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USE OF THE OPTIMAL CONTROL MODEL IN THE DESIGN OF MOTION CUE EXPERIMENTS*

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ABSTRACT

An experiment is presented in which the effects of roll motions on human operator performance were investigated. The motion cues considered were the result of commanded vehicle motion and vehicle disturbances. An optimal control pilot-vehicle model was used in the design of the experiment and to predict system performance prior to executing the experiment. The model predictions and experimental results are compared. Seventy-eight per cent of the model predictions are within one standard deviation of the means of the experimental results. The high correlation between model predictions and system performance indicate the usefulness of the predictive model for experimental design and for prediction of pilot performance influenced by motion cues.

INTRODUCTION

A requirement exists in the Air Force for a predictive human operator pilot model which is sensitive to complex motion environments. Such a model would have a number of important applications. For example, one might use the model to (1) determine whether or not motion cues are used by the pilot in a particular control situation; (2) extrapolate the results of fixed-base simulation to a motion environment; (3) facilitate the design of ground-based simulators; (4) identify situations where misinterpretation of motion cues is likely to cause a pilot response that seriously degrades system performance. At the Environmental Medicine Division of the Aerospace Medical Research Laboratory (AMRL), a research program is being pursued to satisfy this requirement. It is directed towards developing a generalized description of the manner in which a pilot uses motion cues, with the ultimate goal of providing a model that can predict the effects of motion cues on system performance in a variety of control situations.

*The research reported in this article was conducted [illegible] of the Aerospace Medical Research Laboratory, [illegible] Air Force Systems Command, Wright-Patterson Air F[illegible] Ohio. [illegible]tary informed consent of the subjects used [illegible] was obtained as required by Air Force Regulation 80-33. Further [illegible] is authorized to satisfy the needs of the U.S. Government. Reprin[illegible] [illegible]cle are identified by the Aerospace Medical Research Laborator[illegible].

Although a number of experimental studies have been conducted to determine the effect of motion cues on pilot response behavior (1-5), a generalized model has not been developed and tested. Rather, the conclusions reached in these studies have been restricted to the context of the experiments yielding the data. In addition, other than the pitch axis motion experiment performed by vanGool and Mooij (5), the work done in this area has principally been for compensatory systems with the motion cues resulting from vehicle disturbance inputs. At AMRL, we are also interested in the effects of motion cues on performance resulting from commanded inputs as encountered in air-to-air combat situations. Therefore, a series of experiments were performed at AMRL to investigate the effects of motion cues resulting from commanded inputs on tracking performance (6,7,8).

One of the products from this research effort was a modification of the Bolt Beranek and Newman optimal control pilot-vehicle model to account for changes in performance caused by the presence of motion cues due to commanded inputs. Since the pilot model has predictive capabilities, the next step was to ascertain how well it could predict pilot performance under different experimental conditions. The ability of the model to predict human performance and aid in experimental design is the topic of this paper.

A moving base simulator, different from the one used in the earlier series of experiments, was employed. *Different* vehicle dynamics were used and motion cues resulting from both commanded vehicle motion and vehicle disturbances were explored. In addition, the pilot model was used to aid in preliminary experimental design to insure that vehicle motions resulting from pilot inputs would remain within the linear operating range of the simulator. After experimental conditions had been selected, the optimal control pilot-vehicle model was exercised for the various conditions and performance scores were computed. Human tracking was then performed and performance data was collected. The control [illegible]hicle, experimental design and results from model prediction and human trac[illegible]g are presented and discussed in this paper.

