A Simulation Model for Driver's Use of In-Vehicle Information Systems

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A simulation model for predicting driver behavior and system performance when the automobile driver performs concurrent steering and auxiliary in-vehicle tasks is described. The model was used in support of an experimental study to develop evaluation methods and human factors guidelines for in-vehicle information systems. It is an integration of two computerized models: the procedural model and the driver/vehicle model. The procedural component deals primarily with in-vehicle tasks and with the task-selection and attention-allocation procedures, whereas the driver/vehicle component predicts closed-loop continuous control (steering) behavior. Given descriptions of the driving environment and of driver information-processing limitations, the resulting integrated model allows one to predict a variety of performance measures for typical scenarios. Application of the model to experiment design is discussed, and quantitative examples are provided for model calibration and for predicting the effects of in-car telephone use on steering performance.

The U.S. government is promoting an umbrella program known as intelligent vehicle-highway systems (IVHS), the goal of which is to apply advanced electronics, computing, and communications technology to improve highway efficiency and safety. This technology will include advanced in-vehicle information systems to help drivers perform a number of functions, including in-car telephoning, navigation, traffic status monitoring, on-road hazards warning, and vehicle systems monitoring. The safety of such systems is in question because of the potential for in-vehicle displays to divert attention from the primary driving task (*1–3*).

This paper describes a simulation model that was developed to predict driver behavior in support of an experimental study, performed by the University of Michigan Transportation Research Institute (UMTRI) for the U.S. Department of Transportation, to develop evaluation methods and human factors guidelines for in-vehicle information systems (*4*). Given descriptions of the tasks to be performed and of a driver's information-processing limitations, the model predicts a variety of performance measures for typical scenarios. Representative measures include lane deviations, control use and monitoring times for a variety of in-vehicle systems, and various measures of driver attention such as eye fixations times and scan frequencies, task-to-task transitions, and statistics relating to task interruptions.

The primary intended uses of this model are to aid in the design of manned simulation experiments and to help extrapolate experimental results. Preexperiment model analysis is of particular value in situations in which, because of the expense or limited access to resources, it is critical to have the experimental program well defined before starting a set of simulation or on-road studies. By exploring a range of potential experimental variables—typically, much wider than would be practical to explore in properly controlled experiments—one can use the model as an all-digital simulator to predict which choices of parameter values will yield results that are sensitive to experimental variation and which candidate experiments will tend not to show significant effects. Armed with these results, one can presumably make better choices as to which candidate experimental variables to explore, the range of values to be explored, optimal settings for other independent variables, and so on.

Similar types of postexperiment model analysis allow the extrapolation of experimental results to conditions not yet tested. One potential application is to test the generality of design guidelines developed from the experimental data base.

DESCRIPTION OF MODEL

Overview

The model presented here, which is called the integrated driver model (IDM), is an integration of two computerized models: the procedural model and the driver/vehicle model. The procedural model represents the driver of the vehicle in terms of perceptual, neuromotor, and cognitive responses (*5*). Submodels may include visual scanning and detection, auditory perceptual processing, neuromotor reaction time, and choice and decision in the selection of activities. The procedural model deals primarily with in-vehicle auxiliary tasks (i.e., tasks other than continuous vehicle control) and with the task-selection and attention-allocation procedures.

The driver/vehicle model predicts closed-loop continuous control behavior. This model, which is currently used to predict lateral path (steering) control, is based on the optimal control model (OCM) for manually controlled systems (*6*). The structure and predictive value of the OCM have been verified via extensive application to laboratory and operational manual control tasks, and the OCM has been applied successfully to the design of manned simulation studies (*7*). The driver/vehicle model is currently implemented to simulate a constant-speed steering task.

The resulting integrated model allows one to predict continuous steering performance as visual attention is intermittently diverted from the roadway to one or more monitoring locations associated with the auxiliary in-vehicle tasks. The model also allows the driver to attend visually to the roadway

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while processing auditory information. Attention is switched and tasks are selected on the basis of time-varying priorities that consider, at each decision point, the penalties for tasks not performed. The presentation of auxiliary tasks is controlled in part through dependencies on the state of the driving environment as predicted by the model and in part through scripting (i.e., state-independent time-based occurrence of events defined before the model run).

