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# Research on Desirable Adaptive Cruise Control Behavior in Traffic Streams

**Phase 2 Final Report**

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16. Abstract

Phase 2 research on desirable ACC behavior in traffic streams has been aimed at developing microscopic models of driver behavior that are suitable for use in traffic flow simulations containing both ACC-equipped vehicles and humanly driven vehicles. The driver models developed in Phase 2 use parametric coefficients that are derived from sets of data measured during human-manual driving in naturalistic situations on highways, roads, and streets. The relationships employed in the models have been developed from concepts pertaining to kinematics, human behavior, and control system design. Ideas from previous traffic simulation algorithms have been considered and, where understood, utilized in structuring the form of these models. Details of the human-manual driving models and the data processing procedures utilized for characterizing the driving style of individual drivers are described in the Phase 2 report. Results for 143 different drivers are presented in the report. The characteristic parameters pertaining to these drivers indicate a spectrum of significantly different driving styles. Analyses of the influences of these differences in driver characteristics on traffic flow capacity and flow sustainability have been made. The results show major differences in capacity and flow sustainability depending upon the characteristics of the driver involved.

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**Research on Desirable ACC Behavior in Traffic Streams**

**March 31, 2003**

## Executive Summary

This research program focuses on the influences of ACC-equipped vehicles on traffic behavior. The vehicle manufacturing (OEM) partners are motivated to perform this research in order to ensure that their customers have a positive experience with ACC over the long term as ACC steadily increases its presence in the U.S. vehicle fleet. The partners from FHWA are interested in ensuring that the motoring public will have a positive experience in traveling from here to there on the roadway system as advanced technology is introduced into the vehicle population. In the worst-case scenario, which the partnership seeks to avoid, ACC systems of different manufacturers may interact with other vehicles in undesirable modes of motion that may occur spontaneously on the highway. These modes of motion may lead to a possible reduction in the throughput of freeways, as well as the possibility of passenger discomfort. This research is intended to increase the understanding of how various modes of motion occur and to develop microscopic knowledge that can be applied in assuring that strings of ACC vehicles will not have an adverse effect on traffic flow.

The following objectives have been formulated to meet the challenges and concerns expressed above.

1. Identify ACC-system characteristics that significantly influence traffic flow.
2. Evaluate the performance of traffic streams containing both humanly driven and ACC driven vehicles.
3. Provide a research foundation for use in evaluating and enhancing the string behavior of ACC-equipped vehicles operating in traffic streams.

The partnership's research activities have been divided into phases for programmatic and logical reasons that provide an evolutionary approach based upon the current level of microscopic understanding and knowledge concerning the control of velocity and range clearance from vehicle to vehicle in traffic.

The measurement and modeling of the performance of ACC-equipped cars was addressed in Phase 1. Phase 1 was a cooperative effort sponsored by Nissan, BMW, and DaimlerChrysler. Each manufacturer provided UMTRI with a production or pre-production vehicle with an ACC system. UMTRI utilized GPS technology in devising test procedures for non-intrusively exploring ACC performance in typical driving situations involving a confederate preceding vehicle whose position and velocity were being recorded. The GPS data for each vehicle were analyzed using system identification techniques to formulate a linear dynamic model for approximating the range and velocity behavior measured in the neighborhood of various operating states. It was agreed that the data for each manufacturer's vehicle were proprietary information but linear models using prototypical parametric values for the coefficients in the equations were to be used

for analyzing traffic flow. In this manner, the ACC-vehicle parameters used in preliminary traffic flow simulations are representative of current production vehicles.

The main results from Phase 1 are:

(1) The evaluation method produces valid results concerning ACC performance.

(2) Depending on the amount of damping and lead compensation in the ACC algorithm, ACC systems are likely to influence traffic flow, and further study on the comparison of ACC driving and human-manual driving is needed to assess the impact of ACC.

The Phase 1 results were presented to USDOT, thereby leading to FHWA funding for Phase 2. Phase 2 has been aimed specifically at developing microscopic models of driver behavior that are suitable for use in traffic flow simulations that contain both ACC-equipped vehicles and humanly-driven vehicles. The utility and validity of the results from those traffic flow simulations will clearly depend on the quality of the human-manual driving model employed in mixed traffic situations.

The driver models developed in Phase 2 use parametric coefficients that are derived from sets of data measured during human-manual driving in naturalistic situations on highways, roads, and streets. The relationships employed in the models have been developed using concepts pertaining to kinematics, human behavior, and control system design. Ideas from previous traffic simulation algorithms have been considered and, where understood, utilized in structuring the form of these models. Details of the human-manual driving models and the data processing procedures utilized for characterizing the driving style of individual drivers are described in this Phase 2 report. Results for 143 different drivers are presented in the report.

The characteristic parameters pertaining to these drivers indicate a spectrum of significantly different driving styles. These differences represent major differences in the microscopic phenomena occurring in situations involving vehicles traveling in close proximity to each other. Analyses of the influences of these differences in driver characteristics on traffic flow capacity and flow sustainability have been made. The results show major differences in capacity and flow sustainability depending upon the characteristics of the driver involved.

Proposed ideas for Phase 3 research involve applying the results and findings from Phases 1 and 2 to develop an improved understanding of the influence of ACC system features on traffic flow and string performance (flow sustainability). This is envisioned as including not only the development and utilization of an enhanced simulation capability but also the development and utilization of vehicles equipped with a mobile laboratory that can be used to gather data while traveling in traffic streams. Vehicles equipped with a mobile laboratory are envisioned as an ideal platform for studying the microscopic phenomena associated with traffic flow.

The mobile laboratory would include sensors for measuring the range-clearances and range rates between a mobile-laboratory equipped-vehicle and its preceding and following vehicles. Other features might include sensors for measuring the location and speeds of vehicles in adjacent lanes. In addition, the mobile laboratory would include a feature allowing it to be positioned with respect to its preceding vehicle in accordance with control rules, which are representatives of those used in ACC driving or those used in models of manual driving. A vehicle containing a mobile laboratory that has been structured to measure microscopic phenomena will constitute a probe for use in measuring the traffic situation in the vicinity of a single vehicle traveling within a traffic stream.

The combination of simulation and microscopic phenomena vehicles (MPVs) equipped with mobile laboratory capabilities will provide the potential for developing a research foundation to be used in evaluating and enhancing the performance of ACC-equipped vehicles in the traffic stream. The results from Phase 3 are expected to indicate to OEMs those ACC characteristics that they need to consider collectively for ensuring sustainable traffic flow.

In addition, this combination of simulations and MPVs provides the capabilities needed to verify and validate the models of human-manual driving and ACC driving used in traffic flow simulations. It provides the tools needed to effectively address specific traffic flow issues as identified by the partnership.

## Introduction and Background

The objective of the Phase 2 research, presented in this report, is to develop an improved microscopic understanding of driver control of range-clearance and time-gap. This improved understanding of the behavior of human drivers is to be applied in developing a research foundation for use in evaluating and enhancing the performance of ACC vehicles as their number increases in the traffic stream. The Executive Summary provides an overview indicating how the Phase 2 work on driver modeling is an integral element of a program aimed at examining the influence of ACC systems on traffic flow.

The Phase 1 work addressed the development of data gathering and data analysis procedures that are suitable for characterizing the observed behavior of ACC-equipped vehicles in response to changes in speed and location of a preceding vehicle. In Phase 1, well-known system identification techniques were used to identify parametric values for linear models [1]. Similar system identification techniques were applied in Phase 2 but the emphasis in Phase 2 shifted to non-linear models because nonlinear models were shown to provide good utility in matching human-manual driving data as gathered in previous research programs [2,3].

This report covers the modeling, data-analysis, performance-prediction, and traffic-flow analysis activities performed in Phase 2. It concludes with recommendations based upon the results of the Phase 1 and Phase 2 work.

## Overall Approach

The overall approach used in this research program involves four types of activities whose themes may be broadly classified as learning, understanding, contemplating, and knowing. Tasks oriented toward these underlying themes are expected to recur throughout the program. The objectives of this program are served by activities aimed at the following specific, ordered sequence of knowledge development steps:

1. Learning what happens when people are driving with assistance from ACC systems and when people are driving manually.

2. Understanding how the driving process works with or without ACC assistance in typical traffic situations involving control of speed and range clearance.

3. Contemplating what concepts are useful in explaining traffic-flow related aspects of the control of speed and range clearance.

4. Knowing how to apply the results, findings and discoveries of this research in a logical manner.

In summary, we are striving to penetrate the data to discover what it tells us and to express ourselves as logically as we can.

In the context of this program, measurements of ACC performance and driver behavior have been used in learning what ACC systems and drivers do. These measurements have been used in developing basic models describing the behavior of an individual driver-vehicle combination in response to the motions of a preceding vehicle. These basic models provide the foundations for computer simulation of the microscopic performance of each vehicle involved in a traffic stream. In this context, these models reflect our preliminary understanding of the control of speed and range clearance. The development of these models has involved conceptual reasoning. Concepts from kinematics, human-centered design, and vehicle dynamics and control have played an important role in challenging the face validity of these models. The knowledge derived from developing these models and evaluating their parameters provides evidence indicating how ACC logic and driver characteristics may influence traffic flow.

**Concepts Used in Designing the Driver Model**

Engineering design involves considerations at several levels of abstraction as illustrated in Figure 1, which is based upon Rasmussen's work on skills, rules, and knowledge [4]. The following exposition on driver modeling proceeds from functional purpose to a real simulation algorithm that can be exercised to experiment with the model.

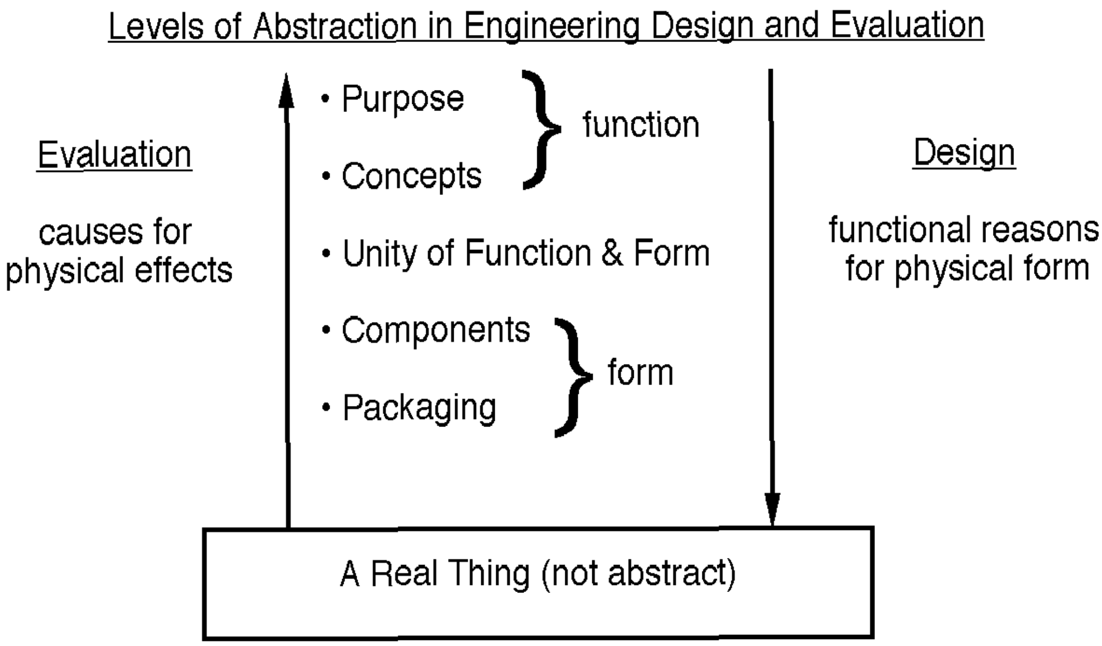



Figure 1. From functional purpose to a real simulation algorithm.

The functional purpose of the driver model is to emulate the microscopic behavior of drivers as they control speed and headway in natural driving situations. The model is to be suitable for use in conjunction with models of ACC driving to aid in assessing the influences of ACC systems on traffic flow.

Figure 2 is an information flow diagram that presents a conceptual view of the driving process from the perspective of a single driver. The labels on the arrows indicate pertinent information about the driving situation where:

- Vp represents the velocity of the preceding vehicle
- V represents the velocity of the subject vehicle
- R represents the range-clearance between these vehicles

• Rdot represents the time-derivative of R, that is, the range-rate

• U represents the control action used to change V

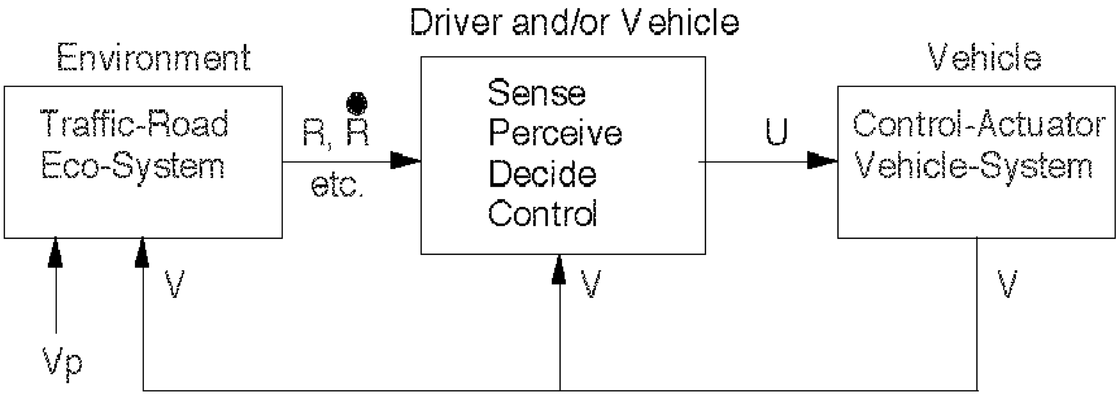



Figure 2. Conceptual view of the driving process from a driver's perspective.

Figure 2 contains blocks representing (1) the driving environment, (2) the driver or vehicle controller where intelligence and/or artificial intelligence is located, and (3) the prime mover in characterizing the driving process. In the context of the modeling work in Phase 2, the center block pertains to the driver. Phase 1 focused on the driver assistance qualities of ACC systems and modeling the command and control properties of existing ACC-systems.

The model of human driving is based upon fundamental premises concerning how a driver senses pertinent information, perceives the meaning of that information, decides on the course of action to take, and controls vehicle acceleration to achieve a desirable driving situation. Figure 3 illustrates the basic variables used in modeling one-on-one driving.