EQUIPMENT

A Multi-Axis Tracking Simulator (MATS) was used as the controlled vehicle for this experiment. Only the roll axis motion capabilities of the MATS were used. The simulator consisted of a single seat cockpit with a television monitor display and side mounted force stick for vehicle control. The cockpit was configured such that the pilot sat one inch above the roll axis of the simulator. The vehicle cockpit was light-tight to eliminate external visual cues. The roll axis system dynamics were identified and simulated on a hybrid computer. The system characteristics are presented in Table I. To test the capabilities of the optimal control pilot-vehicle model, it was decided to investigate the effects of two types of motion cues in this experiment. One was defined as the Command condition because vehicle motion was commanded as a result of following a target and the other the Disturbance condition because disturbance inputs drove the vehicle directly. Both conditions were investigated with and without the drive system on, making a total of four experimental conditions. The block diagram for the experiment, presented in Figure 1, shows all conditions. For the command condition, the

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disturbance input ($\dot{\phi}_{DISTURBANCE}$) was set to zero and for the disturbance condition the target input (ϕ_{TARGET}) was set to zero. A low pass filter with breakpoint at 5 radians per second was added to the vehicle making the equivalent plant dynamics for all experimental conditions as given in equation 1.

$$\text{Plant Dynamics} = \frac{\phi_{PLANT}}{u_{CONTROL}}\frac{(Deg)}{(Lbs)} = \frac{K}{s(\frac{s}{5}+1)(\frac{s}{20}+1)} \quad (1)$$

In addition, a time delay of 95 milliseconds due to digital computation, visual display delay and an in-line signal filter existed in the visual pathway. In the command condition, the task was to follow a target aircraft in the roll axis. The difference between the target roll angle and the controlled vehicle position was provided to the human operator on a 9 inch diagonal television monitor. The inside-out display consisted of a 1.25 inch long rotating line whose center was superimposed upon a stationary horizontal line as indicated in Figure 2. A 0.083 inch perpendicular line at the center of the rotating line provided upright orientation. The angle between the rotating and stationary line depicted the difference between the controlled plant roll angle and the target roll angle. The display was centered in azimuth a distance of 20.5 inches from the controller's eyes. Subjects' sitting heights were such that the display was within 10 degrees of eye level of each subject. For the disturbance conditions, since $\phi_{TARGET} = 0$ the displayed error equalled the bank angle of the controlled vehicle and the task was to null out the bank angle by keeping the controlled vehicle upright.

EXPERIMENTAL DESIGN

With the vehicle to be controlled identified and the four tracking conditions chosen, the next step was to select task parameters for the experiment. The following constraints and design goals motivated the selection of parameter values:

1. To achieve face validity, we desired to simulate roll axis dynamics representative of high performance aircraft in air co- . The dynamics of equation (1) were chosen on this basis.

2. In order to assure that roll motion would be well above the subject's threshold of perception, and to a comparison with a recent study (8), an RMS bank angle of 10 degrees was desired.

3. Physical limitations on the roll rate and roll acceleration of the rotating simulator had to be considered. Specifically, our goal was to achieve experimental RMS roll rates and accelerations that were no greater than 1/3 the corresponding limits so that these limits would be reached less than 1% of the time.

4. A wide bandwidth of pilot response was desired to maximize our ability to analyze the effects of motion cues on pilot response behavior; at the same time, we wanted to avoid a tracking task that was unreasonably difficult.

5. In order to test our model for motion cue utilization, we desired tasks in which motion would have a significant effect on pilot response behavior.

Experimental parameters that we could adjust to meet these goals consisted of (1) RMS amplitude and spectral shape of the tracking input, (2) control gain, and (3) performance criterion.

The input amplitude was adjusted to induce vehicle response of the desired magnitude, and the control gain was adjusted to allow such response to be achieved with comfortable control forces. A second order noise process was considered for the tracking input and the critical frequency of the input spectrum was chosen to achieve the desired balance between measurement bandwidth and tracking difficulty.

To keep RMS response rate and acceleration well below the physical limitations of the rotating simulator, as well as to encourage the test subjects (who were not trained pilots) to respond in a smooth manner, a performance criterion was defined as the weighted sum of mean-squared tracking error and mean-squared vehicle acceleration. That is,

$$C = \sigma^2_{\epsilon_{ERROR}} + W\,\sigma^2_{\ddot{\phi}_{PLANT}} \quad (2)$$

where C is the total "cost", $\sigma^2_{\epsilon_{ERROR}}$ the variance of the tracking error, and $\sigma^2_{\ddot{\phi}_{PLANT}}$ the variance of the acceleration of the vehicle or simulated vehicle, in the absence of motion cues.