Figure 1 contains a diagram of the IDM showing the principal functional elements of the model and the major communications paths. To make maximum use of previous implementations, the continuous control driver/vehicle model and the procedural model are implemented as separate processes.

Driver/Vehicle Model

The major assumptions underlying the driver/vehicle model are the following:

1. The operator is sufficiently well trained and motivated to perform in a near-optimal manner subject to system goals and limitations.
2. The driver constructs an internalized representation ("mental model") of the driving environment in which all dynamic response processes are represented by linear equations of motion.
3. Performance objectives can be represented by a quadratic performance index (e.g., minimize a weighted sum of mean-squared lane deviation and mean-squared control activity).
4. Driver limitations can be represented as response-bandwidth limitations, time delay, and wide-band "noise" processes to account for information-processing limitations.

To obtain a model solution, the user must provide information sufficient to describe the task environment, the performance goals, and the operator's response and information-processing limitations. Because the model is a simulation model, timing parameters must also be specified. The following kinds of input must be specified for the driver/vehicle models:

1. Description of driving environment
   - Vehicle response dynamics,
   - Perceptual variables,
   - Command and disturbance inputs, and
   - Initial conditions;
2. Driver characteristics
   - Mental model of the task environment,
   - Information-processing limitations (S/N),
   - Perceptual limitations ("thresholds"),
   - Time delay, and
   - Motor lag;
3. Simulation parameters
   - Simulation update interval, and
   - Data recording interval.

The flow of information within the driver/vehicle model component is shown in Figure 2. For applications in which the vehicle is maintained at near-constant speed and undergoes relatively low lateral accelerations, the model components enclosed in boxes are implemented as linear dynamic processes for which the behavior of the system states is described by a set of linear differential equations. The vehicle response behavior element contains a description of the dynamic response of the automobile, the kinematic equations that relate turn rate and speed to lateral displacement, and any dynamic response elements that might be needed to model external disturbances.

The cue generation element accepts the system states and external command inputs to generate the set of perceptual cues assumed to be used by the driver. This element contains a linearized approximation that relates the perspective real-world scene cues to system states and command inputs. (For a constant-speed steering task, typical perceptual cues are lane error, drift rate, heading relative to the road, turn rate relative to the road, and road curvature.) These perceptual cues are then corrupted by wide-bandwidth observation noise and delay, where the observation noise reflects both a signal-to-noise type of information-processing limitation as well as perceptual threshold limitations.

The driver's adaptive response behavior is represented by the optimal estimator and predictor, the optimal control laws, and the response lag, with an additional motor noise corrupting the motor response. The mental model noted earlier is a component of the optimal estimator. The estimator and predictor construct a least-squared-error estimate of the current system state, and the (linear) optimal controller generates the optimal control response operating on these state esti-

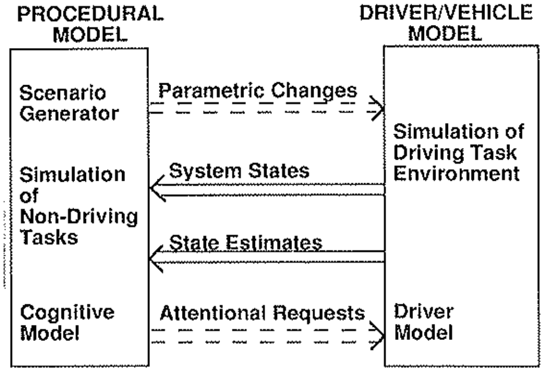

FIGURE 1 Overview of IDM.

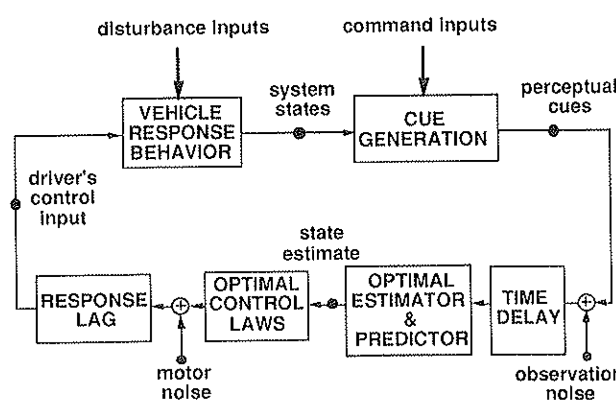

FIGURE 2 Flow diagram of driver/vehicle model.

mates. The motor noise serves to provide some uncertainty concerning the response of the vehicle to the driver's inputs, and the response lag may be thought of as reflecting a penalty for generating a high-bandwidth control response.