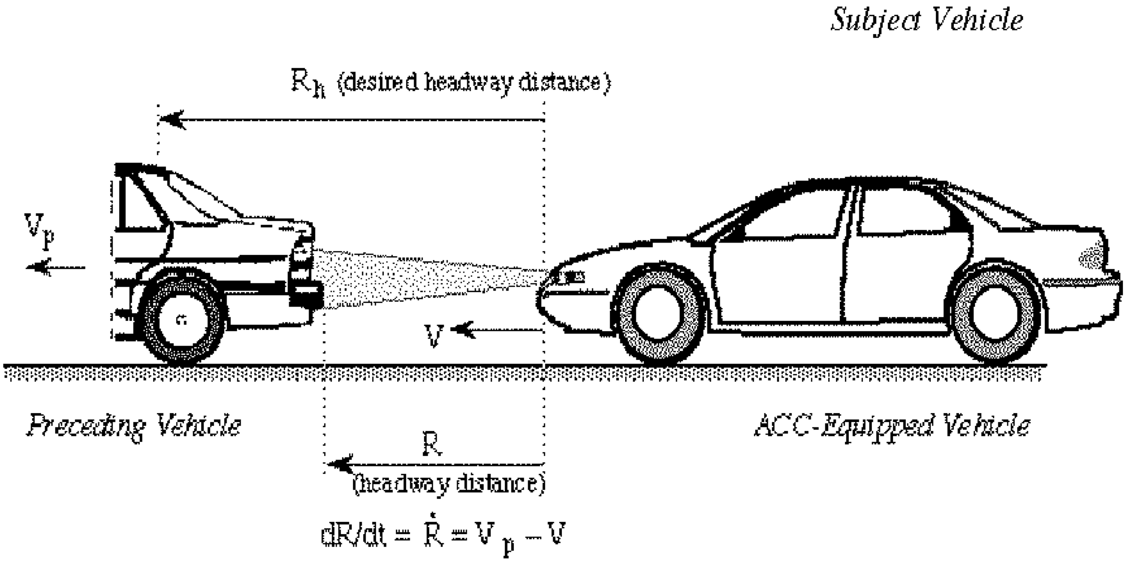
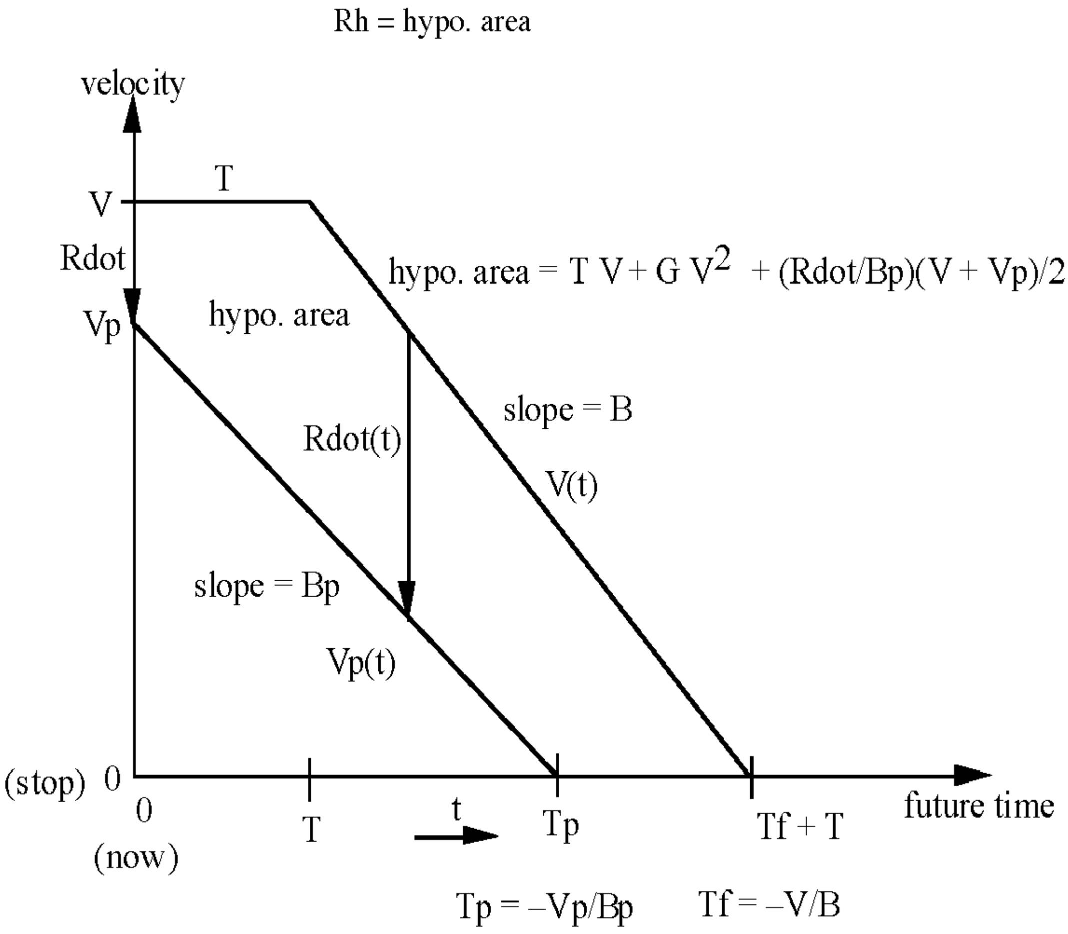



Figure 3. Physical variables sensed in human-manual driving and/or ACC driving.

The modeled driver has visual capabilities for sensing range-clearance R, range rate Rdot, and the velocity V as shown in figures 1 and 3. The modeled driver uses this sensed information to assess the current driving situation. Based upon this assessment, the driver of the following vehicle decides on a course of control action that will determine the acceleration/deceleration Vdot of the following vehicle.

The fundamental premise underlying the model of the driver is that the driver adjusts speed in striving for a comfortable range clearance and its associated time gap. In this modeling approach, the driver's feeling of comfort is related to the driver's view concerning the relative risk of rear-ending the preceding vehicle. In a broad sense, the model is based upon the idea that drivers are concerned that they might crash.

The equations for the modeled driver are based upon the idea that the driver learns and chooses to drive such that the hypothetical situation illustrated in Figure 4 will not cause a crash if the driver is attentive. The equations presented in figure 4 are crucial elements in the development of this model of driver behavior.




$$e = er + erdot$$

where $er = R - (A + T\,V + G\,V^2)$ and $erdot = -(Rdot/B\,p)\,(V + Vp)/2$

Figure 4. Velocity-time diagram illustrating the driver's hypothetical concern.

In extreme situations, the modeled driver brakes as hard as necessary to avoid a crash by stopping within the range clearance available. Unless engaged in an all-out stop, the modeled driver repeatedly (about once a second) asks, "What if the hypothetical situation were to happen now?" If the range R, minus a zero-speed range margin A, is currently greater than the range allowance implied by the "hypo area" (the area between the hypothetical velocities shown in the velocity-time diagram in figure 4), the driver may speed up. If the range is less than the range allowance, the driver will slow down. These are the basic conceptual ideas behind the model of driver behavior.

Figure 4 portrays a constant deceleration analysis where Bp represents the level of deceleration (about –2.7 m/s$^2$) that the driver learns to use in determining a command U that will lead to a satisfying value of Vdot. Bp is the hypothetical deceleration of the preceding vehicle. B is the hypothetical deceleration of the subject vehicle. G is equal to [(1/2Bp) –(1/2B)] and it is a fundamental parameter, which is important in distinguishing differences between drivers and in determining steady-following characteristics. If G = 0, T represents a linear constant time-gap parameter for a driver who intends to decelerate at the hypothetical deceleration rate of the preceding vehicle. Otherwise, T is simply the linear parameter in the non-linear expression for the "hypo" area Rh as given in figure 4.

**Parameters Employed in Representing Steady Following**

The variables describing the dynamical state-space of vehicle operation are R, the range clearance from the preceding vehicle, and V the vehicle speed. The range rate, Rdot, is the time rate of change of the range, R, and Rdot is equal to the relative velocity between the preceding vehicle with velocity, Vp, and the subject vehicle with velocity, V. Hence, Rdot = Vp – V. In steady following, Rdot is approximately zero. The preceding vehicle and the following vehicle are traveling at approximately the same speed. This is one of the conditions needed for steady following. (If Rdot is not equal to zero, R will change since new values of R depend upon the integral of Rdot with respect to time.)

The other condition needed for steady following is that the subject (following) vehicle is not accelerating. This means that Vdot, the time rate of change of velocity, V, is approximately equal to zero. The idea is that the driver will change speed (by using either the brake or the accelerator) if the driver's perception of range and speed is not to the driver's liking. If the driver wants to hold speed constant, the driver holds Vdot = 0.

The computer simulation for predicting vehicle responses to changes in Vp or to situations in which R does not equal A + T V + G V$^2$ will include routines for integrating Rdot to obtain R and Vdot to obtain V. For the vehicle to be in a steady following situation, both Rdot and Vdot need to be approximately equal to zero. If Rdot and Vdot are not approximately equal to zero, the vehicle is not in a steady-following situation.

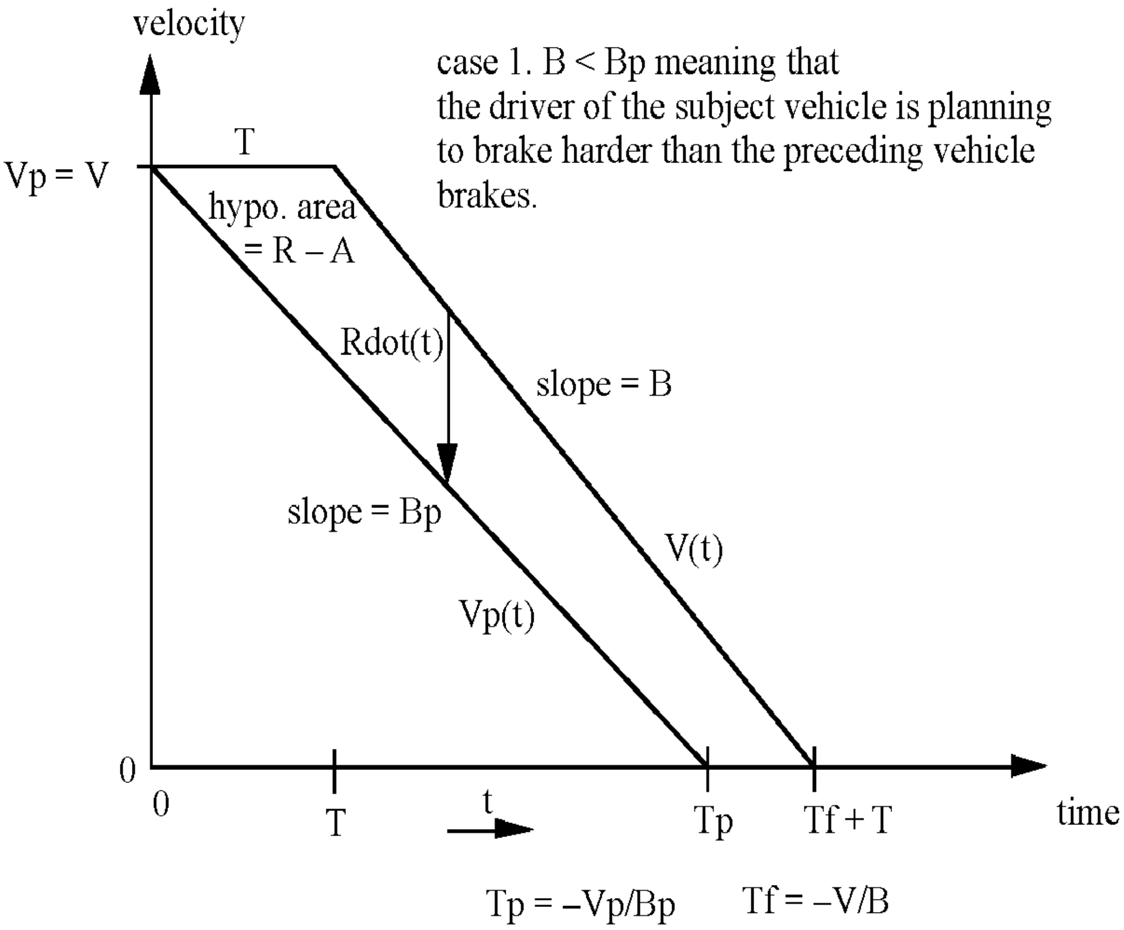
In terms related to the driver model, the steady-following relationship, **R – (A + T V + G V$^2$) = 0,** will be satisfied when the driver is satisfied with the driving situation and the preceding vehicle is moving at approximately constant velocity. The driving concept involved is that the driver will adjust velocity until the driver's desired steady-following relationship is satisfied with Rdot = 0 and Vdot = 0 approximately. The data from different drivers indicate that different drivers have different styles of steady-following behavior. These styles are characterized by substantially different values for the parameters T and G.

So far in this discussion, we have not considered the transient response entailed in getting from a current driving state to the steady-following relationship. This will involve developing rules describing how the driver chooses to accelerate (or decelerate). However, control ideas and other associated dynamic matters are beyond the scope of this discussion of steady following. Dynamics and control matters will be treated in the next section.

Figure 5 is a diagram whose purpose is to illustrate how the driver decides (in this model) to make acceleration (Vdot) equal to zero. Experience has shown that the approach described next is not easy to follow. It is wise to attack the Vdot = 0 situation before attempting to understand more complicated situations in which Vdot does not equal zero.

The idea is that the driver operates from moment to moment (where moments may be about one second apart depending upon the driver). At each decision moment the driver decides what to do during the time between the current moment (now) and the next decision moment. The idea is that the driver uses the current, perceived values of V, Rdot, and R to calculate Vdot, which in this steady-following case turns out to be equal to zero. The conditions for steady following require that Rdot = 0 which means that Vp = V. Hence, the initial values of V and Vp are equal in figure 5, which differs from figure 4 in that regard. (Rdot does not equal zero in figure 4.)

In the context of understanding this driver model, people tend to have difficulty in keeping straight the difference between what the driver is thinking might happen from what is actually happening as the vehicle proceeds along the road. In figure 5, the quantity, t, represents a time variable extending into the future from t = 0 ("now"). Figure 5 portrays a driver's mental image of a hypothetical situation in which the preceding vehicle will have commenced decelerating at rate, Bp, at t = 0. In the case illustrated in figure 5, the deceleration, B, of the following vehicle is less than Bp (where B and Bp both have negative values). As indicated by the equations and relationships in figure 5, this means that the parameter, G, is less than zero.




$$\boxed{\begin{array}{l}\text{hypo. area} = R - A = T\,V + Tf\,V/2 - Tp\,Vp/2 \text{ or} \\ \qquad R = A + T\,V + G\,V^2 \text{ where } G = ((1/2Bp) - (1/2B)) < 0\end{array}}$$

Figure 5. A driver style in which G < 0 and B < Bp.

Based upon past experience, the driver of the following vehicle anticipates that the driver of the preceding vehicle might decelerate at a rate of Bp $m/s^2$. Deceleration at the rate Bp would probably happen very infrequently on the road involved, but the driver's range allowance for contingencies depends upon the value of Bp used to represent the driver in the model. Empirical results, derived in other research work [2], show that a value of Bp that is equal to approximately minus 2.7 $m/s^2$ yields a good fit to measured behavior for many drivers in many situations. This value of Bp has been used as a starting point for this program.

The driver is presumed to have learned what the scene out the front window should look like during steady following. The figure indicates that the driver model allows a time period T (the model's parameter, T) in which he or she expects to hold Vdot equal to zero. Hence, V would stay constant for a period of T seconds in this hypothetical model of the driver's control processes. After that, the driver anticipates that he or she will decelerate at a rate of B $m/s^2$, if the driver of the preceding vehicle were to decelerate at a rate of Bp $m/s^2$.

This concept of driver behavior has been described as if it were a cognitive process, but it is believed to be a learned skill and the driver may have little ability to provide a coherent description of how this is done. As far as we know, the driver just does it based upon what the driver sees. (We have no way to measure directly what the driver is thinking or how his or her mental processes are functioning.)

In the hypothetical world that the driver has created, time moves forward toward anticipated hypothetical events as described above and as shown in figure 5. The area between the V(t) and Vp(t) curves in figure 5 represents the integral of the time history of Rdot(t) in the hypothetical world created in the driver's mind. In other words, this means that the driver can do what has been anticipated if the actual value of R at this moment matches the value of R that was envisioned as acceptable in the driver's mind.