The immediate effect of introducing a penalty for vehicle acceleration was to limit the gain of the subject's response; the larger the weighting W, the lower the pilot gain. Pilot gain directly influenced overall man/machine system bandwidth, which in turn influenced roll rate and roll accelerations achieved during tracking.

Task parameters were selected in the following way. An initial set of parameters was chosen based on knowledge gained from previous experimental studies, and predictions of pilot-vehicle performance were obtained with the pilot-vehicle model. Task parameters were readjusted in an attempt to better meet the experimental constraints, and the system was reanalyzed. We iterated on this procedure until satisfied with the expected outcome of the experiment.

The optimal control pilot-vehicle model used in this procedure has been described in the literature (9-12) and is reviewed briefly in a companion paper (13). Independent pilot-related model parameters were held fixed throughout this procedure at values obtained from previous analysis. Specifically, time delay was set at 0.17 second, the "motor time constant" (a first-order lag associated with pilot response) was 0.1 seconds, and the "noise/signal ratio" (to account for pilot response randomness) was set at -20 dB. Visual-only tracking was represented by considering only tracking error and tracking error rate in the set of informational quantities available to the pilot. Roll angle, roll rate, and roll acceleration of the simulated vehicle were added to this informational set to account for the presence of motion cues.

As a result of this iterative design process, the following task parameters were selected. The force stick gain was adjusted to produce 10 degrees/second vehicle roll rate for one pound of force measured at thumb height on the control grip and the cost weighting W (equation 2) was set to 0.1. In addition, both the target and disturbance inputs were constructed from 13 sinusoids whose amplitudes were selected to simulate random noise processes having power spectral densities of the form

$$\Phi_{ii}(\omega) = \left| \frac{K}{(j\omega + \omega_i)^2} \right|^2$$

where ω_i was 1.6 rad/sec for the target input and 2.0 rad/sec for the disturbance input. Input amplitude was adjusted to provide an RMS target input of 10 degrees and an RMS disturbance input of 14 deg/sec. In order to prevent subjects from learning the input waveforms during the experiment, a random number generator was used to vary the phase relationships of the input sinusoids from one experimental trial to the next.

EXPERIMENTAL PROCEDURE

Six healthy college students between 18 and 25 years of age were used for the experiment. Subjects tracked each condition each day. Tracking under each condition was considered one run. Each run lasted 165 seconds and the four conditions or runs were presented in a random order each day. At the end of each run, subjects were presented their three performance scores for that run: total cost C, error variance σ^2_{ERROR} and weighted acceleration $0.1\,\sigma^2_{\ddot{\phi}_{PLANT}}$. They were instructed to minimize the total cost C. In addition, they were told that it was the sum of the other two, that the error score was related to how much error they allowed and that the acceleration score was related to how smoothly they tracked. They were not told predicted scores, nor were they told how to divide their total score between error and acceleration. To maintain subject motivation, subjects were also made aware of each other's performance scores. Each subject wore a flight helmet with intercom capability while performing the tracking task. The subject was permitted to perform the task briefly prior to each scored run in order to adjust mentally and physically to the tracking task.

Performance scores were plotted daily in order to evaluate subject and group performance. Once the error scores indicated that the subjects had "learned" the tracking tasks for all experimental conditions, tracking was continued for another eight days and time history data was collected for subsequent analysis. From these last eight days of runs, performance scores were computed for each subject for each condition, making a total of 48 measurements per condition. For purposes of comparing the experimental results to predicted values for each condition, the results of the six subjects were averaged together.

RESULTS AND DISCUSSION

Once subject training had been accomplished, data was collected for eight days for all subjects. Training was considered completed when subject performance, as measured by total cost C for all conditions, had reached asymptotic levels.

