Initial Study toward a Methodical Approach for the Engineering of

Driver Assistance Technology

Final Report

to

Bayerische Motoren Werke AG (BMW)

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16. Abstract

This study lays a foundation for studying stop-and-go Adaptive Cruise Control (ACC) while exploring a methodical approach that might guide the development and evaluation of driver assistance systems (DAS), as a class. The project included 1) a survey of related human factors literature, 2) new empirical measurements of stop-and-go driving, including staged stopping tests and normal driving on freeways and surface streets, 3) processing and analysis of the recovered data, 4) development and initial validation of a computer model representing manual stop-and-go control, written in Matlab Simulink code, and 5) examination of a "model-difference" method for isolating the events in records of manual driving in which the actual driver departed markedly from an apparent headway-only control criterion. The state of progress toward developing a long-term methodical approach for the engineering of driver assistance systems is also discussed. The next step in this research is to incorporate the manual control model developed here as the active high-level algorithm in an ACC-controlled vehicle.

17. Key Words adaptive cruise control, stop and go, naturalistic driving measurements, driver assistance systems, driver modeling	18. Distribution Statement

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EXECUTIVE SUMMARY

Driving measurements, data processing, model development, and model-based analyses were undertaken to lay a foundation for studying stop-and-go adaptive cruise control (ACC) as well as to begin creating a methodical approach for guiding the development and evaluation of driver assistance systems (DAS), as a class. This study built upon UMTRI's prior capabilities in ACC measurement, data analysis, and modeling, concentrating on the manual control of stop-and-go driving as a baseline for considering the application of ACC to this driving regime. Using stop-and-go as the case-in-point application, it then sought to advance at least some basis for methodical development of DAS systems even though fundamental theory is broadly lacking in this arena. What is truly needed, of course—a "science of driving"—does not exist. What is sought as a pragmatic alternative is an approach that will cut down product-development time and render a useful basis for understanding system performance, in light of the complexity of each driver-assistance application.

This project was exploratory. It undertook a set of subtasks which, although yielding results that are instructive in their own right, do not by themselves constitute a compellingly methodical path toward the development and evaluation of stop-and-go ACC. Five kinds of tasks were pursued:

1) A survey of related human factors literature was performed. It showed that a) certain basic aspects of human visual and psychomotor performance and even cognition at the "production" level are understood at least in a rudimentary way, and b) previously published modeling concepts do provide a helpful background for developing a model of manual stop-and-go headway control, but c) the complete dimensions of human control during stop-and-go driving go vastly beyond published knowledge.

2) Lacking a developed scientific understanding of the driving process for the stop-and-go application, new empirical measurements were conducted under as naturalistic a driving exercise as was practicable. Using vehicles equipped with ACC-type sensors and other instrumentation, data records were obtained from both staged stopping tests and normal driving on Detroit-area freeways and surface streets in order to compile a useful base of stop-and-go manual driving data.

3) These data were processed and examined from many points of view in order to: a) reveal essential elements of the manual control of speed and headway in stop-and-go

environments, and b) guide the creation of a model that would explain as much of the manual control behavior as possible. The data exist in a Microsoft Access format and are readily portable for examination by others.

4) A model of manual stop-and-go control developed for this project was then validated against the measured data. The differences between model predictions and measured data were studied for possible model refinements, and the overall modeling challenge was appraised in light of this experience to gain a first-round measure of the complexity resident in stop-and-go control. The model structure divided the range and range-rate phase space into seven zones, each with its own rules for modulating speed, based upon a hybrid of considerations from visual psychometrics, sliding control analysis, crash-avoidance rationalization, and empirical fitting. The model was created in MATLAB/SIMULINK®code and could be downloaded as an ACC control algorithm with little difficulty.

5) The continuous *model-difference* was computed between what the modeled-driver would have done and what each test driver did when tracking a preceding vehicle in actual tests, as a means of isolating the events in which the actual driver departed markedly from an apparent headway-only control criterion. A few video records were examined coincident with these events to identify the conditions that provoked what were called the *altercontrol* responses of the driver. That is, the driver exhibited altercontrol whenever responding to something other than the immediate headway constraint. Transitions to altercontrol are thought to reveal circumstances in which, if ACC were enabled, either a driver intervention would ensue or the driver's judgement on ACC system acceptability would probably be influenced in a significant way.