One can now compute the integral of the hypothetical Rdot (where Rdot(t) = Vp(t) –V(t)) using the geometrical relationships portrayed in figure 5 to aid in computing the total enclosed-area, Rh, between the hypothetical curves for V(t) and Vp(t). Note that Rh is theoretically less than zero since Rdot(t) is negative as shown in figure 5. However Rh represents an area, which is a positive quantity. Now, if R – A = Rh, the condition for steady following is satisfied in the driver's mental image of the situation. The resulting expressions for steady following are as follows:

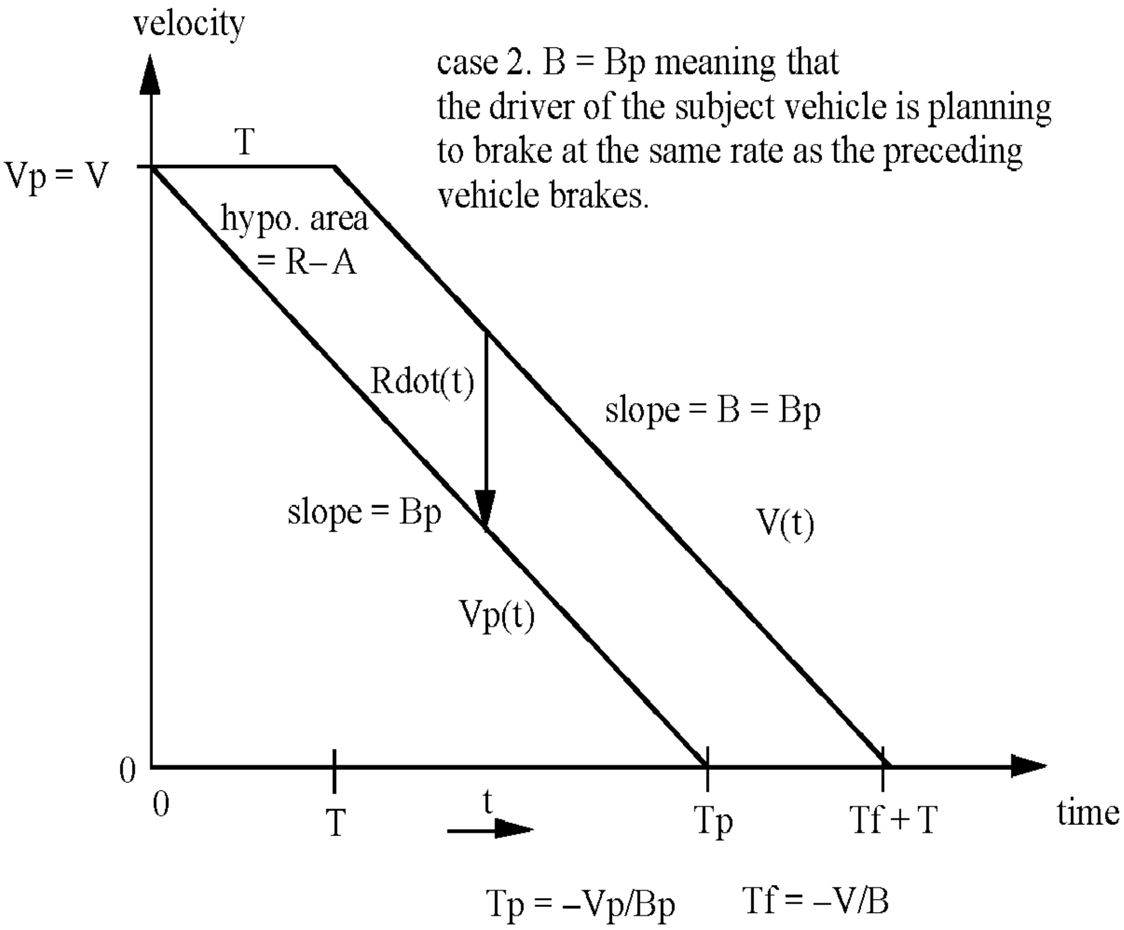
$$R - A = VT + V^2/2Bp - V^2/2B = VT + G\,V^2$$

In this equation, Vp(0) = V(0) = V and the parameter G = (1/2Bp –1/2B). Or, in a convenient, algebraically equivalent form, G = (B – Bp)/2BBp.

At first exposure, the resulting equation may seem to have appeared by a mysterious process. However, its utility lies in fitting the data. Perhaps it only represents a heuristic concept to be used for interpreting the data. In that regard, how might the equation be interpreted? First, R is associated with the location of the driver's eye, which is the driver's range sensor and it is located behind the front of the vehicle. In this sense, A is a distance margin that the driver provides so that the front of his or her vehicle will stop at a satisfactory distance behind the rear of the preceding vehicle. T is a time margin, which (when multiplied by V) converts to a distance margin that the driver allows before relatively hard deceleration might be required. And G has an interesting interpretation involving the hypothetical decelerations of the two vehicles.

Case 1, which was shown in figure 5, involves a negative value of G. To provide an illustrative numerical example, let Bp = –3 m/s$^2$ and B = –4 m/s$^2$ so that B < Bp and G = –1/24 = –0.042 s$^2$/m. The point to observe is that a negative value of G indicates a driving style in which the driver expects to brake harder than the preceding vehicle brakes.

Figure 6 illustrates the hypothetical situation as envisioned by a driver who expects to brake at the same rate as the preceding vehicle brakes. This means that G = 0 and the steady-following relationship between V and R is linear.

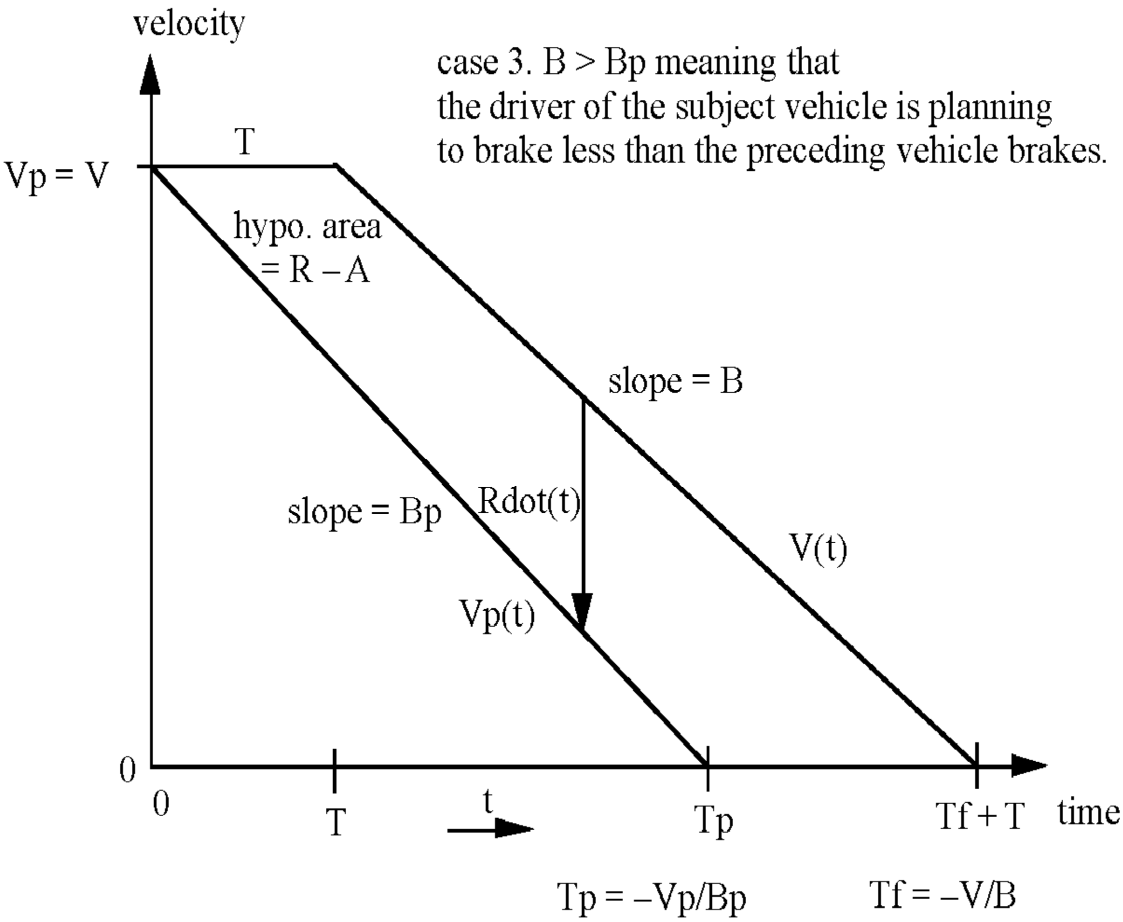



$$\boxed{\begin{array}{l} \text{hypo. area} = R - A = T\,V + Tf\,V/2 - Tp\,Vp/2 \text{ or} \\ \qquad R = A + T\,V + G\,V^2 \text{ where } G = ((1/2Bp) - (1/2B)) = 0 \end{array}}$$

Figure 6. A driver style in which G = 0 and B = Bp.

Comparing the sizes of the hypothetical (hypo) areas shown in figures 5 and 6 leads to an important observation. These figures were constructed so that Vp, V, T, and Bp as shown in figure 6 are equivalent in size to those shown in figure 5. However, the hypo area in figure 6 is greater than the hypo area in figure 5. This means that the driver style portrayed in figure 6 represents a larger range clearance than that illustrated in figure 5. In other words, for all else equal, drivers with $G < 0$ will follow at closer ranges than that employed by a comparable driver but with $G = 0$.

Now consider figure 7 for which $G > 0$. Clearly, the hypo area in figure 7 is larger than that shown in figures 5 and 6. The point is that larger G (in the algebraic sense where $1 > -2$) implies a greater range clearance.




$$\text{hypo. area} = R - A = T\,V + Tf\,V/2 - Tp\,Vp/2 \text{ or}$$
$$R = A + T\,V + G\,V^2 \text{ where } G = ((1/2Bp) - (1/2B)) > 0$$

Figure 7. A driver style in which G > 0 indicates a relatively long range-clearance.

Clearly, the value of T influences range clearance and larger values of T imply a greater range clearance.

The basic conceptual ideas behind the steady-following basis-function, $\mathbf{R - (A + T\,V + G\,V^2) = 0}$, have now been presented. Equations that resemble those encountered in Gipps's work may be obtained by applying the quadratic formula to solve for V as a function of R [5].

The design transition step in the level of abstraction from function to form (unifying function to form) needs to be considered next in developing the driver model. The basis functions for human-manual driving have been programmed using the computing components available in MATLAB SIMULINK. SIMULINK is capable of providing the computer code needed to exercise the driver model. In that context, the next step in developing the model of human-manual driving is to use naturalistic data to evaluate parametric values for the coefficients T and G that appear in the steady-following basis-function.

The sources of naturalistic data used for evaluating T and G are databases containing measured results from two previously completed projects, specifically, the ICC FOT [6] and FOCAS [7].

The FOCAS project involved 36 drivers driving for about one hour in the middle of a weekday on a freeway loop between Ann Arbor, Michigan and Detroit Metropolitan Airport. There were four freeway segments involved, along with some travel on surface streets between UMTRI and the freeway.

The ICC FOT involved 108 drivers, driving wherever, whenever and however they wanted. These drivers used the subject vehicle as their personal car. They drove manually without ACC available for one week. Then, they drove with ACC available for at least one more week, but they could choose to drive manually if they wanted to. Only the manual driving data has been studied in phase 2 of the current study. The drivers constituted a sample of the licensed drivers in Southeastern Michigan. The sample was balanced to cover age, gender, and experience with conventional cruise control. (Data for 107 of the 108 drivers were available to process in Phase 2.) In total, human-manual driving data were processed for 143 different drivers.

The procedure for analyzing steady-following data involved the use of the relational features of the databases involved. Steady-following information was selected by screening the data for situations in which Rdot and Vdot were approximately equal to zero. The free flow speed called "Vset" was determined for each driver. (This is the speed the driver chooses to go when range is large in that driver's view of the situation.) Then data for range clearances and speeds such that the equation $R = A + T\,V + G\,V^2$ applies were used to find best-fit values of T and G, using A = 3 m as in CORSIM [8]. The steps in this process produced results, like those shown in figure 8, for each driver.

The upper left graph indicates data points for one-on-one situations with proceeding vehicles up to 120 m away and speeds up to approximately 35 m/s. These data are for the driver with code-number 32 in the ICC FOT study. Note the two long-range tails at about 18 m/s and 30 m/s. These tails are due to the set speeds, Vsets, that driver 32 chooses to use on freeways (about 30 m/s, or 68 mph) and on main arterial roads (about 18 m/s, or 40 mph). The upper right figure contains a histogram of range and a distribution of range in red. It is used to separate the range data at the 65th percentile into short and long range data. The long-range data is used to make the histogram shown in the lower left figure, because that histogram is used to determine Vset for freeways.

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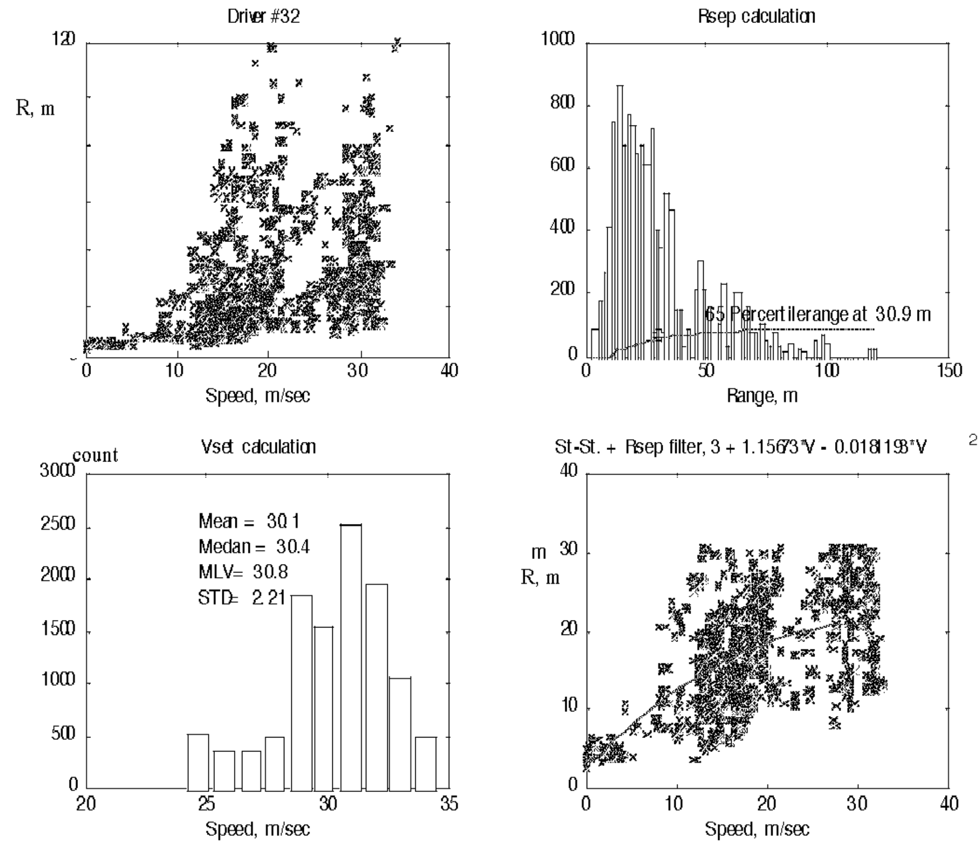



Figure 8. Illustration of the results from steady-following data analysis.

Results like those shown in Figure 8 were obtained for each of the 143 drivers included in the Phase 2 research. The key results with regard to traffic flow are the values of Vset and the values of T and G for steady following. As shown in the equation above the lower left graph in figure 8, the values for T and G for driver 32 are T = 1.157 and G = – 0.0181. The values of Vset, T and G for an individual driver characterize the driving style (tendencies) of that driver. The values determined for each driver from the FOCAS and ICC FOT studies are tabulated in Appendix A. The results for Vset, T, and G have been sorted from smallest to largest value and plotted in ascending order in figures 9 through 14. Figures 9 through 11 apply to the FOCAS data and figures 12 through 14 apply to the ICC FOT data.