From the collected data, various system parameter values were computed and averaged together across days and subjects. The experimental results along with the predicted model values are given in Table II for the command condition and Table III for the disturbance condition. The experimental values include the mean and standard deviation resulting from averaging together the six subjects' results. From Tables II and III we can see that the model predictions are quite accurate, 28 of the 36 predictions are within one standard deviation of the means of the experimental values and the remainder are within two standard deviations of the mean.

To better compare predicted and experimental results across conditions, these values are also presented graphically for total cost (PERFORMANCE SCORE) and pilot input (RMS CONTROL FORCE) in Figure 3, for plant position (RMS ϕ PLANT) and system error (RMS ϕ ERROR) in Figure 4, and plant velocity (RMS $\dot{\phi}$ PLANT) and acceleration (RMS $\ddot{\phi}$ PLANT) in Figure 5. Experimental conditions are indicated on the abscissa of each graph, C/M indicates the command with motion condition, C/S command-static, D/M disturbance-motion and D/S the disturbance-static condition. From Figure 3 we see that with the model we were able to predict total performance score and the control force the pilot used for the four conditions. The same trends can be observed in Figures 4 and 5 for the vehicle motions and the error the pilot allowed.

The experimental results also indicate that our design goals were achieved. One of the requirements was that the control tasks not be unreasonably difficult. The control forces used by the subjects (Figure 3) indicate that the tasks were not excessively difficult to control and that the forces were within the design region of 0.5 to 1.5 pounds. To insure that the roll motion would be well above pilot thresholds, we desired an RMS bank angle of approximately 10 degrees. From Figure 4 we see that this requirement was also met. For the disturbance motion case, the subjects were able to reduce the bank angle error below what the model predicted. Also for the static-disturbance case, the model predictions were less than the experimental results. As mentioned earlier, there existed a 5 ms time delay in the visual loop that was not present in the motion cue loop. Model predictions did not include the presence of the visual time delay. These circumstances may account for the differences between the model predictions and experimental results. The physical limitations of the simulator, namely a velocity limit of 60 deg/sec and an acceleration limit of 100 deg/sec^2, had to be considered during motion tracking. Our design goals were to achieve experimental RMS roll rates and accelerations that were no greater than 1/3 the corresponding limits. The experimental results (Figure 5) indicate that these goals were satisfied.

As stated earlier, the motion sensitive aspects of the model were developed for experimental conditions different from those investigated in this study and a different simulator with narrower bandwidth vehicle dynamics (8). These facts further emphasize the usefulness of the predictive capabilities of the model. The next step in the study was to determine what model parameter adjustments were needed to improve the match to the data. This is the subject of a companion paper in these Proceedings. By readjusting the model parameters, we hope to gain additional insight into how the pilot utilizes motion information.

CONCLUSIONS

The major objectives of our experimental program have been (1) to investigate the usefulness of the model as an experimental design tool, (2) to demonstrate the ability of the model to predict the influence of motion cues on pilot-vehicle performance for different tracking tasks and (3) to provide a data base from which we could improve our understanding of how the pilot utilizes and is effected by motion cues. In conclusion, we feel the results of this experiment demonstrate the usefulness of the predictive optimal control pilot-vehicle model. With the model, we were able to predict pilot-vehicle response for the various motion cue conditions. In addition, by making use of the model, the experimental design process was not only simplified, we were assured that useful data could be collected.