This project was confined essentially to the study of manual stop-and-go driving. A modest data set and an associated model describing the mechanics of manual control in this domain have set the stage for a more orderly examination of stop-and-go ACC in a subsequent phase of the work. It is recommended that the next step in this research include the implementation and trial operation of an ACC-controlled vehicle whose high-level algorithm is basically that of the manual driver model developed here. It is also recommended that the domain of altercontrol be catalogued at least in an introductory way so that an orderly scoring of the ACC driving experience can be related to the headway-determined versus altercontrol phenomena that are observed within manual driving.

1.0 Introduction

This document constitutes the final report in a research study sponsored by Bayerische Motoren Werke AG (BMW) at the University of Michigan Transportation Research Institute (UMTRI). The overarching goal of this research is to create a methodical approach for guiding the development and evaluation of driver assistance systems (DAS), as a class. This long-term purpose was pursued in an incremental fashion here, by using stop-and-go adaptive cruise control (ACC) as the case-in-point application. Although actually focusing the investigation on manual control of stop-and-go driving, the study sought to advance an initial basis for methodical development and evaluation of a stop-and-go ACC system controller in subsequent phases of the work. Since fundamental theory is broadly lacking in this arena (that is, no "science of driving" exists upon which to postulate the functional principles for ACC system design or its evaluation), a pragmatic approach is sought. Such a methodical approach would seek to cut down product development time and render a useful basis for understanding system performance, by means of only a "necessary and sufficient" treatment of the complexity that is embedded both within an individual driver's behavior and across the sociological influences arising from other nearby drivers.

A review of the literature was followed in this study by driving measurements, data processing, model development, and model-based analyses in order to create a baseline understanding of manual control of stop-and-go driving. Each of the individual subtasks in this effort is presented and discussed in sections 2 through 5 of this report. In section 6, the elements that might comprise a methodical approach for DAS development and evaluation are discussed in the context of the subtasks. Conclusions and recommendations are presented in section 7. The report also contains an appendix A, which presents brief comments on documents examined from the human factors literature, appendix B, which presents the MATLAB/SIMULINK®diagrams covering a developed model of manual stop-and-go control, and appendix C, which contains a set of plots comparing model results with measured data.

2.0 Literature Review

In undertaking this literature review, perhaps the greatest challenge has been to bound the scope of the question. When considering a stop-and-go ACC system, relative to an ACC system that provides only low levels of deceleration, one must take into consideration a much broader view of the driving environment. In many respects, the challenge of understanding the driving environment grows immensely. The traditional approach of concentrating on the vehicle immediately in front of the equipped vehicle may no longer apply, as stop-and-go ACC is no longer limited to a simple following task. The dynamics of the driving task broaden with stop-and-go ACC and may, in fact, have to consider multiple preceding vehicles, as well as vehicles in adjacent lanes. Unfortunately, although not surprisingly, a review of literature found no reported research that was specific to stop-and-go ACC, nor was there any literature regarding driver behavior while stopping in traffic (with the exception of an article by Ludmann et al., 1997).

Rather than adopt a single approach to describing and understanding driver behavior specific to the use of stop-and-go ACC system, it was felt that an initial look at a variety of approaches was warranted. Schiff and Arnone (1995) state that driving "involves the integrated activities of sensing, perceiving, deciding, and acting. Before any decisions or actions can be made, the human factors scientist must become aware of phenomena in the sensing and perceiving realm." This includes being able to identify *what information* is relevant in the driving task, understanding *how drivers detect* this information, examining *how they respond* naturally to it, and finally, developing systems that can respond in a manner that is not in conflict with the driver's natural response or expectations of the system (*model*). Therefore, this review was approached in sections, not completely independent of one another, which address recent literature in the areas of classical sensory psychophysics related to driving, ecological psychology and driving, mental workload and mental modeling of the driving task, driver braking and steering behavior in response to obstacles, and modeling of driver behavior.

2.1 Historical Background

Previously there have been two dominant, although not totally independent, approaches for representing driver behavior, a classical sensory-psychophysical approach and an ecological approach to perception. Perhaps nowhere is the historical account of these different approaches better described than in a book chapter by Schiff and Arnone. Beginning with the early work of Gibson on flow theory, to the recent trends in calculating time-to-collision, Schiff and Arnone outline the different research paths taken by proponents of the two approaches to driver perception. It is the opinion of Schiff and Arnone that practitioners in the fields of engineering and human factors need to carefully choose their research methods in order to ensure ecological validity, while continuing to recognize the substantial contributions of sensory psychophysics and incorporating principals of human factors design. Further emphasized is the need to recognize the complexity of driving, and the fact that it is not a simple sensory task.