The form and quantification of the estimator, predictor, and controller are determined by the specific problem formulation according to well-developed mathematical rules for optimal control and estimation (*8,9*). Model outputs consist of quantities similar to those measurable in a manned simulation (e.g., time histories for all important system variables), as well as quantities that cannot be directly measured (e.g., the driver's estimate of the value of any system variable).

The driver's assumed mental model of the driving environment is a key feature of the driver/vehicle model. Typically, the driver is assumed to be sufficiently well trained in the specific driving task to allow the mental model to replicate the model of the physical environment. However, the consequences of the driver's misperception of the external world can be explored by making the mental model different from the world model in terms of parameters values or structure.

When the driver is required to share attention between the vehicle control task and one or more auxiliary tasks (e.g., look at the rearview mirror, tune the radio), performance of the control task will in general degrade. The effects of such interference are accounted for in one of two ways. For intervals in which visual attention is directed away from the roadway cues to some other visual input, the mathematical "driver" receives no perceptual inputs relevant to vehicle control, and the model continues for a short time to generate control inputs based on the internal model only.

The driver is assumed to attend simultaneously to vehicle control and to auxiliary tasks requiring speaking or listening. In this case the driver is assumed to continue to fixate visually on roadway cues, but central-processing resources are now shared between the two tasks. The effects of less than full cognitive attention to the driving task is modeled by degrading the driver's signal-to-noise ratio—in effect, by increasing the observation noise level (*10*). Either type of attention-sharing tends to decrease the portion of the driver's control response that contributes to effective control and to increase the stochastic component of the driver's control, with the net effect of degrading vehicle control performance.

Procedural Model

Besides acting as the supervisory element of the integrated model, the procedural model simulates the in-vehicle auxiliary tasks and performs task selection. First considered is the task selection algorithm, and then the overall logic of the procedural model is discussed.

Task Selection Algorithm

Task selection is based on assumptions that are generally consistent with the multiple-resource theories of Wickens and Liu (*11*). Specifically, it is assumed that

- If two or more tasks require different visual fixation points, only one such task may be performed at any given instant.
- If two or more tasks require listening or speaking, only one such task may be performed at a given instant.
- If one task requires visual inputs and another requires auditory inputs, the tasks may be performed concurrently (with presumably some performance degradation) if they require different "processing codes" (i.e., one requires spatial processing, the other verbal processing).
- Task selection is based on the perceived relative importance of competing tasks and is computed by minimizing the expected net penalty of tasks not performed.
- If an auditory and a visual task are performed concurrently, cognitive attention is allocated according to the penalty functions.
- When a task is first attended to, or first reattended to following attention to another task, attention must remain on this task for some minimum "commit time," after which the driver is free to allocate attention as described.

Note that the steering task (which requires attention to the road) is always competing for attention. The logic for selecting a task when multiple tasks compete for attention is diagrammed in Figure 3.

Model Inputs and Outputs

The following kinds of input must be specified for the procedural model:

- Description of activities (hard-coded)
  - –Models of performance versus time, and
  - –Penalty functions (penalty for not performing task);