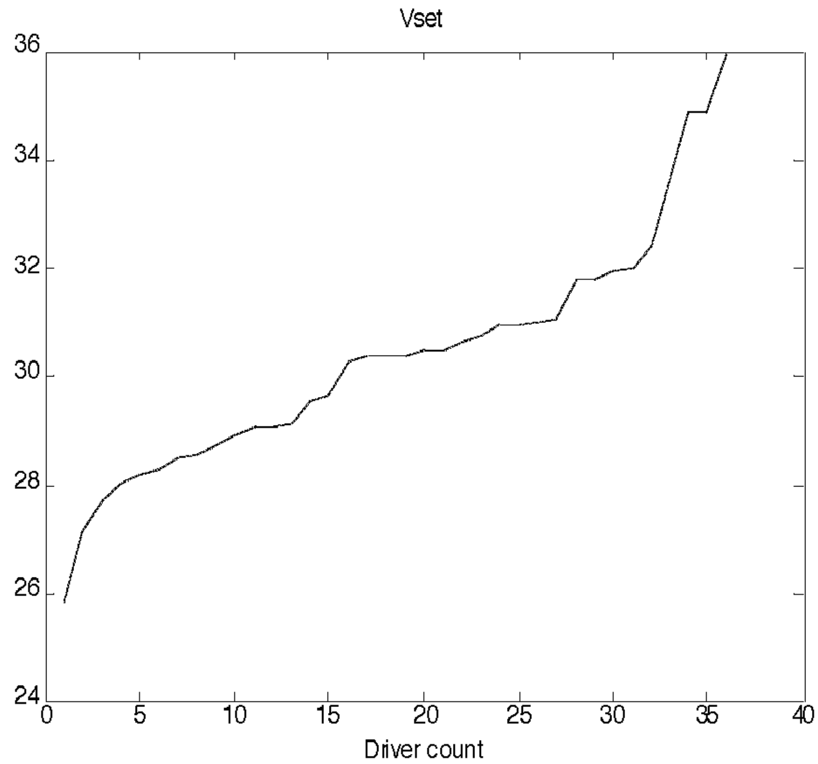



Figure 9. Vset, m/s, sorted into ascending order, FOCAS.

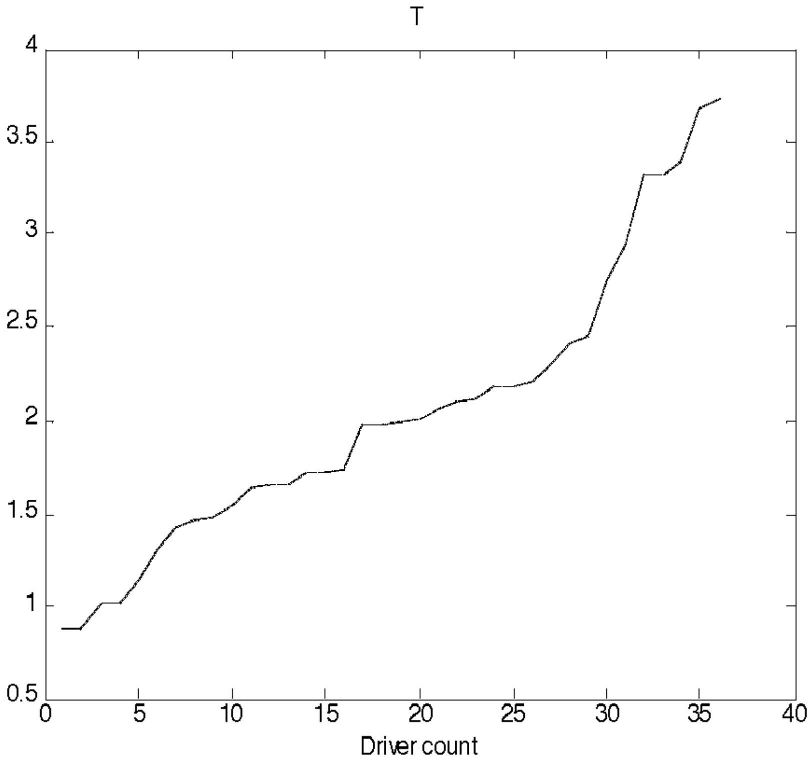



Figure 10. T, sec., sorted into ascending order, FOCAS.

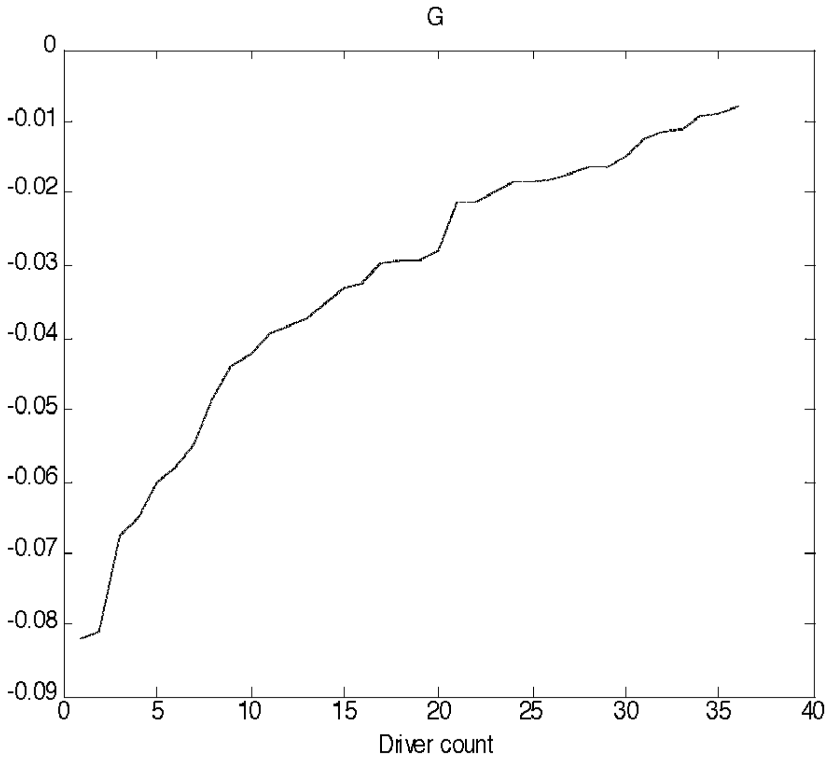



Figure 11. G, $s^2/m$, sorted into ascending order, FOCAS.

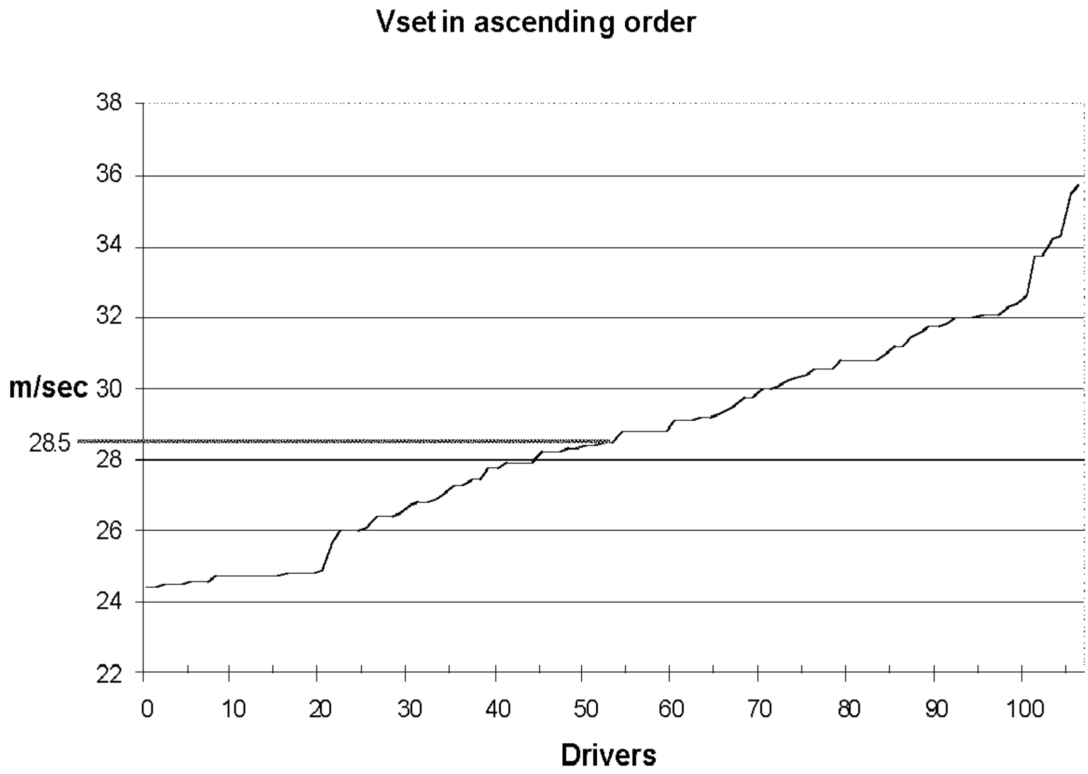



Figure 12. Vset in ascending order, ICC FOT.

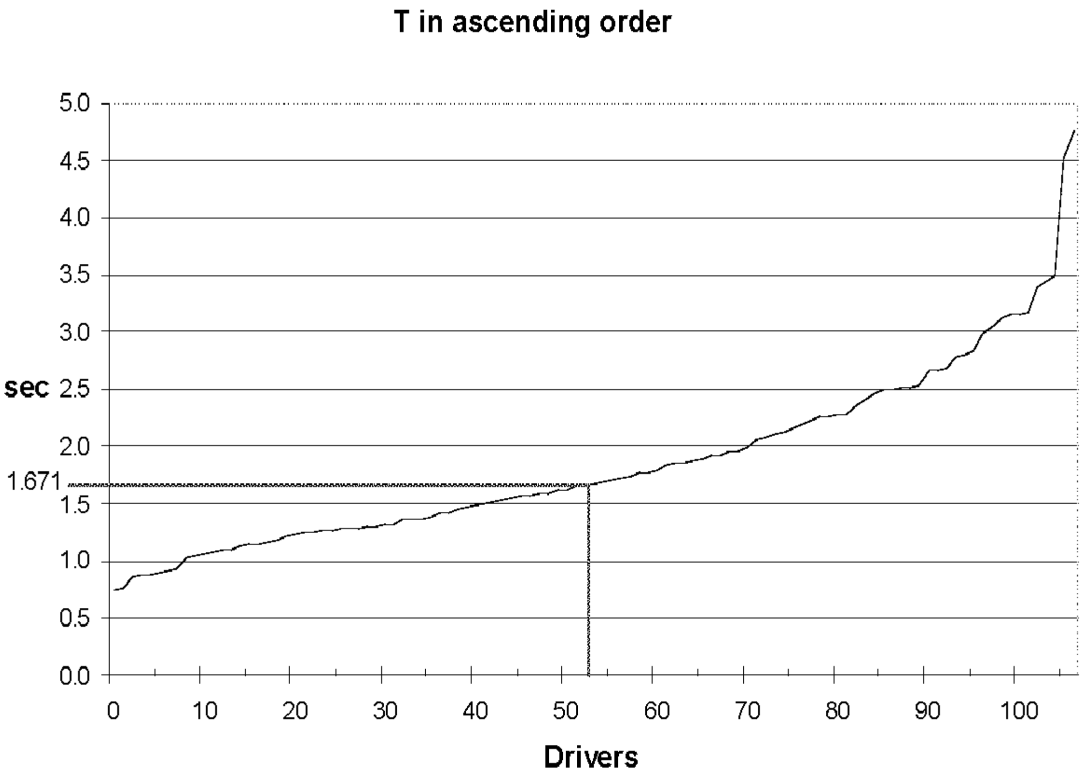



Figure 13. T in ascending order, ICC FOT.

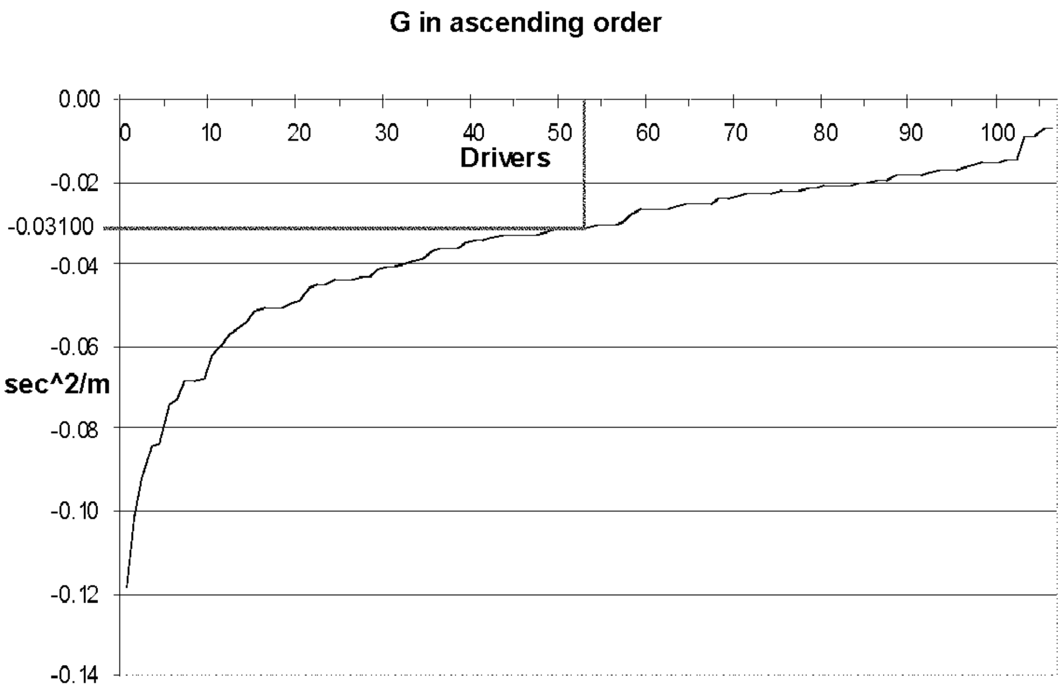



Figure 14. G in ascending order, ICC FOT.

Figures 15 and 16 show the tendency for the values of T to be related to those for G.

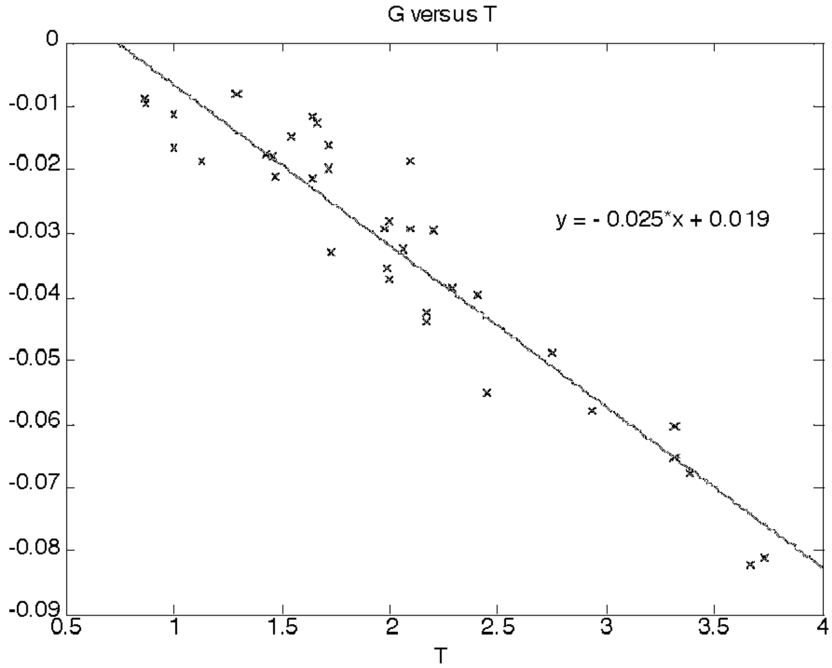



Figure 15. The relationship between G and T, data from FOCAS.