> *"Of all the skills demanded by contemporary civilization, the one of driving an automobile is certainly the most important to the individual, in the sense that a defect in it is the greatest threat to life. But despite the consequent importance of knowledge about the nature and acquisition of this skill, no more than a beginning in this direction has been made by psychologists, and that chiefly in the field of devising tests to measure some of the inferred components. A systematic set of concepts is needed in terms of which we can describe precisely what goes on when a man drives an automobile, and such a theory, if it is to be useful, must have practical as well as psychological validity."*

Such was the opening statement of an article written by James J. Gibson and Laurence Crooks in 1938. More than 60 years since the publication of this article, it can be legitimately argued that psychology, and perhaps more specifically the fields of human factors, ergonomics, and cognitive psychology, are not considerably closer to understanding the global nature of "what precisely goes on when a man" or woman "drives an automobile." Although a good deal of effort has gone into understanding various perceptual components of the driving task in isolation, there remains a great deal of inference regarding the task of driving. To date, the process of understanding driver behavior has focused almost exclusively on basic models of visual perception, in isolated and/or situation-specific scenarios with little attention to the overall task we know as driving.

Gibson and Crooks emphasized in their article what they termed the "field of safe travel." They described this field as an indefinitely bounded zone that included all the elements a driver needed to take into consideration at any given moment of the driving task. Elements prominent in the shaping of the field of safe travel were the driver's motivation, perception of the driving environment, and expectations (based in part on learned behavior). This field, stated the authors, could be thought of as a zone that protruded from the front of the automobile, bounded in part by the physical constraints of the roadway, but chiefly determined by the presence of objects (especially, other vehicles). We know today, however, that this "zone" actually extends around the entire perimeter of the vehicle, the bounds of which are heavily dependent on the driving scenario or maneuver.

Gibson and Crooks described several driving scenarios, and how a driver might adjust his/her field of safe travel on the basis of these scenarios (e.g., following a lead vehicle, negotiating an intersection, allowing for pedestrians crossing the street, etc.), as well as potential obstacles to the drivers' ability to appropriately adjust their field of safe travel. A skilled driver, it was said, "recognizes the valances of obstacles quickly and automatically projects their clearance-lines correctly." Here, the term "valance" constitutes a scalar repulsion or attraction attribute that characterizes every element in the near-field driving environment. What Gibson and Crooks were attempting to describe is a theoretical framework for a very complex psychomotor process in which the driver's expectations are combined with perceived information in order that decisions can be made on how to control the vehicle within this environment.

The work of Gibson and Crooks became the basis of much of Gibson's later work. It included a functional approach to visual psychophysics, which sought to describe how humans perceive dynamic optical information, and in turn how this information is used to move through space (i.e., walking, driving, flying, etc.). What makes the Gibson and Crooks article such a compelling starting point for the discussion of stop-and-go ACC, or any form of driver assistance system, is the recognized scope of information that is required by the driver. Specifically, it is suggested that the shape of the field of safe travel is determined by the driver's motivation, perception of the driving environment, and expectations that are based on learned behavior.

The challenge in designing stop-and-go ACC may lie primarily in identification of the later two components, since driver motivation can be largely, although not completely, addressed by permitting adequate driver input to the system (i.e., headway adjustment, set speed, etc.) and fitted control strategies (e.g., the maximum level of ACC control authority vis-à-vis the ACC functionality). The question therefore becomes: how does the driver perceive the driving environment, and what are his/her expectations? Furthermore, can this be modeled such that the driver's supervisory tactics are understood and that the system's influences on supervisory performance can be meaningfully expressed and measured? Concerning the system itself, we desire that conflicts posed by sensed obstacles be recognized quickly and automatically, the same as a driver perceives them, and that control actions be executed that conform to the driver's expectations. If a system cannot be designed to perceive and behave in the same manner as a driver, then the limits of system capability must be conveyed to facilitate supervisory transitions.