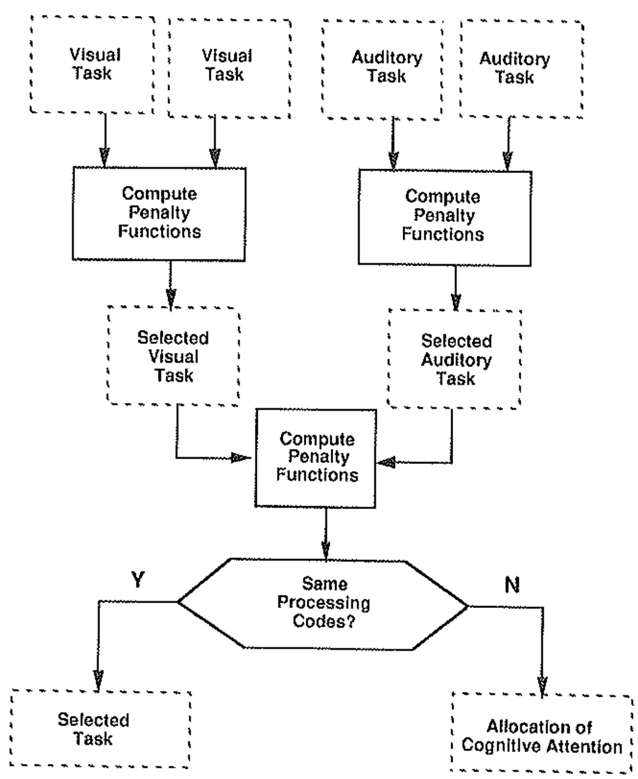

FIGURE 3 Task selection logic.

- Script of events: times at which activities are spawned; and
- Simulation parameters: simulation update interval.

The description of activities (auxiliary in-vehicle tasks) must be implemented in the computer code, unlike all other procedural and driver model inputs, which are specified at run time.

An auxiliary task may consist of one simple activity (e.g., glance at the rearview mirror) or a sequence of activities, such as the telephone task described later in this paper. An elemental activity may require visual attention (eyes) or visual and manual attention (eyes and hand).

Two categories of parameters need to be specified for each activity: parameters that relate to the performance of the task, and parameters that determine the relative importance or urgency of the task. Performance is usually defined by one or more time parameters, which may include (a) times to move eyes and hands, if necessary, in preparation for the task; (b) time to complete the task; and (c) minimum commit time following initial (re-) attention to the task. Some tasks are described by a simple task-completion time. Other tasks are defined by a rate of progress, with the driver allowed to interrupt after some commit time and later continue the task.

For tasks that consist of sequences of activities, sequencing rules need to be implemented, as do rules for which sequences of tasks must be performed as a unit before the driver is allowed to select another task. (For example, in an in-car telephoning task, the driver may be assumed to dial the entire area code before deciding whether to look back at the road or to continue dialing.)

Penalty functions for in-vehicle tasks may be specified as a single number or as a number that (typically) increases with time, up to some limit, until the task is completed. A different kind of penalty function is used for the driving (steering) task, namely, the predicted probability of exceeding a lane boundary within a "prediction time" that consists of the time required to perform the in-vehicle task segment plus an assumed time to recover control of vehicle path upon reattending to the road. This computation is based on the driver's current estimate of lane deviation, drift rate, and heading and is similar to the time-to-line-crossing metric proposed by Godthelp et al. (*12*).

The output file produced by the procedural model includes time histories of the driver's visual fixation point, the position of the driver's free (nonsteering) hand, and measures of performance for each in-vehicle task in progress (e.g., number of words read so far from the visual monitor, time elapsed since initiation of the task). As with a manned simulation experiment, posttrial analysis of model outputs can be performed to yield a variety of performance statistics, such as means and standard deviations for all continuous variables relevant to the steering task (including variables internal to the driver), statistics relating to the duration of a given in-vehicle tasks, and statistics on dwell times and intervals of inattention.

Simulation Cycle

After the model has been initialized, the simulation cycle is executed once per update interval until some stopping criterion has been reached (typically, a stopping time specified at the start of the run). The cycle begins with a check on which new tasks, if any, are to be added to the active list (the set of tasks now competing for the driver's attention). New tasks may be spawned according to the time-based script or because of completion of an antecedent subtask.

If the task currently attended to is locked up, the driver must continue to attend to that task. If the task is not locked up, the task selection algorithm is executed to determine the task to be next attended (which may be the same task). Active tasks are updated, and simulation variables needed for post-simulation analysis are recorded in the output file.

MODEL CALIBRATION

To the extent that the driving tasks of interest may differ in important respects from driving tasks modeled previously, a certain amount of initial empirical data is desired to calibrate the model for the baseline experimental condition. Calibration data may be needed for the driving task, the auxiliary in-vehicle tasks, or both, depending on the amount of preexisting data relevant for model calibration.