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TABLE I

MULTI-AXIS TRACKING SIMULATOR

ROLL AXIS CHARACTERISTIC

TRANSFER FUNCTION: $\frac{\phi_{PLANT}\ (deg)}{u_{CONTROL}\ (pounds)} = \frac{K}{(\frac{s}{20} + 1)}$

POSITION LIMIT: $\phi_P = \pm 90$ deg

VELOCITY LIMIT: $\dot{\phi}_P = \pm 60$ deg/sec

ACCELERATION LIMIT: $\ddot{\phi}_P = \pm 1$[illegible] deg/sec^2

TABLE II

PREDICTED VERSUS EXPERIMENTAL RESULTS FOR THE

COMMAND CONDITION

VARIABLE	UNITS	STATIC PREDICTED	STATIC EXPERIMENTAL MEAN	STATIC EXPERIMENTAL 1σ	MOTION PREDICTED	MOTION EXPERIMENTAL MEAN	MOTION EXPERIMENTAL 1σ
Total Cost	--------	67.[illegible]	72.3	8.9	53.1	66.1	7.5
Cost on ϕ_E	--------	52.4	50.7	11.9	45.5	48.2	11.1
Cost on $\ddot{\phi}_P$	--------	14.5	12.2	9.7	7.57	17.90	8.64
σ_u	pounds	0.730	0.75[illegible]	0.120	0.516	0.66[illegible]	0.156
σ_{ϕ_P}	deg	10.1	9.[illegible]	0.9	6.37	7.63	1.25
$\sigma_{\dot{\phi}_P}$	deg/sec	6.86	7.10	1.1[illegible]	4.84	6.74	1.6[illegible]
$\sigma_{\ddot{\phi}_P}$	deg/sec^2	12.1	14.6	3.1	8.70	12.9	3.51
σ_{ϕ_E}	deg	7.24	7.06	0.7[illegible]	6.75	6.90	0.78
$\sigma_{\dot{\phi}_E}$	deg/sec	11.7	11.9	0.7	10.7	11.8	0.79

TABLE III

PREDICTED VERSUS EXPERIMENTAL RESULTS FOR THE

DISTURBANCE INPUT CONDITION

VARIABLE	UNITS	STATIC			MOTION		
		PREDICTED	EXPERIMENTAL		PREDICTED	EXPERIMENTAL	
			MEAN	1σ		MEAN	1σ
Total Cost	--------	178	[illegible]	[illegible]	91.0	78.6	15.3
Cost on ϕ_E	--------	86.2	81.6	11.4	37.2	[illegible]	[illegible]
Cost on ϕ_P	--------	91.5	[illegible]	16.7	54.4	58.1	9.2
σ_u	pounds	1.56	1.55	0.14	1.49	1.49	.08
σ_{ϕ_P}	deg	9.29	8.81	1.80	6.1	4.2	1.5
$\sigma_{\dot{\phi}_P}$	deg/sec	12.1	11.9	1.3	7.76	5.81	1.41
$\sigma_{\ddot{\phi}_P}$	deg/sec^2	[illegible]	[illegible]	5.0	23.3	24.0	1.9

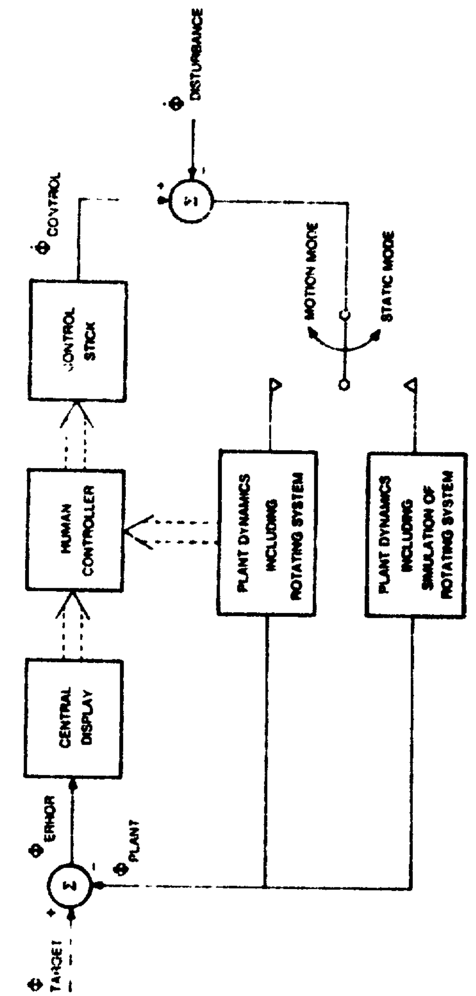

FIGURE 1. System flow diagram.