Appendix A presents citations of pertinent research literature, with brief summaries included for many of the articles. The ultimate approach toward understanding driver behavior, like that argued by Schiff and Arnone, must include the integration of the central driver activities including sensing, perceiving, deciding, and acting. While there is no evidence in the open literature of a comprehensive model of driver behavior in stop-and-go traffic, the research listed in the appendix provides several critical elements toward that end.

2.2 Summary

While a review of literature found little that was specific to stop-and-go driving behavior or driver behavior with ACC, numerous articles, from a variety of research arenas complement or provide insight to the development of a stop-and-go ACC system. In addition, other publications are cited in subsequent sections of this report, as the published work was used in the consideration of driver modeling. On the basis of the literature reviewed, significant effort remains before we will gain a working understanding of what in a stop-and-go environment goes on in the mind of a person driving.

3.0 Staged Tests of Stop-and-go Driving

The data collected in 1996 during UMTRI's field operational test (FOT) of ACC failed to capture information on stop-and-go driving due to a lockout of sensory data when the preceding vehicle's speed fell below 30% of the speed of the host vehicle. Accordingly, the two separate test activities that were undertaken during the present study both involved revisions in the software of the FOT vehicles so that this lockout provision was disabled, thereby yielding range and range-rate measurements down to zero speed, albeit with some incidence of false detection of other standing objects. The first of the new tests were of the staged variety, by which two vehicles were driven through various stopping sequences on a 0.6 km portion of local road that was closed to through traffic. In the discussion that follows, the test methods, results, and general observations from staged testing are presented.

3.1 Test Method

Eight UMTRI employees, excluding engineering personnel who were active in driver assistance research, were asked to participate in a one-hour driving exercise that involved stopping behind a confederate vehicle that was driven by an UMTRI technician. Subjects were asked to come to a stop behind the confederate vehicle, when necessary, as if they were driving behind this vehicle in normal stop-and-go traffic. A total of 26 stops were done by each subject at mild braking levels per the test procedure outlined below, from a nominal initial speed of 35 mph (56 km/h). Human-use approval was obtained from the University's Internal Review Board for these tests and a human factors professional accompanied each subject while test driving was underway.

Both test vehicles were 1996 Chrysler Concorde sedans equipped with all of the instrumentation that had been provided for their earlier use in the FOT project. The vehicles were driven only in the manual mode of control, with the ACC feature deactivated. Throughout the tests, the Leica ODIN-4 infrared sensor outputted range and range-rate data that continually tracked the headway condition down to stop. Data collected continually in both vehicles against the common GPS time base allowed later synchronism of signals from one vehicle to the other such as, for example, in measuring latency in the subject's response, following the illumination of brake lamps in the preceding vehicle. Although a complete description of the instrumentation system is given in the FOT report [3], it suffices here to say that the recorded variables included range, range-rate, velocity, and the state of the brake pedal switch on both test vehicles, with 10-Hz sampling. The record was obtained first via an on-board hard disk and later downloaded into a Microsoft Access database.

3.1.1 Test Procedure

The basic test procedure involved the subject vehicle stopping as necessary in response to stopping by a preceding confederate vehicle. Tests were done in two segments that were differentiated by the initial headway state that caused the subject to brake. In both cases, the test subject began at a nominal initial speed of 35 mph (56 km/h).

In the first segment, the subject braked in response to brake application by the preceding vehicle, from an initially comfortable, headway-keeping condition. At a random location along the course, the technician in the preceding vehicle braked to a complete stop, using a calibrated U-tube manometer to guide in the achievement of a nominal steady rate of deceleration between 0.1 and 0.3 g's. The subject then responded, braking as necessary to take up a final stopped position. (Notwithstanding the instruction to subjects to behave "as in normal stop-and-go driving," it was observed that final headway values were somewhat longer than are observed in more naturalistic stop-and-go contexts, presumably as a result of the missing psychological factor by which drivers perceive the expectations of others behind them—absent in this case—to close up the gap in queued traffic. A total of 18 stops were conducted in this first segment of the tests. In six of the stops, and in random placement during the sequence of 18 stops, a supplemental "go, again" segment was executed after the subject vehicle had come to a complete halt. That is, the preceding vehicle moved forward again a distance of 10 to 20 meters and stopped a second time, whereupon the subject likewise moved ahead and stopped again, thereby representing behavior under the "creeping" type of movements that often prevail during stop-and-go driving.