The continuous control component of the IDM has been validated against a considerable body of laboratory tracking data and has been found able to replicate these data with nearly invariant values for driver-related independent model parameters for idealized cueing conditions (*13*). These data provide an initial selection of independent model parameter values, which may be modified as necessary to account for the nonideal control environment associated with real-world driving tasks.

The procedural component of the IDM is new and is therefore in need of a more substantial calibration effort. To the extent that specific data are lacking for the in-vehicle tasks of interest, one may use data obtained from the human performance literature (e.g., times to make eye and hand movements, times to read words of text, times to read numbers, etc.) and later refine relevant model parameters as additional empirical data become available.

As an example of a typical calibration exercise, the calibration exercise performed for the Green and Olson in-vehicle display project just before preparation of this paper is summarized. Data from four subjects were provided for the baseline driving task performed on the UMTRI driving simulator. This simulator contained a steering wheel as an input device and a relatively sparse visual scene roughly approximating nighttime viewing conditions. The highly simplified vehicle response dynamics, although not a true representation of automobile steering response behavior, provided a workload representative of a driving task (*14*). The subject's task was to remain near the middle of the lane while driving at constant speed on a road having a sinusoidal curvature with a period of about 26.5 sec and a zero-peak lateral deviation of about 4 ft. The data base used for model calibration consisted of one 4-min trial from each of four subjects.

To calibrate the model, first the task-related model parameters were set to reflect the simulator dynamics and roadway curvature. Then driver-related model parameters were selected as follows:

- Response delay was set to 0.2 sec, on the basis of laboratory tracking data.
- An information-processing metric (implemented as a noise-to-signal ratio) was quantified, on the basis of laboratory tracking data.
- Perceptual noise terms were specified to reflect a visual or indifference threshold of 0.305 m (1 ft) and 0.305 m/sec (1 ft/sec) for path error and path error rate. These numbers were set substantially higher than associated with idealized laboratory tracking displays to reflect the relative difficulty of obtaining precise information from the simulated perspective roadway display.
- A trade-off between allowable path error and allowable steering wheel activity was modeled by adjusting an effective driver response bandwidth parameter.

Within-trial mean and standard deviation scores for path error and wheel displacement were computed for each of the four experimental trials, and intertrial means and standard deviations of the standard deviation scores were computed. Model runs were then generated for various values of the bandwidth parameter until an acceptable joint match to the average path error and wheel deflection scores was obtained. The following table shows that model predictions matched the experimental standard deviation scores to within two standard deviations (and to within 10 percent):

Variable	*Experiment*	*Model*
Path error (m)	0.210 (0.22)	0.195
Path error (ft)	0.689 (0.072)	0.640
Wheel deflection (degrees)	17.7 (1.15)	19.1

Figure 4 shows 2-min segments of the wheel deflection time histories generated by one of the subjects and by the model using the parameters calibrated as described. Because the human controller is represented as a mathematically linear system plus noise, and because the road curvature was sinusoidal, the wheel response is expected to consist of a sinusoidal component of the same frequency as the road sinusoid, plus a stochastic disturbance about this sinusoid. Figure 4 shows that this qualitative description appears to fit both the model and the experimental data, which offers additional validating evidence of the model as a predictor of performance trends. The discrepancies between the high-frequency components of the model and experimental time histories reflect the fact that, by definition, the model cannot replicate (other than statistically) the stochastic component of the driver's time history.

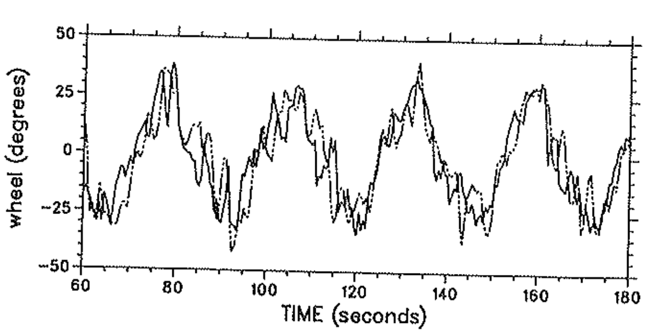

FIGURE 4 Experimental and predicted wheel time histories: solid curve = subject; dashed curve = model.