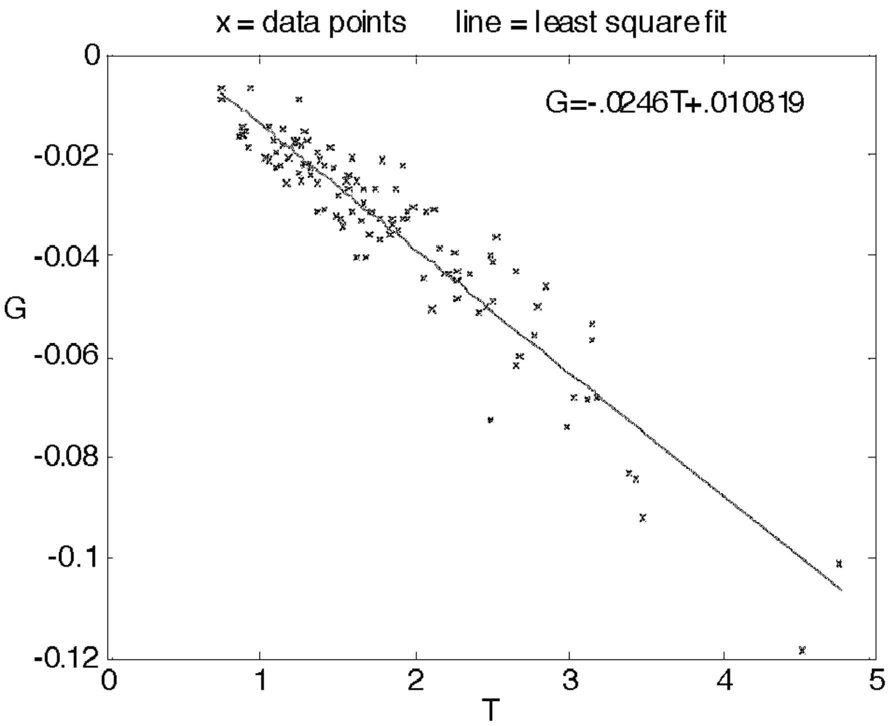



Figure 16. The relationship between G and T, data from ICC FOT.

The steady-following results portrayed in figures 9 through 16 are the basis for the following findings.

• The steady-following parameters, Vset and T, vary over a wide range of values depending upon the characteristics of the driver involved.

• The parameters T and G are approximately related by G = – 0.025 T + 0.013 for human-manual driving.

These findings have significant implications regarding the capacity of traffic flow since flow capacity (Fc for an individual driver) is related to Vset and the density (Dset) at Vset for steady flow. (The following items apply here, Rset = A + T Vset + G $(\text{Vset})^2$ and Dset = $(\text{Rset} + \text{L})^{-1}$ and L is the vehicle length and Fc = Vset Dset.) These matters will be discussed further in the section entitled "Traffic Flow Characteristics Related to Longitudinal Control Properties."

**Parameters Employed in Representing Transient Behavior**

Linear and non-linear models of human-manual driving have been considered in phase 2. The techniques used for fitting a linear model to the data were the same as those used in phase 1. They involve standard methods available in MATLAB for obtaining least square fits to time histories of measured data for range clearance and velocity. However as phase 2 progressed, the emphasis shifted to non-linear techniques associated with the non-linear equations portrayed previously in Figure 4. From a theoretical point of view, linear equations may represent approximations suitable for small perturbations of the variables in the underlying non-linear equations. These perturbation ideas could be pursued further in later phases of this research program. Some of the ideas behind perturbation analysis apply here in a restricted sense because the following material is aimed at transient behavior when traveling near highway speeds at slightly less than Vset, typically about 28 m/s. This means that the following data analysis is based upon reducing the steady-following errors "$e_R$" and "$e_{Rdot}$" (shown in figure 4) toward zero using linear gain factors. This procedure may not be satisfactory for situations involving panic hard braking, but those situations are treated conservatively in the modeled driver in order to avoid crashes in simulations whose purpose is to study traffic flow.

Figure 17 provides an overview of the structure of the non-linear model. It is a SIMULINK diagram as used in exercising the model to study the one-on-one response of the modeled driver to the velocity Vp of the preceding vehicle. As shown in the figure, the model consists of two integrators, one for determining V from Vdot and the other for determining R from Rdot. This represents the traditional method for using integrators to solve differential equations. There is a zero order hold that emulates the driver's characteristic to update and hold Vdot from one decision moment to the next decision moment. The diagram shows two subsystems for computing $e_{Rdot}$ and $e_R$ using the equations given in figure 4. The transient response parameters are labeled C1 "lead and damping" and C2 "frequency". The values of these parameters have been chosen to match measured results for situations in which Vp decreases by a small amount.

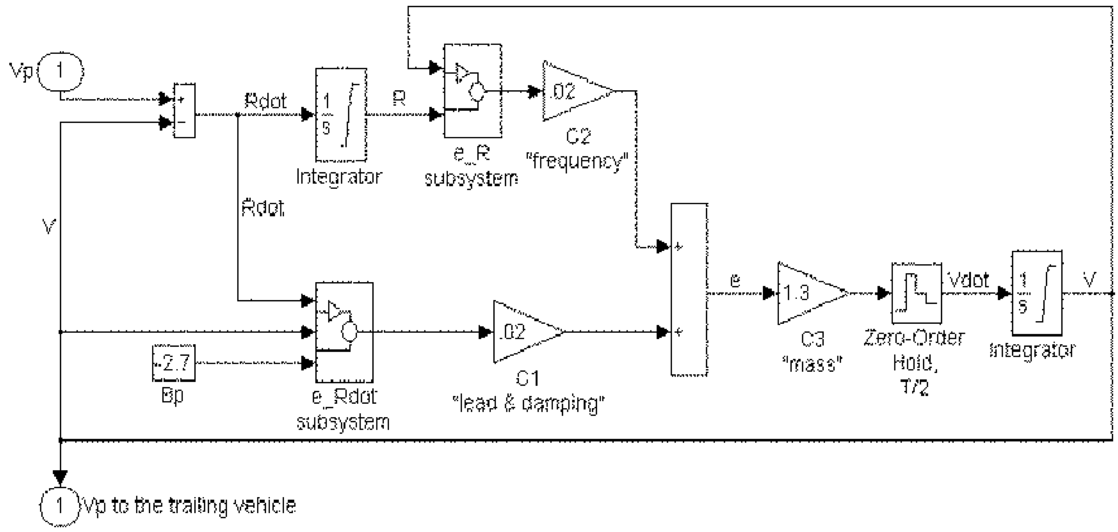



Figure 17. Diagram of the non-linear model.

At this point in the development of the driver model, the data need further analyses to determine values of C1, C2, and C3 for each of the 143 drivers. However, one observation is clear. Many drivers have values of C1 such that range and velocity will undershoot/overshoot their steady following values as these variables approach steady following. For example, see figure 18, which uses the steady-following values of T and G for driver 7 in the ICC FOT study.

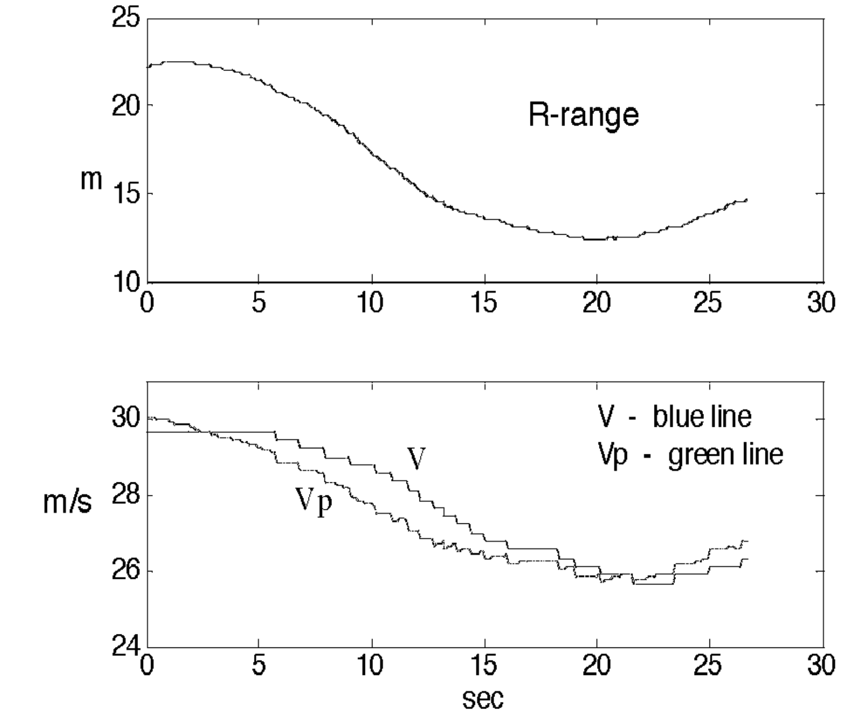
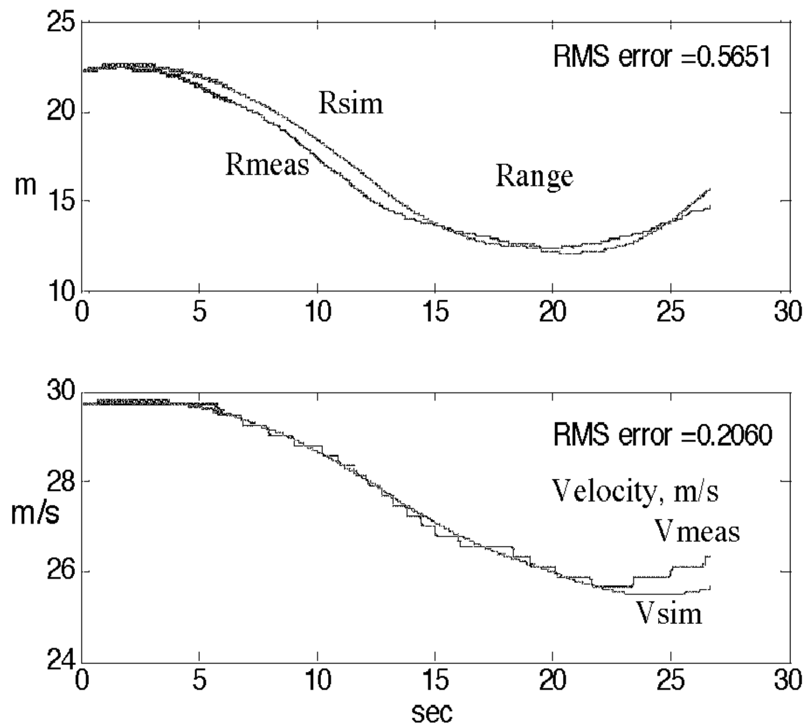



Figure 18a. Measured transient response data from driver 7 with the lead vehicle decelerating.




(Blue lines measured. Green lines simulated.)

Figure 18b. Transient-Response data-fitting, Driver #7, C1=.0240, C2=.0157, C3=.929

The point about over/undershoot is important with respect to the performance of a string of nearly identical vehicles and drivers. The microscopic phenomena concerning undershoot can be used to explain why traffic flow tends to breakdown at density levels beyond Dset, which is the density at capacity. The influences of the over/undershoot phenomena will be discussed in the next section entitled "Simulation Results Concerning Inherently Sustainable Strings."

Figure 18 also contains simulated results based upon the modeled driver portrayed by figure 17, using the error equations displayed in Figure 4. In this case, the values of C1, C2, and C3 have been adjusted to get a good fit to transient data for driver 7. The RMS errors are 0.57 m in range and 0.21 m/s in velocity. Experience indicates that this is a good fit for this type of fitting procedure. Figure 19 presents similar results for driver 9 in the ICC FOT study. Driver 9 has a value of T = 2.25 compared to T = 1.5 for driver 7. The fit is good in this case as well.

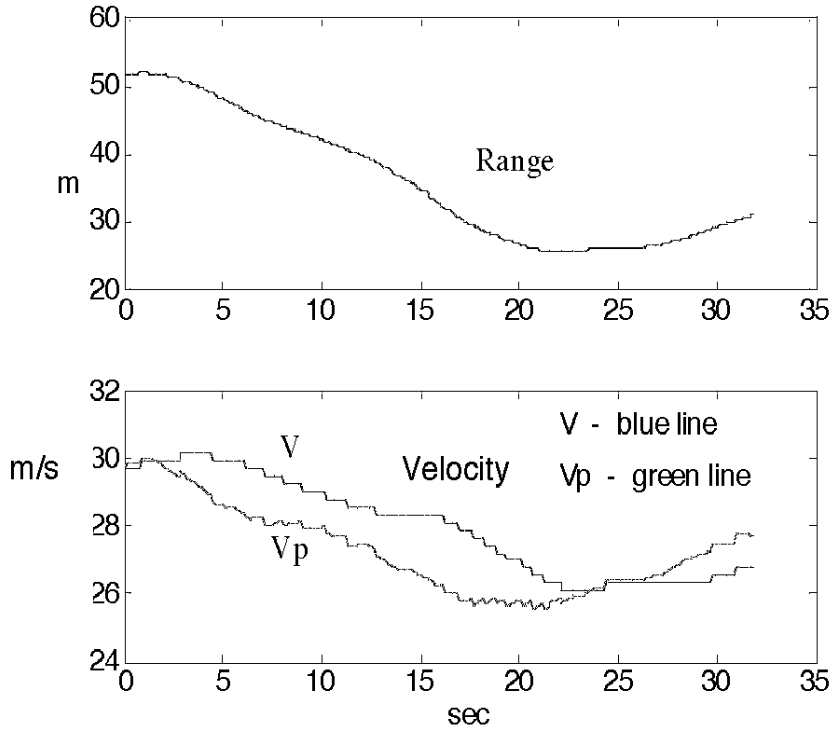
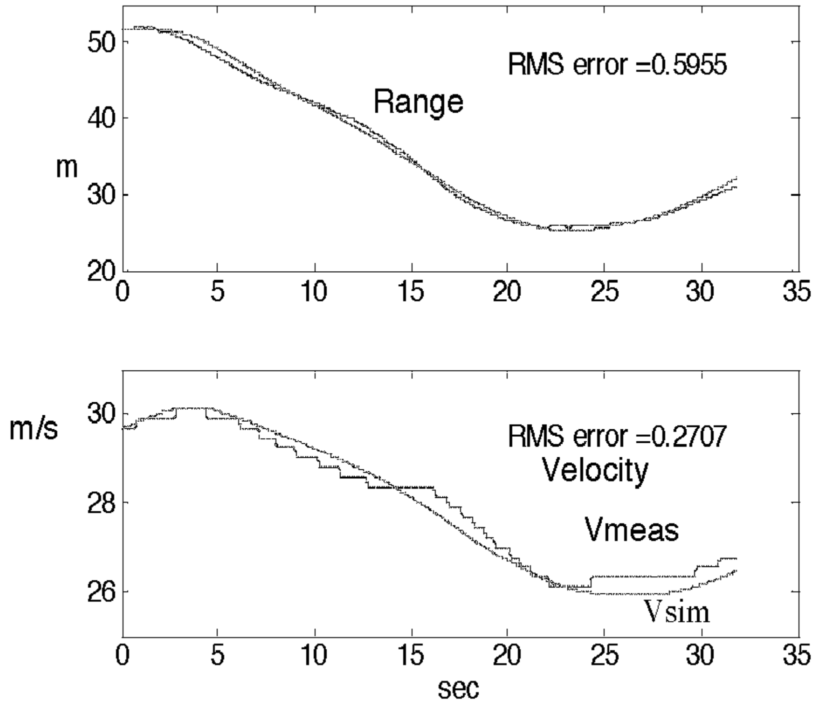



Figure 19a. Measured transient response, driver 9 input string




(Blue lines measured. Green lines simulated.)

Figure 19b. Transient-response data-fitting, Driver # 9, C1= .01675, C2=.0089, C3=1.00

The parameters C1, C2, and C3 have interpretations based upon a mass-spring-damper analogy. The names "frequency", "mass", and "lead and damping" in Figure 17 are meant to convey the meanings of C1, C2, and C3. These names are helpful in manually fitting data for the second order system implemented to represent a driver as in figure 17. However, a programmable algorithm for determining transient parameters (C1, C2, and C3 in figure 17) can be created to handle databases involving large numbers of drivers. This step needs to be completed in a new phase of research. Nevertheless, based upon the current work, one can observe that if $G < 0$, the lead and damping (C1) associated with the human-manual driving data is not likely to be large enough to prevent over/undershoot. Since $G < 0$ for all 143 drivers studied, it is anticipated that all of the modeled drivers are likely to exhibit over/undershoot characteristics.

There are a number of other observations that follow from the process of examining and penetrating data from human-manual driving. One observation concerns the variability within a single driver. People do not always adopt the same control behavior under repeated episodes of the same nominal driving circumstances. For example, figures 20 and 21 show fits to the data for drivers 7 and 9. These were the drivers portrayed in figures 18 and 19 except longer periods of time around the time periods used previously are involved. When the fitting is done in these extended situations, the values of C1, C2, and C3 are different from those found previously.