After the initial eighteen test stops, an additional six stops were conducted in which the preceding vehicle was already stopped in the roadway before the subject vehicle arrived. To accomplish this, the subject was asked to wait at the turnaround point while the confederate driver proceeded to approximately the middle of the course, and stopped. The subject then pulled out onto the road and proceeded at a steady speed of approximately 56 km/h until they encountered, and braked to a stop comfortably behind, the previously stopped confederate. Clearly, this latter test segment was to characterize the encounter with stopped traffic ahead, recognizing that the rear-end crash scenario, "lead-vehicle not moving" [17] has a special significance in the statistical crash record, (accounting for approximately 3/4 of all rear-end crashes in the United States).

3.1.2 Test Sequence

The test sequence is shown below. This sequence was employed in every case by the driver/technician in the confederate vehicle but was not known to the subject driver, ahead of time. The "creep" indication at the right denotes the cases in which the preceding vehicle moved ahead a short distance and stopped again, following a complete stop by the subject.

- Segment 1

Test Run	Confederate Vehicle Nominal Braking Level (g's)	Creep?
1	0.2	No
2	0.1	No
3	0.3	No
4	0.1	Yes
5	0.3	No
6	0.2	Yes
7	0.2	No
8	0.1	No
9	0.3	Yes
10	0.3	Yes
11	0.2	No
12	0.1	No
13	0.3	No
14	0.1	Yes
15	0.3	No
16	0.2	No
17	0.2	Yes
18	0.1	No

- Segment 2

Runs 19 through 24
(The subject vehicle came to a stop from an initial speed of 35 mph (56 km/h), behind the previously-stopped confederate.)

3.2 Results

Four types of test results will be shown in this section. They are 1) example time histories depicting the three differing test procedures, 2) aggregated data showing the influence of initial range and lead-vehicle deceleration level on the latency in brake applications by the subject, 3) the characteristics associated with the brake-onset response of subjects approaching the previously stopped vehicle in the roadway, and 4) distributions of the deceleration response of subjects in the differing tests.

3.2.1 Sample time histories discussing highlights

Shown in Figure 1 is a set of time histories that are more or less characteristic of the stopping responses seen in each of the tests in which the lead vehicle simply braked to a halt from an initial condition of steady headway-keeping. The figure shows in its top two plots the velocity and deceleration comparisons of both vehicles followed, at the bottom, by the range value at which the vehicles were separated throughout the stop. In the velocity comparisons, we see that the subject's velocity remained continuously above that of the lead vehicle, thereby causing range to shrink monotonically throughout the stop. (Please note that the peculiar inflection in the velocity traces at approximately 28 ft/sec, both going down and going up in speed, constitutes an anomaly of the Chrysler engine controller, through which the speed measurement is recovered on both vehicles. The anomaly is something of a distraction in these data but does not represent an actual change in the velocity profile of the vehicles, themselves.)

In the Vdot comparisons, we see that the subject apparently released the throttle within approximately one second of the rise in the lead vehicle's deceleration (at approximately t = 1.5 sec) and then applied the brake after a total of approximately 3 seconds (beginning at approximately t = 4.5 sec). The subject's initial braking level was initially brought to a higher value of deceleration than that of the lead vehicle, eventually dissipating only as the lead vehicle came to a stop. Having sustained a monotonic velocity difference all the way to a stop, the range steadily declined to a final value of approximately 33 ft (10m) when stopped. This final range value is an example of the somewhat longer-than-natural result that was commonly observed in these staged tests, lacking the induced compression that seems to derive when many vehicles form up in a queue. Note that the initial range in this test was approximately 133 ft (41m).

In Figure 2 are shown time histories representing the tests in which the lead vehicle brakes to a halt and then begins to creep forward and stop again after the subject vehicle has reached its stopped condition. Again, the top two plots compare the velocity and deceleration responses of both vehicles, with the range variable shown at the bottom. The velocity comparison shows that the subject velocity remains invariably behind the velocity response of the lead vehicle, either above it while decelerating or below while accelerating such that range grows monotonically during lead-vehicle acceleration and shrinks monotonically during lead-vehicle deceleration.