APPLICATION OF MODEL TO EXPERIMENT DESIGN

Three kinds of independent model parameters are most likely to be varied when the IDM is used to help design experiments involving in-vehicle displays: (a) the in-vehicle tasks, (b) factors influencing the difficulty of the primary driving task, and (c) driver performance capabilities. The in-vehicle tasks are presumed to be the primary variables of interest and would be programmed into the IDM for testing. Driving-task parameters such as roadway curvature profile, speed profile, wind gusts, and vehicle dynamics may or may not be of interest as experimental variables. If not, and if the experimenter is free to select one or more of these variables, the IDM can be useful in selecting parameter values that provide a driving workload (or range of workloads) that results in a reasonable sensitivity of driving performance to the in-vehicle tasks.

Finally, the model can be used to predict the extent of driver population effects on performance trends by suitably varying driver-related parameters of the driver/vehicle model. For example, one might represent the older driver as having one or more of the following: larger response delay, less aggressive response behavior, less efficient information-processing capability, and larger commit time after switching attention.

To illustrate how the model might be applied in this manner, a modeling activity is reviewed that was performed for the in-vehicle display project in progress at the time this paper was written. The model results presented in the following were obtained without the benefit of knowledge of results to generate some a priori performance predictions for subsequent comparison with data.

The model was run for the baseline driving-only condition described earlier, and for one of the experimental tasks involving in-car telephone usage. The telephone task modeled here involved the following steps:

1. Flip to the next page of an index-card telephone directory on the seat next to the driver.
2. Read the name of the person to be called. (For this condition, the subject knew the telephone number from memory and needed to be prompted only as to the person to be called.)
3. Pick up the handset.
4. Dial 1 + area code.
5. Dial the exchange.
6. Dial the last four digits.
7. Press the Call button.
8. Conduct a 30-sec conversation.
9. Press the End button.
10. Set the telephone down.

Model analysis was based on the assumed performance times given in the following table for the component activities underlying the 10 steps listed:

Activity	*Performance Time (sec)*
Eye movement	0.2
Hand movement between buttons on handset	0.2
Hand movement between devices	0.4
Flip page	1.0
Read name	0.8
Pick up, set down handset	0.4
Push button	0.2

A hand (thumb) movement of at least 200 msec was assumed prior to entering each digit of the telephone number. Minimum dialing times were thus 1.2 sec for the three-digit exchange and 1.6 sec for four-digit combinations.

Except for the 30-sec conversation, the mathematical "driver" was required to time-share visual attention between the simulated roadway scene and the telephone. (The driver was assumed to obtain no useful roadway information while looking at the telephone.)

The driver was assumed to perform each of the visual and manual tasks in the preceding list without interruption. When a task was completed and a subsequent visual or manual task became current, the model determined whether the driver should continue with the next telephone task segment or glance at the road for at least a predetermined minimum interval (400 msec). Similarly, if the driver was looking at the road while an in-vehicle visual task was pending, the model determined whether it was appropriate for the driver to resume the telephone task sequence. The decision algorithm was as follows:

1. Predict the probability of exceeding a lane boundary over a prediction time that consists of the time required to perform the next telephone task segment plus an assumed time to recover control of vehicle path upon reattending to the road.
2. If the probability exceeds 1 percent, attend to (or continue to attend to) the roadway cues; otherwise, attend to the telephone task.

The driver was assumed to obtain roadway cues while conversing, but with some performance decrement. While the conversation was in progress, the model allocated cognitive attention between the driving and conversational tasks according to instantaneous driving performance. [See elsewhere for a discussion of how the effects of cognitive attention-sharing on continuous control performance are modeled (*10*).] Attention allocation was quantized to the nearest 0.25, with the restriction that the driver always allocated at least 25 percent attention to the driving task.

The model predicted an increase in root-mean-square lane error of about 60 percent: 0.19 m (0.62 ft) for the baseline task, 0.32 m (1.05 ft) for the experimental driving plus telephone condition. Figure 5 shows the path error time histories for the baseline (solid curve) and telephone task (dashed curve). Because the same random number sequence was used to produce the stochastic portion of the driver's response, the differences between the two curves reflect the effects of the concurrent telephone task and are not confounded with run-to-run variability.