These differences are partly due to data fitting ambiguities but they are also due to variability in driver characteristics. Human-factors studies indicate that people perceive range clearance within ±12 percent and they have a threshold on sensing Rdot that is significant [9]. In addition, the anatomy and physiology of the eye indicate that a driver must be looking directly at an object to detect its relative velocity (Rdot). These factors provide a basis for explaining some of the variability in the performance of a single driver. The least square errors in R in figures 20 and 21 are approximately 3 to 4 meters. At first this may seem large but it is about the same as the driver's range resolution at range clearances on the order of 30 m. In addition, the moment when the driver notices that Rdot has exceeded the threshold on Rdot may not be synchronized with when the driver samples and holds a new value of Vdot. Furthermore, a driver's intentions and stresses change for reasons like being late. Drivers will adjust their style of driving from time to time. All of these factors are expected to contribute to considerable variability in observed behavior.

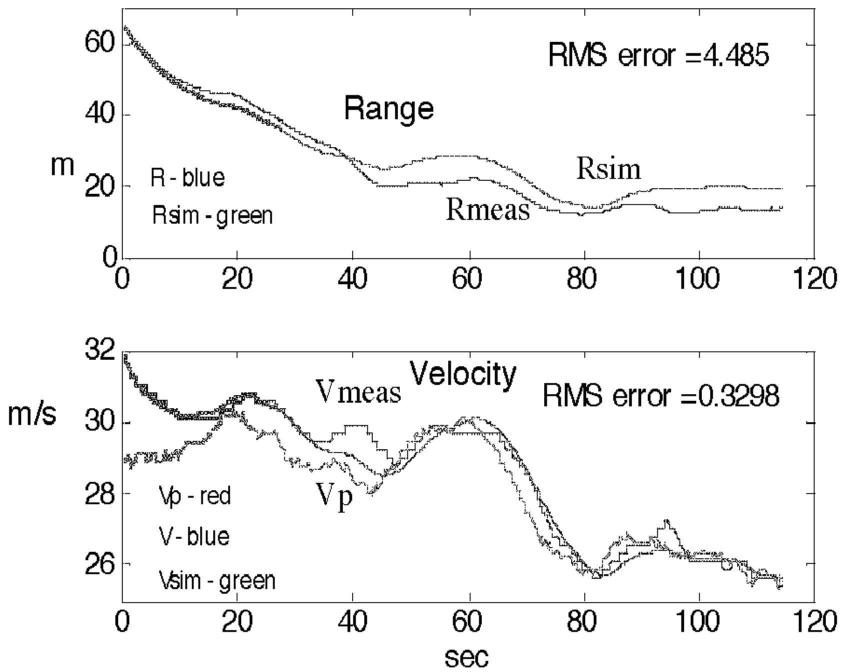
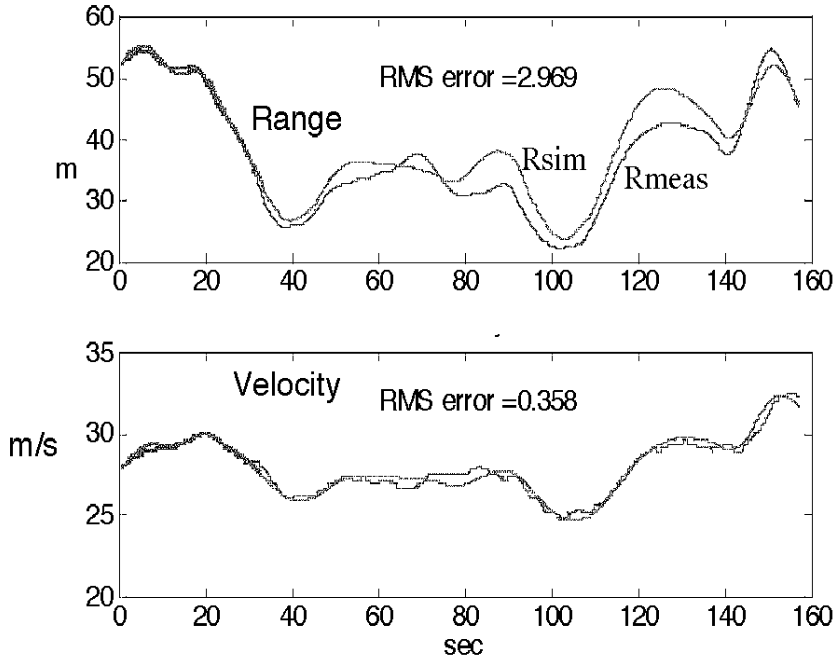



Figure 20. Driver 7 for full stream with C1 = .026, C2 = .0106, C3 = 1.0




(Blue lines measured. Green lines simulated.)
Figure 21. Driver 9 with full stream with C1=.0181, C2=.007, C3=1.0

There are factors in interpreting human-manual driving data that have been classified as "altercontrol" [10]. The idea is that the driver is not always controlling range and velocity for the purpose of maintaining range clearance. A simple example is when range is large enough and the driver simply doesn't care as long as Rdot is positive (the vehicles are separating). A subtler example that has been observed involves drivers closing the range-clearance gap ahead so that a driver in an adjacent lane will not take the gap. On the other hand, some gracious drivers may let a gap open up so that someone in an adjacent lane will have comfortable room for changing lanes. Sometimes drivers are maneuvering so that they can take a gap in an adjacent lane. Experience in examining data has shown that it is not uncommon to select approximately 10 data streams like those shown in figure 18 and then find that three of them appear to involve altercontrol. Given the presence of altercontrol phenomena, the selection of data samples to use in evaluating driver characteristics is not as straightforward as the researcher would like it to be. Nevertheless, these phenomena need to be considered in processing naturalistic data.

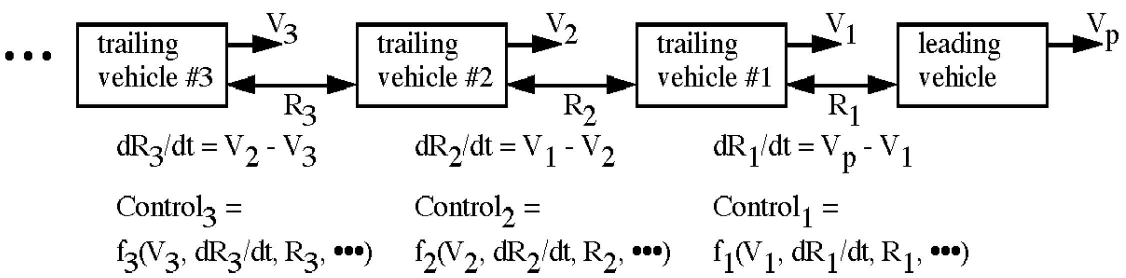
The modeled driver as portrayed in figure 17 has been completed by incorporating the decision to operate at Vset when the steady following rules would say to operate at speeds above Vset. This provides the long-range tails for each road type that are present in figure 8. Other constraints require that R not become less than A and that V not become less than zero. These represent simplifications that are acceptable for a preliminary simplified model. They could receive further attention in future research, but they are adequate for using simulation to gain insights into the influences on driving behavior of the basic parameters describing driver characteristics.

The data that have been analyzed so far are not readily processed to recognize each driver's gap-taking preferences and tendencies for changing lanes. Those characteristics need to be included in microscopic simulations of traffic flow, and they have been studied elsewhere, for example [11], but further observations emphasizing microscopic, individual tendencies for each driver are in order.

Although the study of transient behavior involves many nuances, phase 2 research provides evidence supporting the following observations. First, values for the transient parameters in the driver model can be found to fit measured transient responses well. Second, the results of the data analysis indicate that drivers have a general tendency to over/undershoot the velocity and range behavior of the preceding vehicle. The modeled driver emulates these tendencies.

**Simulation Results concerning Inherently Sustainable Strings**

The driver model for one-on-one situations can be extended to model a string of vehicles with identical longitudinal control characteristics. The duplication features of modern computer simulation systems such as SIMULINK make this process very easy. Duplicating the basic model as often as desired can create a string of any desired length. The idea is illustrated in figure 22.




Conceptual diagram of a string of N + 1 vehicles with sensed variables ($R_i$, $dR_i/dt$, and $V_i$), and control rules ($Control_i$) for each of i = 1 to N trailing vehicles.

Figure 22. A string of vehicles consisting of one-on-one situations in series.

In figure 22, trailing vehicle #1 responds to the velocity $V_p$ of the leading vehicle, which is the preceding vehicle for trailing vehicle #1. The idea of a string is that vehicles cannot change lanes and they will respond to the velocity of their preceding vehicle. Hence, trailing vehicle #2 responds to the velocity of trailing vehicle #1 and so on until the last vehicle in the string is reached. Observe that $Rdot_2 = dR/dT_2 = V_1 - V_2$, etc.

Currently, many researchers are investigating string stability. (For example, a frequently referenced work is [12], which provides sufficient conditions for one type of string stability.) There are generally accepted results for linear systems. However, the types of systems observed for driver behavior (or ACC performance) may be non-linear and involve decision and switching rules, whose influences on string performance are not readily comprehended. Given the ease, with which string simulations can be created, string simulation provides a practical pragmatic means for assessing the influences of driver or ACC-system characteristics on string performance. The assessment procedure for studying a single set of driving characteristics involves examining the results of string simulation to see whether the maximums and minimums of range and velocity increase or decrease in response to a velocity change of the leading vehicle.

(The ACC systems discussed here are autonomous and do not involve cooperative communication channels involving the transmission of information from the road environment and/or nearby vehicles. This is how the acronym "ACC" is used.)

The suggested string calculation appears to be a hypothetical one for a given driver, since it is unlikely that a string of identical drivers driving identical vehicles with no possibility of changing lanes will occur in the real world. However, for ACC systems this is a possibly practical situation and one that has been arranged and tested. See reference [6] volume III. From tests and analyses of ACC systems, a concept of "inherently sustainable strings" has been developed in phase 2. A set of driver or ACC system characteristics is said to have inherently sustainable string performance if there is no over/undershoot of range and velocity from vehicle to vehicle going back in a string of identical driver/vehicle combinations.

Figure 23 illustrates results from a string simulation based upon the steady following and transient parameters for driver 7 in the ICC FOT study. In this case the simulated string consisted of a lead vehicle and four following vehicles. There are five velocities and four ranges to be considered in examining the results for this five-vehicle string. Examination of figure 23 indicates that driver 7 does not have inherently sustainable string performance. The range and velocity time histories undershoot the performance of each preceding vehicle in the string.

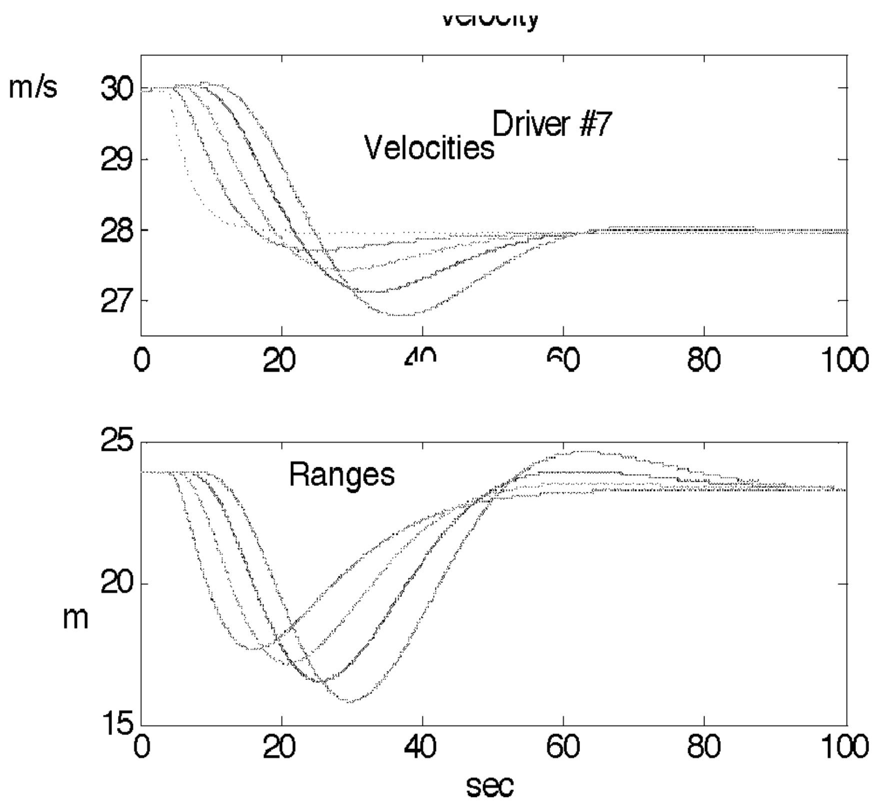



Figure 23 . A string of identical vehicles showing unsustainable flow for driver 7.

Although there are no close encounters between trailing and leading vehicles in this five-vehicle string, it is clear that the range clearance to the preceding vehicle decreases from vehicle to vehicle going back into the string. If the string were long enough, eventually a trailing vehicle would need to stop in order to prevent a collision with its preceding vehicle. In this sense, the parameters for driver 7 do not represent those required for inherently sustainable string-flow.

A similar set of results are presented in figure 24, pertaining to driver 9 whose characteristic parameters differ significantly from those of driver 7. In particular T = 1.51 for driver 7 and T = 2.26 for driver 9. However, as previously discussed the value of the transient response parameter C1 does not appear to be large enough in comparison to C2 to provide an inherently sustainable string for either driver 7 or 9.

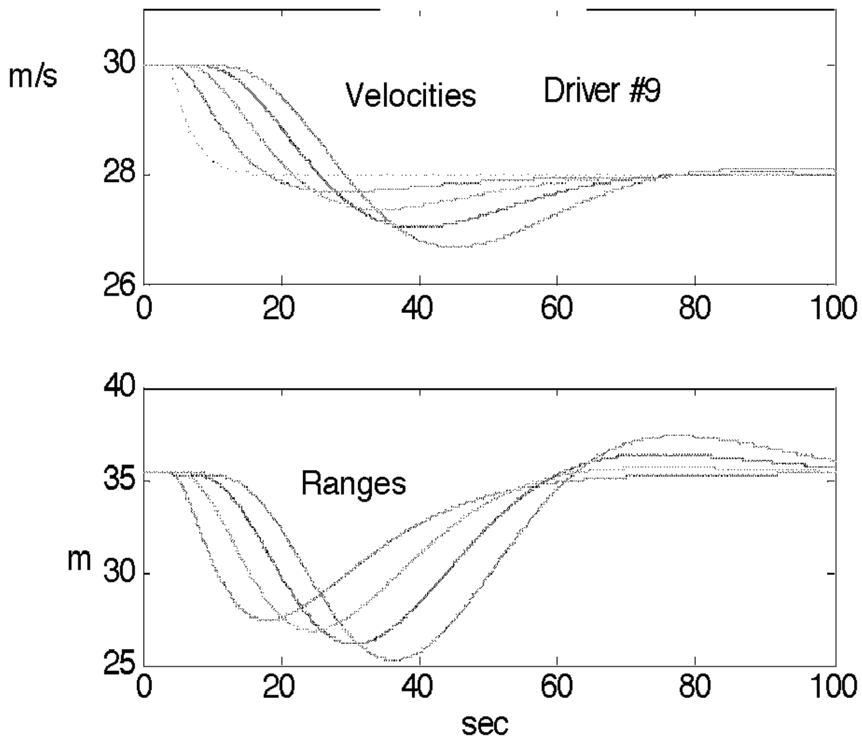



Figure 24. A string of identical vehicles showing unsustainable flow for driver 9.

