  
 Driver: Robert Herman  
 Observer: Rafael Cal y Mayor  
 Starting Mileage: 92.78  
 Starting Time: 11:55:36

<u>Time of Stop</u>	<u>Time of Start</u>	<u>Comments</u>
11:55:53	11:56:13	Signal
11:57:18	11:57:40	Signal
12:00:09	12:00:19	Signal
12:00:52	12:01:17	Signal
12:01:34	12:01:36	Stop Sign
12:01:49	12:01:52	Stop Sign
12:02:07	12:02:10	Stop Sign
12:02:23	12:02:55	Signal
12:03:12	12:03:39	Signal
12:03:57	12:04:17	Signal

End of 2-Mile Trip: Time 12:04:23  
 Milage Reading 94.78

TABLE A.5. DATA FOR THE FIRST 2-MILE TRIP OF TEST VEHICLE NO. 2 IN THE SECOND ERGODIC EXPERIMENT IN AUSTIN

Date: February 24, 1981  
 Driver: Han-Jei Lin  
 Observer: Freydoon  
 Starting Mileage: 64.5  
 Starting Time: 12:02:45

Time of Stop	Time of Start	Comments
12:02:54	12:03:01	Signal
12:03:55	12:04:10	Signal
12:04:43	12:05:27	Signal
12:05:55	12:06:22	Signal
12:06:35	12:06:51	Signal
12:07:20	12:07:24	Signal
12:08:37	12:09:08	Signal
12:09:25	12:09:30	Pedestrian
12:09:43	12:09:49	Signal
12:10:08	12:10:26	Signal
12:10:31	12:10:38	Left Turn
12:10:52	12:11:22	Signal
12:11:43	12:12:15	Signal

End of 2-Mile Trip: Time 12:13:09  
 Mileage Reading 66.5