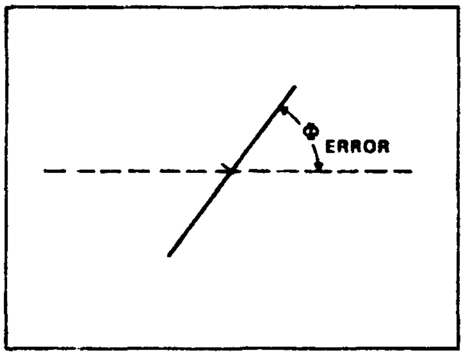

FIGURE 2. Visual display.

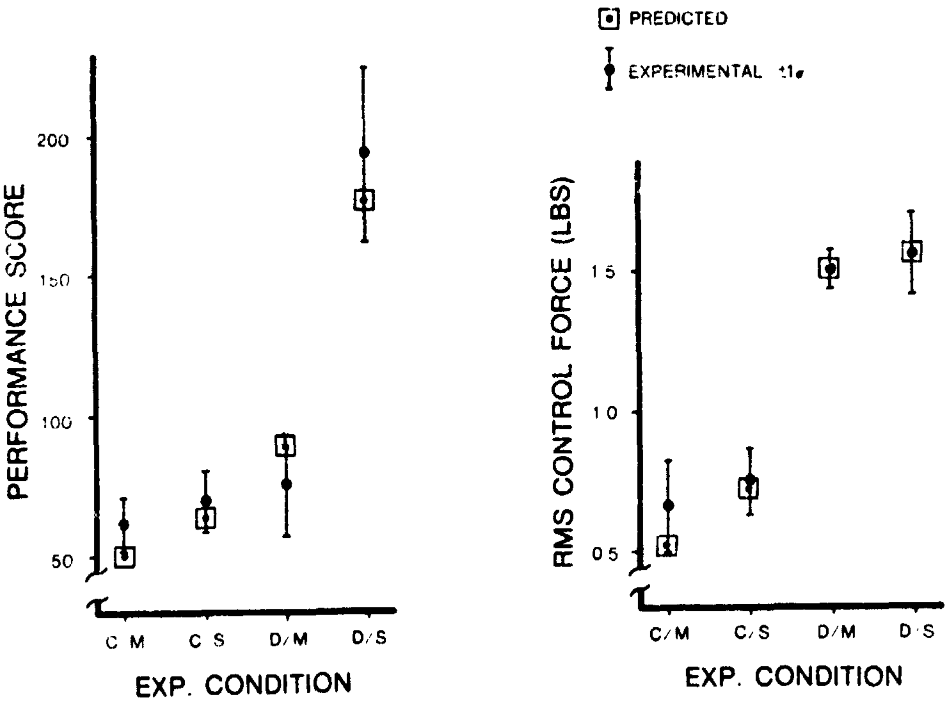

FIGURE 3. Comparison between model and experimental results for performance and control force.