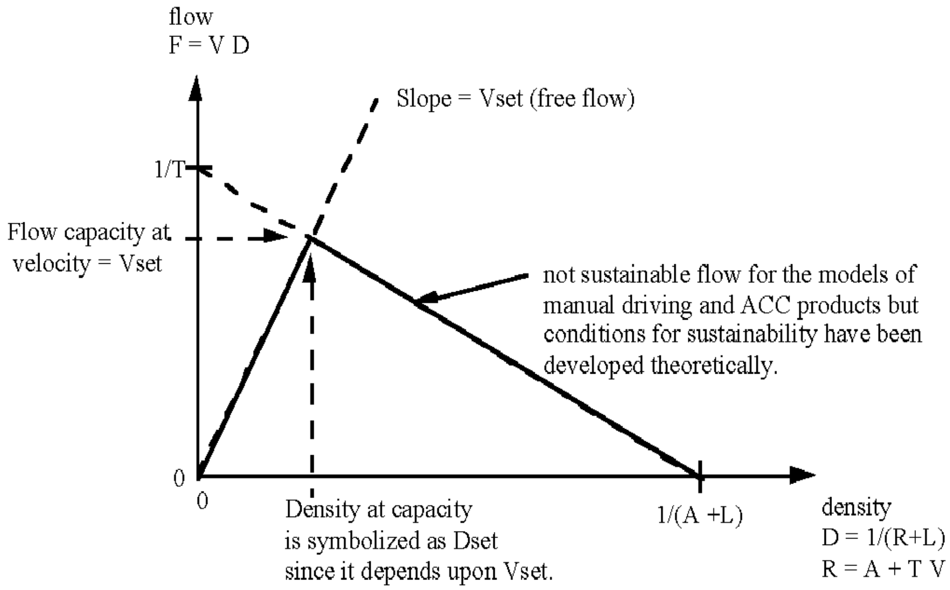
An important point to observe here is that an ACC algorithm can be programmed to employ any of the steady-following driver characteristics that were observed in phase 2 (including those for drivers 7 and 9). However, in ACC systems, the transient response parameters can be adjusted (at least in theory) to make strings of identical vehicles have inherently sustainable flow. This requires adding more lead compensation and damping (making (C1) larger). The analysis supporting this was done in phase 1 and reported in [13]. The concept of inherently sustainable string performance plays an important role in the discussion of traffic flow presented in the next section.

**Traffic Flow Characteristics Related to Longitudinal Control Properties**

Relationships between longitudinal control characteristics of ACC systems and drivers as determined in phases 1 and 2 and the capacity and sustainability of traffic flow are addressed in this section.

Figure 25 illustrates basic ideas concerning flow–density relationships and the influences of Vset and steady-following characteristics on that relationship. In this example G= 0 so that flow F and density D are linearly related and the diagram is simple to construct. Specifically for this case, the flow, F, equals [-(A + L) D + 1](1/T) where L is the vehicle length and A and T are steady following parameters.

(For all the drivers studied G was less than zero but an ACC system could be made with G = 0. The influences of G < 0 will be examined after this simpler example has been used to establish certain basic relationships.)




Linear constant time-gap (T)
steady-following flow-density diagram

Figure 25. Hypothetical flow-density diagram in which G = 0.

At low traffic density, drivers may proceed at Vset because there is room to pass any slower moving vehicles that they may encounter. In this sense Vset is the free flow speed observed in traffic flow data. Figure 25 simplifies the general situation in that one free-flow speed rather than a distribution of free flow speeds is shown.

Also, to cope with complexity, the diagram is for single values of A, T, and L. This is a matter of convenience for discussing concepts and ideas. In a general microscopic simulation of traffic, these parametric values would be distributed amongst different types of drivers according to on-road observations.

Returning to figure 25, once the density gets high enough, drivers will be close enough to the preceding vehicle that they will slow down to follow a steady-following relationship. In this example, the steady following relationship is R = A + T V and the density D is given by D = 1/(R + L). This means, after some algebraic operations, that the flow F = V D = [-(A + L) D + 1](1/T) when density is greater than the density at Vset, which is the density at Rset = A + T Vset in this case.

The flow at capacity occurs at Vset in this example. For the set of parameters (A + L) = 8, T = 1 s and Vset = 30 m/s, the flow at capacity Fc would be 30/38 = 0.789 vehicles/s. This is a large flow ( Fc = 2840 vehicles/hour), but in practice, capacity is restricted by the drivers who chose smaller values of Vset and larger values of T.

Figure 26 illustrates the influences of the parameter G on the capacity of flow. In this example G = - 0.01 $s^2$/m.

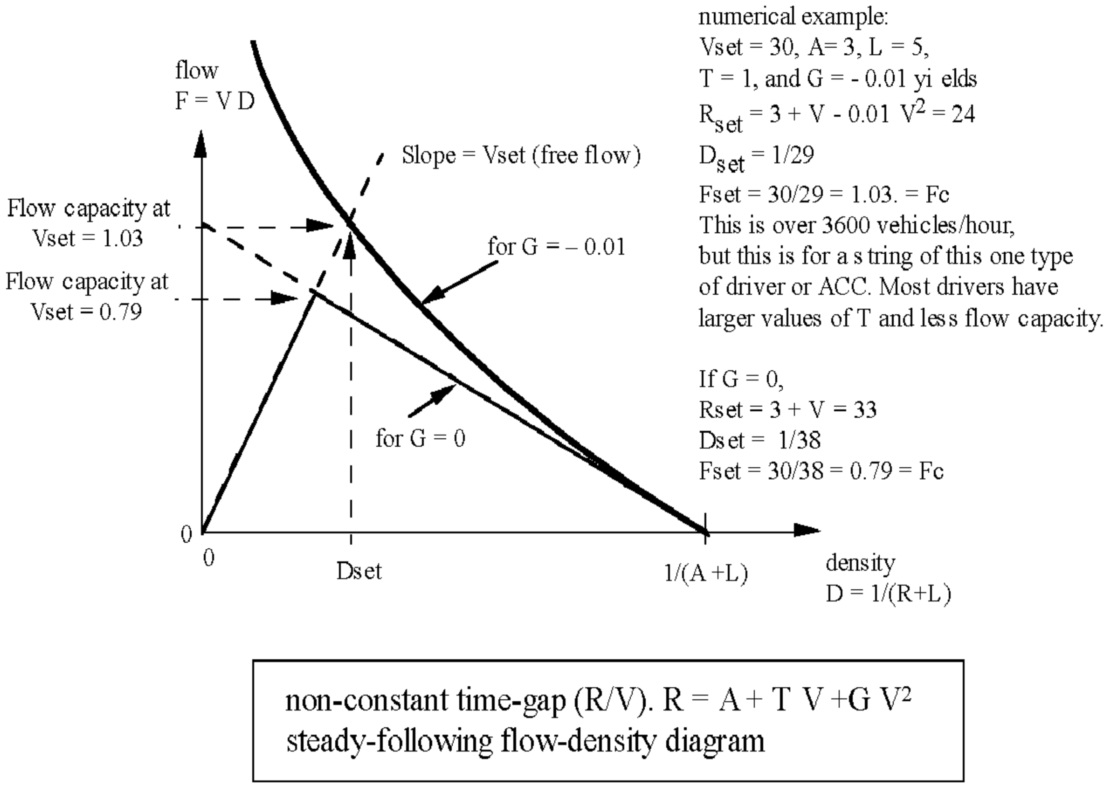



Figure 26. Flow-density diagram and example illustrating the influence of G.

The results for a numerical example are included in figure 26. The values of A, L, T, and Vset are the same as those discussed in connection with figure 25 except that G equaled 0 in that case. The figure clearly indicates and the numerical example shows that the value of G has a significant influence on capacity. The capacity for the G= 0 case is 0.79 vehicles/s and it is 1.03 vehicles/s for G = -0.01 $s^2$/m.

Figure 27 presents a numerical example showing the interaction of T and G. The results again show the significance of the value of G on the capacity of the flow. The basic finding is that a non-linear steady-following relationship of the form R = A + T V +

G $V^2$ with G < 0 will improve capacity depending upon the magnitude of G. The influences of larger values of T can be off set by larger negative values of G.

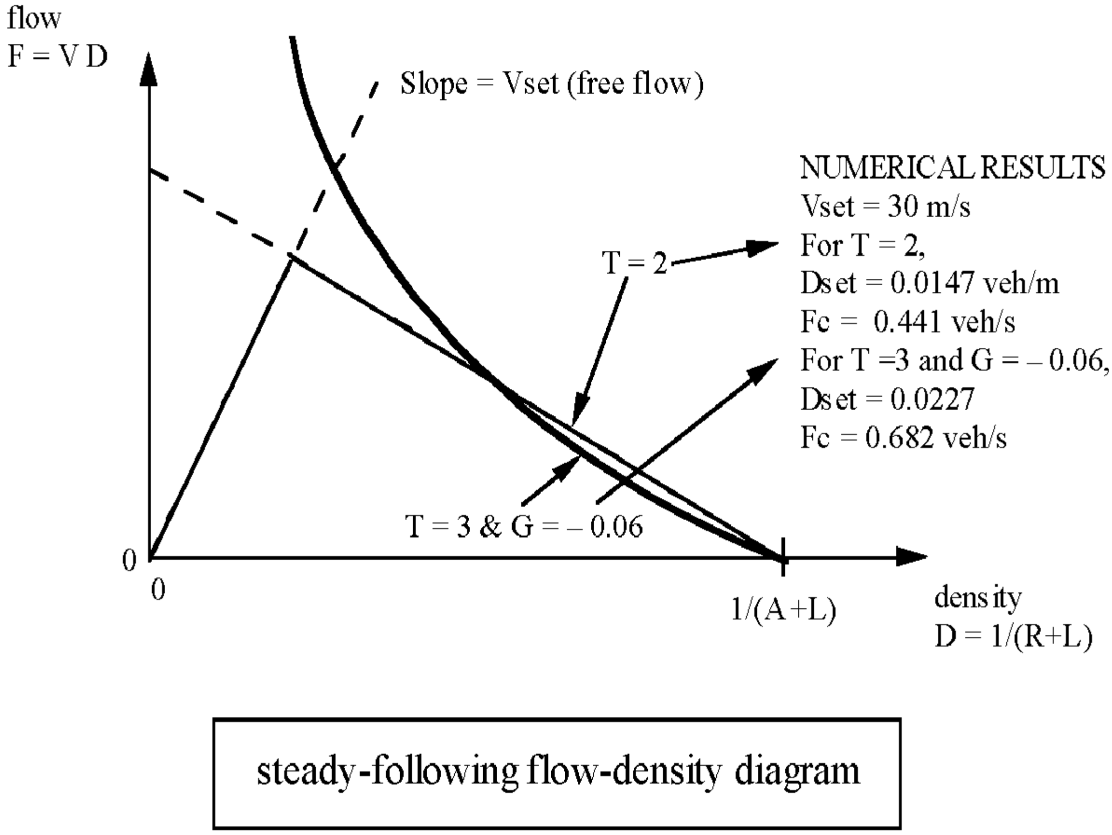



Figure 27. Flow-density diagram indicating the importance of G as T increases.

Based upon the type of analysis illustrated in figures 25, 26 and 27, the values of Dset and Fc have been computed for each of the ICC FOT and FOCAS drivers. See figures 28 and 29, for example. These results show a wide spread of values for the capacity of a flow consisting exclusively of each type of driver. It is anticipated that for a traffic stream involving a mixture of driver types, the drivers with the lowest values of Fc would control the overall capacity. This is based upon the idea that as the density increases the opportunity to pass a slower moving vehicle is eliminated. Hence, a trailing vehicle is forced to go at the speed of its preceding vehicle whether the driver wants to or not.

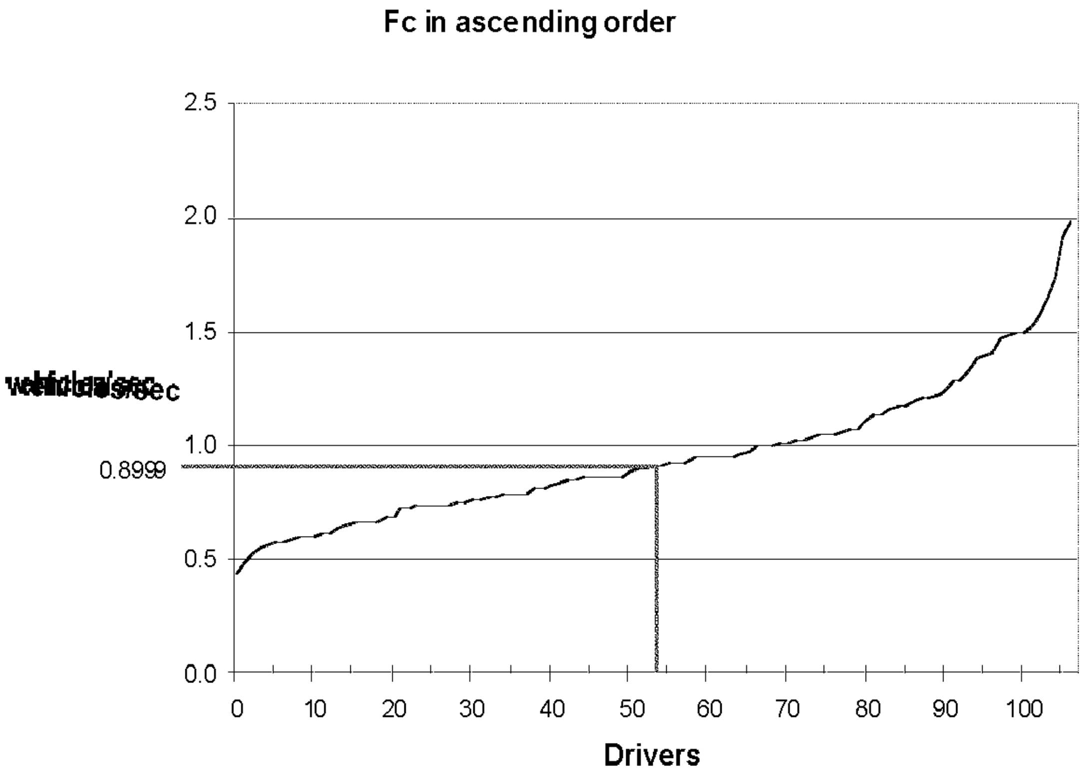



Figure 28. Fc capacity in ascending order, ICC FOT data.

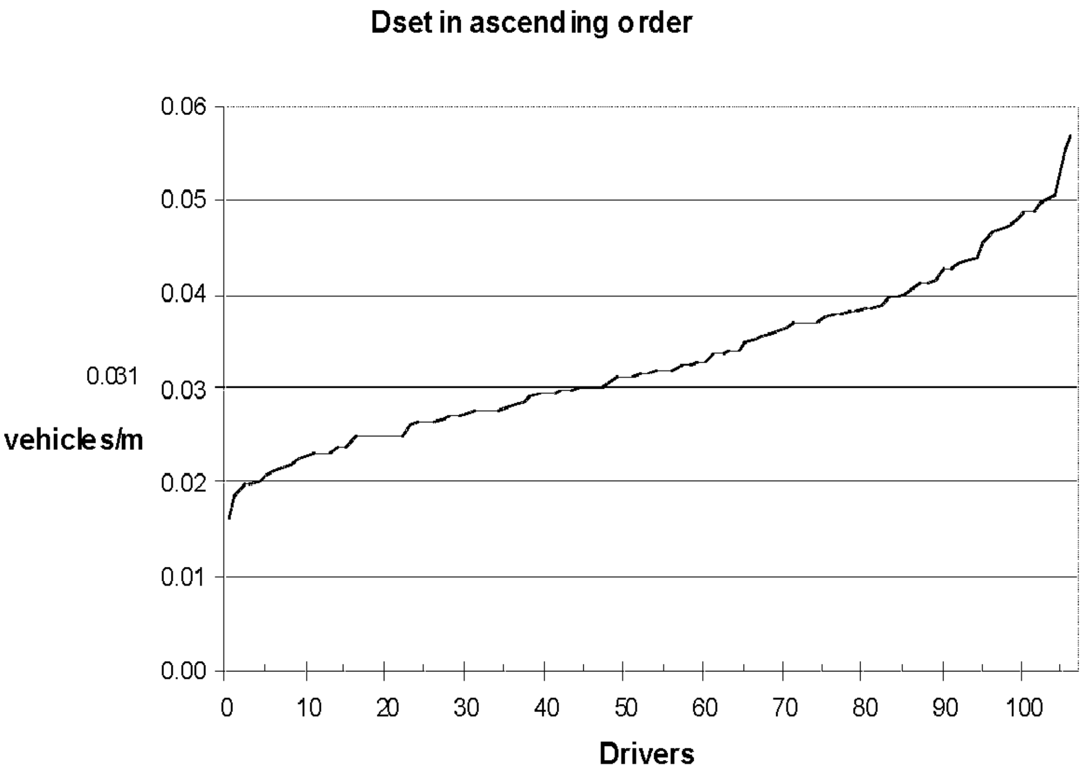



Figure 29. Dset (density at capacity) in ascending order, ICC FOT data.