As expected, larger error peaks are shown for the experimental task. Comparison of this figure with the cognitive attention timeline of Figure 6 shows that performance decrements were predicted for the portions of the task when conversation was in progress, as well as when visual attention was shared between driving and telephone start-up tasks. For this curve, a value of 1 indicates full attention to the road, a value of 0 indicates full visual attention to the telephone task, and values between 0 and 1 indicate a reduced level of cognitive attention to the roadway cues while conversing. According to this timeline, the "driver" made three minimal 0.4-sec glances and one 0.8-sec glance to the road while performing the preconversation telephone tasks.

This discussion is intended to illustrate the kinds of performance predictions available from the model.To make a more definitive prediction of performance trends, a number of model runs per condition would be made with different random sequences in order to account for run-to-run variability of the type expected in an experiment. Then a statistical analysis would be performed on the model predictions—just as would be done with experimental data—to predict whether performance differences across experimental conditions are likely to be significant.

DISCUSSION OF RESULTS

Because its predecessor (the optimal control model) has been in existence for about two decades, the driver/vehicle component of the IDM is supported by a substantial amount of validation data. Although the calibration data presented in this paper are not sufficiently rich to allow identification of all the independent driver-related parameters, these parameters have been shown to be individually identifiable from laboratory tracking data using specialized identification techniques (*13*). There is thus a firm foundation for quantifying some of these parameters on the basis of past data. Furthermore, the ability to match performance in a variety of control situations with a near-invariant set of parameter values tends to validate the basic model structure.

In contrast to the driver/vehicle model, the recently developed procedural model component is not similarly sup-

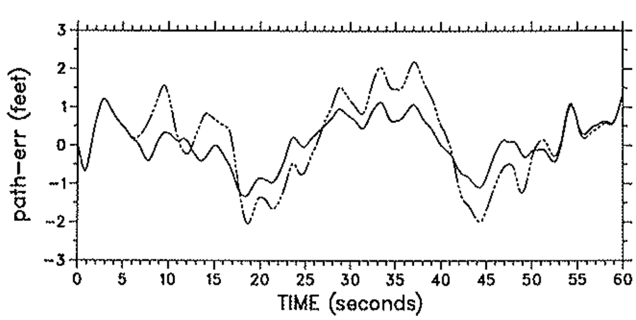

FIGURE 5 Predicted path error trajectories for baseline and experimental conditions: solid curve = steering only; dashed curve = steering while telephoning (1 ft = 0.305 m).

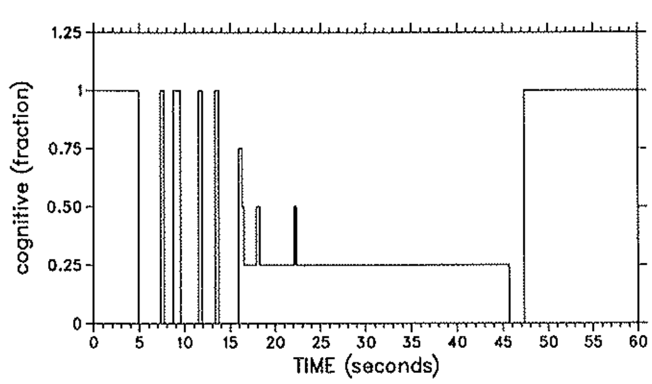

FIGURE 6 Predicted attention to driving task while performing concurrent telephone task.

ported by data. This is particularly true of the task selection procedure and associated penalty functions, for which the goal was to develop algorithms that are plausible and consistent with what is known about task-sharing behavior and with approaches used by others in modeling multiple-task performance (*11,15,16*). Validation of this aspect of the model awaits the availability of experimental data against which to test model behavior.

The model need not mimic all relevant aspects of human response behavior to meet the intended uses that have been suggested here, which are to help design experiments and to extrapolate experimental results. Instead, it is enough that the model be able to reliably predict performance trends resulting from changes in the task environment and to do so with a minimum of preexperiment calibration and with a well-defined set of procedures for quantifying independent model parameters. This is still a tall order, and validation data will be needed to test the model's capabilities in this respect.

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