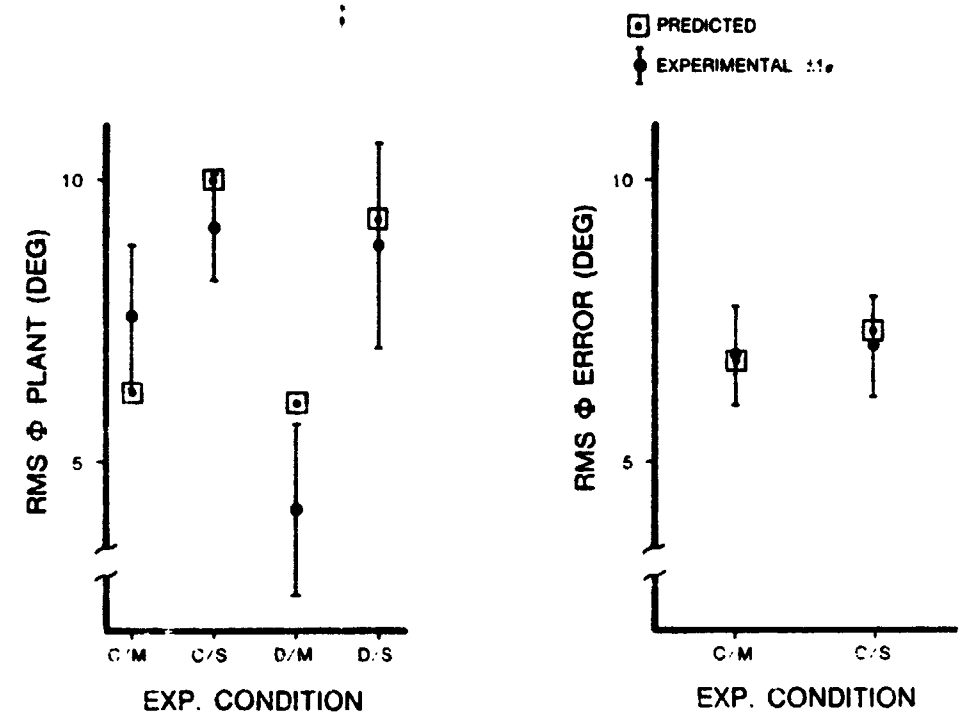

FIGURE 4. Model and experimental results compared for vehicle position and system error.

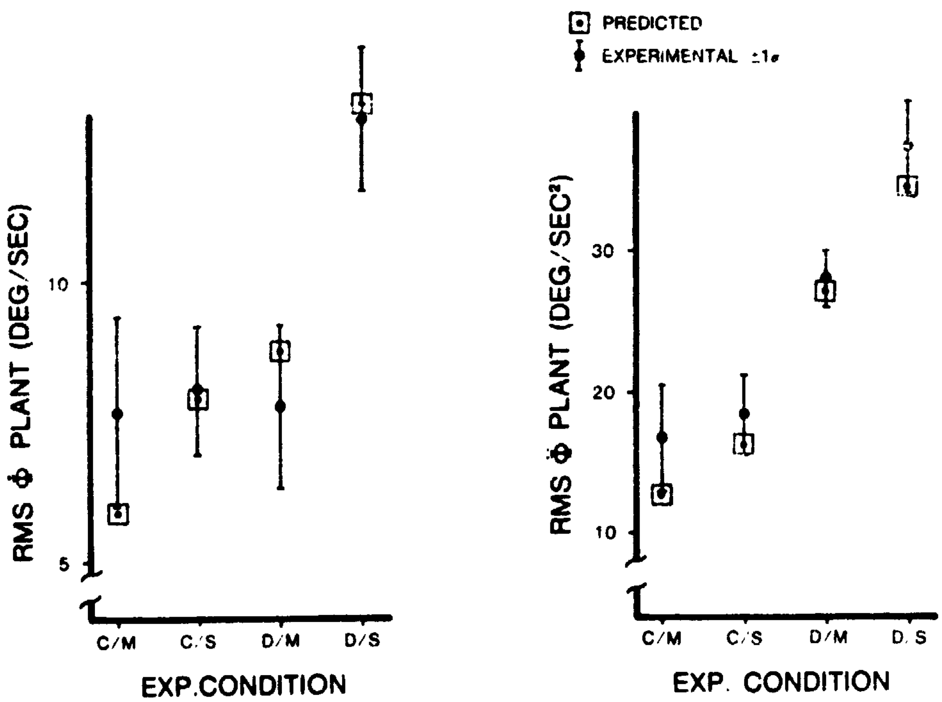

FIGURE 5. Comparison between model and experimental results for vehicle velocity and acceleration.