The next figure addresses a different type of question. Figure 30 involves situations in which vehicles are trying to operate at densities above Dset, the density at capacity.

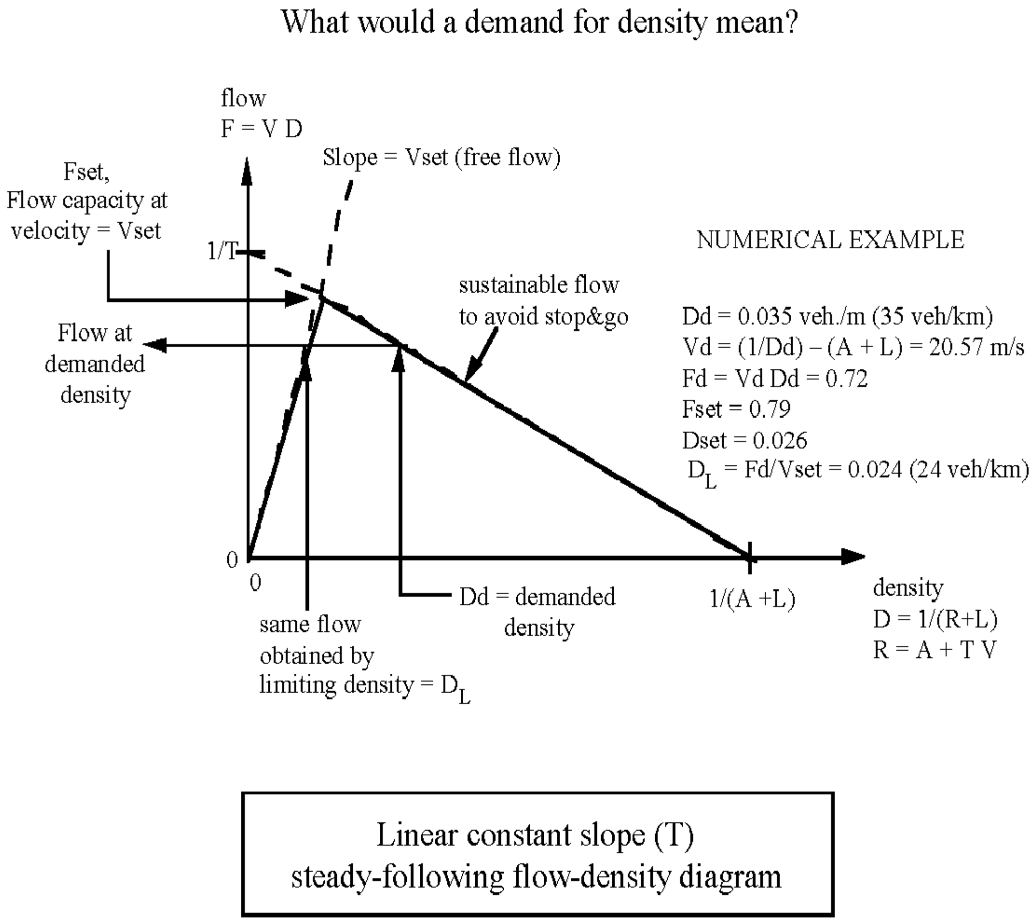



Figure 30. Flow-density diagram illustrating where sustainable flow would be helpful.

The point of the numerical example shown in Figure 30 is that theoretically more vehicles could get on the road (i.e., density could be higher) if vehicles were capable of inherently sustainable flow. In the example, there is almost a 50 percent increase in density compared to that attained by restricting density at a comparable flow (0.72 veh/s in this case). Although it may be very difficult and practically impossible to get drivers to drive with the necessary anticipation to sustain this flow, one might design ACC systems to do so. That would be theoretically possible, but it is not known whether people would like it. This is an area that could be studied in phase 3. None of the ACC systems used in the ICC FOT or FOCAS projects produce inherently sustainable flow. The measurements done in phase 1 indicate that current ACC systems are much like human-manual driving with respect to the inability to provide sustainable flow at high densities.

## Summary of Conclusions and Findings from Phase 2 Research

*Learning what happens when people are driving manually.*

Naturalistic data from the ICC FOT and FOCAS research programs provided the quantitative information used for learning how people control the range clearance to a preceding vehicle and the speed of their vehicle. This information was available in a relational database, thereby allowing it to be readily queried. The results of these queries have provided parametric values as needed for a model, which can be used for emulating human-manual driving. The model and the values of the parameters associated with the model describe the human-manual driving characteristics of the 143 different drivers studied in phase 2.

*Understanding how the driving process works in typical traffic situations involving control of speed and range clearance.*

The human-manual driving data have been used to develop findings concerning the steady-following characteristics of drivers and their lack of an inherent capability for sustaining steady following in a string of similar driver-vehicle combinations. The equations for the model are based upon the premise that drivers follow other vehicles in a way that expresses their personalized style for avoiding rear-end crashes. Based upon this premise, a constant deceleration analysis was used to generate basis functions that were used to fit actual naturalistic driving data and to yield parameters that captured each driver's personalized style.

The basis function used in the model for fitting steady following data is $R = A + T V + G V^2$ where R is the steady following range clearance and V is the velocity at steady following. The data show and the model contains a free flow speed, Vset, which drivers seek when the range clearance and roadway characteristics are viewed as appropriate for that speed. This provides the long-range tails observed at Vset for each road type. (Drivers select a free flow speed for each road, apparently depending upon their assessment of that road and its environment.) The model has provision for deciding when to use Vset and when to use R, Rdot, and V in determining the desired speed of travel. Two important findings concerning driver characteristics are as follows:

• The values of the free-flow speed parameter Vset and the steady-following parameter T both vary widely depending upon the personalized characteristics of the driver involved.

• The parameters T and G are approximately related by $G = -0.025\,T + 0.013$ for human-manual driving. The value of G was less than zero for all 143 drivers.

Although the study of transient behavior involves many nuances, phase 2 research provides evidence supporting the following basic observations.

• First, values for the transient parameters in the driver model have been found to fit measured transient responses well.

• Second, the results of the data analysis imply that drivers in general will have a tendency to over/undershoot the velocity of the preceding vehicle and the steady following value of range clearance.

The modeled driver emulates these tendencies using nonlinear expressions, which are functions of velocity, for determining acceleration corrections due to range discrepancies and also due to range-rate discrepancies

At this point in the development of the driver model, the data need further analyses to determine values of the transient-response parameters for each of the 143 drivers. Nevertheless, based upon the current work, one can observe that if $G < 0$ and $T <$ approximately 2.5 s, the lead and damping term associated with the human-manual driving data is not likely to be large enough to prevent over/undershoot. For drivers with values of $T >$ approximately 2.5 s, their time histories frequently indicate a non-linear tendency of these drivers to limit their response to positive (or even very slightly negative, Rdot < 0) range-rate errors. This means that these drivers have a tendency to avoid closing on a preceding vehicle. They hang back letting their time-gap increase.

There are a number of other observations that follow from the process of examining and penetrating data from human-manual driving. One observation concerns the variability within a single driver. People operate with limited accuracy in perceiving range, range-rate, and velocity. In this sense, the values of the transient response parameters involve some uncertainty and are representative of likely values in a given situation. Furthermore, driver intentions and stresses change from time to time, causing them to adjust their style of driving. Another observation involves "altercontrol", which covers driver intentions to change speed for reasons other than those related to range clearance. Given the presence of altercontrol, the selection of data samples to use in evaluating driver characteristics is not as straightforward as the researcher would like it to be. Nevertheless, these phenomena need to be considered in processing naturalistic data to obtain parameters describing driver characteristics pertaining to range clearance per se.

The modeled driver has been completed by adding constraints that require that range, R, not become less than the stopped vehicle clearance, A, and that V not become less than zero. These represent simplifications that are acceptable for a preliminary simplified model. They could receive further attention in future research, but they are adequate for using simulation to gain insights into the influences of the basic parameters describing driver characteristics on the flow of traffic.

The data that have been analyzed so far are not readily processed to recognize each driver's gap-taking preferences and tendencies for changing lanes. Those characteristics need to be included in microscopic simulations of traffic flow. Observations emphasizing microscopic, individual lane-changing tendencies are in order.

*Contemplating what concepts are useful in explaining traffic-flow related aspects of the control of speed and range clearance.*

From tests and analyses of ACC systems, a concept of "inherently sustainable strings" has been employed in phase 2. A set of driver or ACC system characteristics is said to have inherently sustainable string performance if there is no over/undershoot of range and velocity from vehicle to vehicle going back in a simulated or tested string of nearly identical driver/vehicle combinations.

An important point to observe here is that an ACC algorithm can be programmed to employ any of the steady-following driver characteristics determined in phase 2. However, in ACC systems, the transient response parameters can be adjusted to make strings of these types of identical vehicles have nearly inherently sustainable flow. The analysis supporting this was done in phase 1 and reported in [14]. The concept of inherently sustainable string performance plays an important role in considerations of traffic flow in high-density situations.

Relationships between longitudinal control characteristics of ACC systems and drivers as determined in phases 1 and 2 and the capacity and sustainability of traffic flow have been addressed in phase 2. These are done at a high level of abstraction appropriate for engineering design and evaluation purposes.

To cope with the complexity introduced by a wide range of human-manual driving characteristics, analyses involving individual sets of the steady-following characteristics were performed. These analyses show the influences of T and G on the capacity of the flow. The flow at capacity occurs at Vset in these analyses. The value of G has a significant influence on capacity. For example, the capacity for a typical G= 0 case is 0.79 vehicles/s and it is a phenomenal 1.03 vehicles/s for G = -0.01 $s^2/m$ and all else remaining the same.

The values of Dset (density at capacity) and Fc (flow at capacity) have been computed for strings of each of the ICC FOT and FOCAS drivers. These results show a wide spread of values for the capacity of a flow consisting exclusively of each type of driver. It is anticipated that for a traffic stream involving a mixture of driver types, the drivers with the lowest values of Fc would control the overall capacity. This is based upon the idea that as the density increases the opportunity to pass a slower moving vehicle is eliminated. Hence, a trailing vehicle is forced to go at the speed of its preceding vehicle whether the driver wants to or not.

Numerical examples performed in phase 2 show that theoretically more vehicles could get on the road (i.e., density could be higher) if the involved vehicles were capable of inherently sustainable flow. In a typical example, there is almost a 50 percent increase in density compared to that attained by restricting density at a comparable flow (0.72 veh/s in this example). Although it may be very difficult and practically impossible to get drivers to drive with the necessary anticipation to sustain this flow, one might design ACC systems to approach this. That would be theoretically possible, but it is not known whether people would like it. This is an area that could be studied in phase 3. None of the ACC systems in the ICC FOT or FOCAS projects could produce inherently sustainable flow. The measurements done in phase 1 indicate that current ACC systems are much like human-manual driving with respect to the ability to provide sustainable flow at high densities.

*Knowing how to apply the results, findings and discoveries of this research in a logical manner.*

Phase 2 has produced significant discoveries and findings concerning the ACC system characteristics that may significantly influence traffic-flow. Specifically, the influences of Vset, T, and G on capacity are now better understood. To the extent that ACC systems have properties that correspond to these parameters, the influences of ACC systems are better understood.

The driver modeling work advances our ability to predict and evaluate results for mixed traffic involving both ACC and manually controlled vehicles. These new capabilities are now available for use in experimenting with models (i.e., simulation) and challenging their validity. In particular, the subject and utility of the concept of inherently sustainable strings and its relevance to mixed traffic flow can be studied.

The recommendations that follow in the next section are based upon the scientific and engineering challenges remaining to be met in providing a research foundation for use in evaluating and enhancing the string behavior of ACC-equipped vehicles operating in traffic streams. The discussion in the previous subsection introduces areas where there is need for further measurements involving driver and traffic behavior. This need supports the development of a mobile laboratory and its installation in vehicles for observing microscopic phenomena in traffic streams.

**Recommendations for Applying the Findings from Phases 1 and 2**

In summary, action-oriented recommendations based on the experience gained and the findings developed in phases 1 and 2 are as follows:

(1) Use simulation techniques to study issues concerning microscopic phenomena pertaining to traffic flow and ACC systems.

(2) Design, develop, and verify the operational capabilities of microscopic-phenomena vehicles (MPVs) containing a specially designed mobile laboratory (ML). Verify and validate the operational capabilities of the MPVs and their MLs on a proving grounds and then in traffic.

(3) Collect data in traffic streams using prescribed protocols for MPV behavior and analyze the data collected by the mobile laboratory, thereby improving the understanding and modeling of pertinent aspects of traffic phenomena involving ACC-equipped and humanly driven vehicles.

With regard to recommendation (1), the partners have identified certain issues as candidates for consideration. (The partners have not decided whether these items are acceptable to them in a phase 3 activity.) With respect to ACC systems, these issues include further development and refinement of the driver models for:

- lane changing
- using the accelerator pedal during ACC
- take over from ACC at low speed
- resuming ACC
- behavioral characteristics on multi-lane roads

The partners have identified (1) dense traffic near instability, (2) levels of braking and acceleration in stop-and-go and/or creep-and-go situations, (3) different types of roads, and (4) the influences of weather as possible areas of study. They see the need for comparisons with experimental and measured data to aid in verifying the models and in attaining plausible results in microscopic analyses.

With regard to recommendation (2), the main purpose of the mobile laboratory is to measure microscopic variables of interest in the traffic stream. These variables are range to nearby vehicles, their range rates, velocity of the mobile-laboratory equipped-vehicle, and its location. These variables have been measured and stored in several field operational tests involving UMTRI, for example [6,7]. Hence, pertinent design activity and experience related to measuring and storing data and creating databases are available.

One possibility involving the OEM partners is for them to furnish ACC equipped cars and for them to aid in providing access to data from the range and range rate sensors in those cars. The sensors used in ACC operation provide the basic information that is critical to the utility of the mobile laboratory function in microscopic performance vehicles (MPVs).

In order to examine following vehicles (behind the MPV) a rearward looking sensor for measuring ranges and range rates is needed. This capability has been provided in the USDOT 100-car-study [15] and it could be added to the OEM or US DOT vehicles used as MPVs in traffic studies.

The mobile laboratory (ML) would be expected to provide two additional features as the program progressed. They are (1) the ability to control/constrain the longitudinal control behavior of the MPV within prescribed bounds and (2) the capability to measure gap sizes in adjacent lanes as needed for emulating/predicting the maneuvering behavior of vehicles in traffic streams as the density increases

The ACC systems in OEM vehicles provide one form of control/constraint over range clearance and speed control. Furthermore, UMTRI has developed prototypical ACC systems for longitudinal control. These have involved algorithms that are readily installed in programmable electronic control units. These types of units were used to supply control commands to engine and transmission actuators in the ICC FOT cars. They were also used to provide baking commands to smart brake boosters in the FOCAS study for NHTSA.

With regard to measuring gaps in adjacent lanes, the US DOT has published measured results as obtained in studies of merging events and crashes involving merging [11]. Although the traffic studies proposed here tend to emphasize flow rather than crash behavior, we are interested in the same microscopic phenomenon, i.e., taking a gap in an adjacent lane.

The third recommendation concerns using mobile-laboratory-equipped vehicles to gather data on pertinent aspects of microscopic phenomena influencing traffic flow. The analysis of this data provides the basis for validating models and providing evidence supporting the validity of predictions made by these models.

In conclusion, the purposes of the recommended actions based on the findings of phases 1 and 2 are to:

Expand our knowledge of the driving process.

Define desirable ACC characteristics, in light of such knowledge.

Aid the automotive sector in enhancing ACC performance.

Aid the public sector in assuring reliable traffic flow in the future.

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