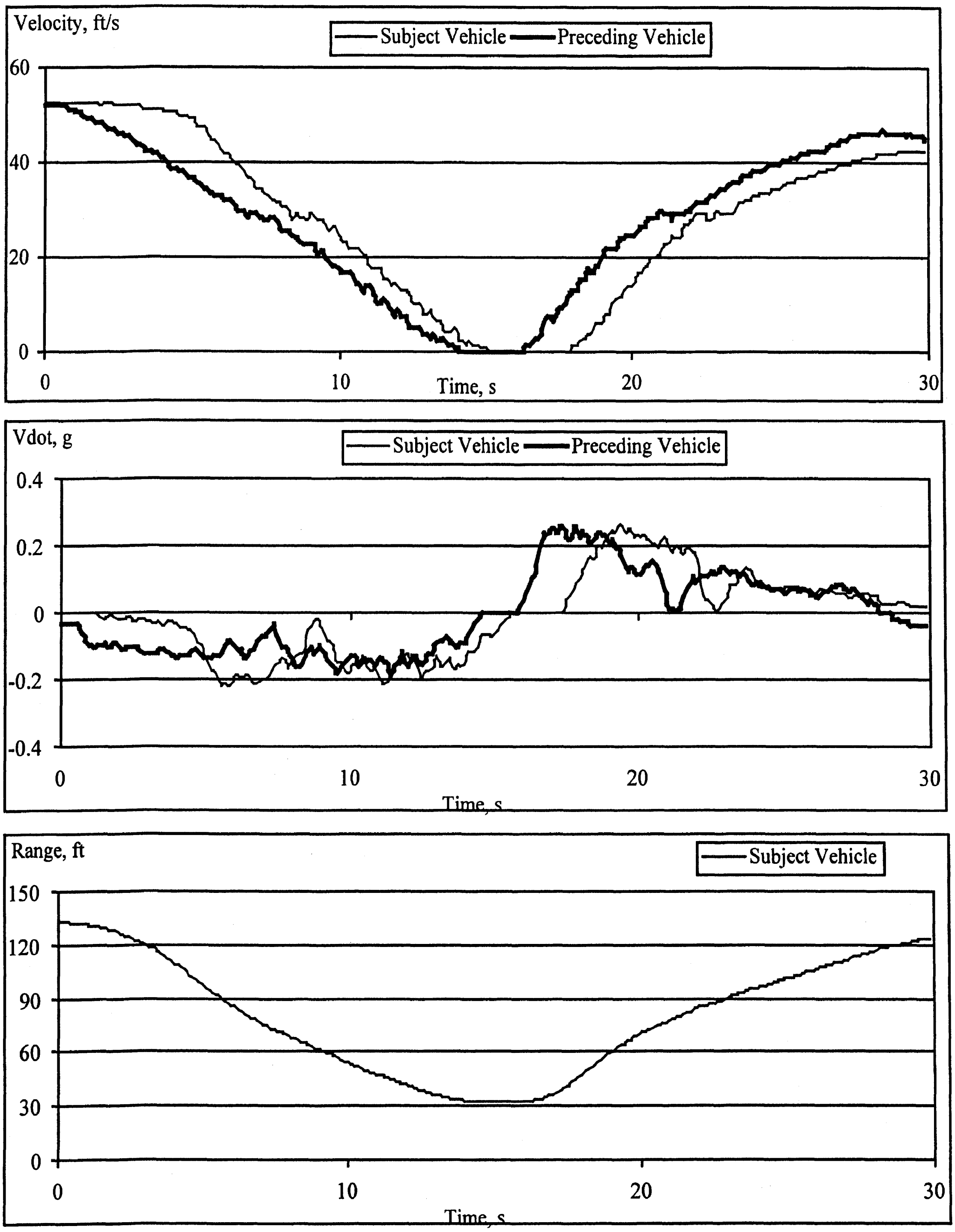

Figure 1. Sample time history of stop-and-go driving

In the Vdot comparisons, we see that the subject seems to be anticipating the second stop such that both vehicles reach zero speed at almost exactly the same time (i.e., at t = 19 sec). The startup delay, when the creep-forward maneuver begins, is approximately 1 sec, but may be more meaningfully described by the additional headway clearance that has accrued following lead-vehicle movement than from the elapse of time, itself. Note that the initial range in this test was approximately 108 ft (33m). Later in this section we shall relate the initial range values, and the deceleration levels of the lead-vehicle's braking, to the time latency of the subject's braking response following the onset of braking by the confederate.

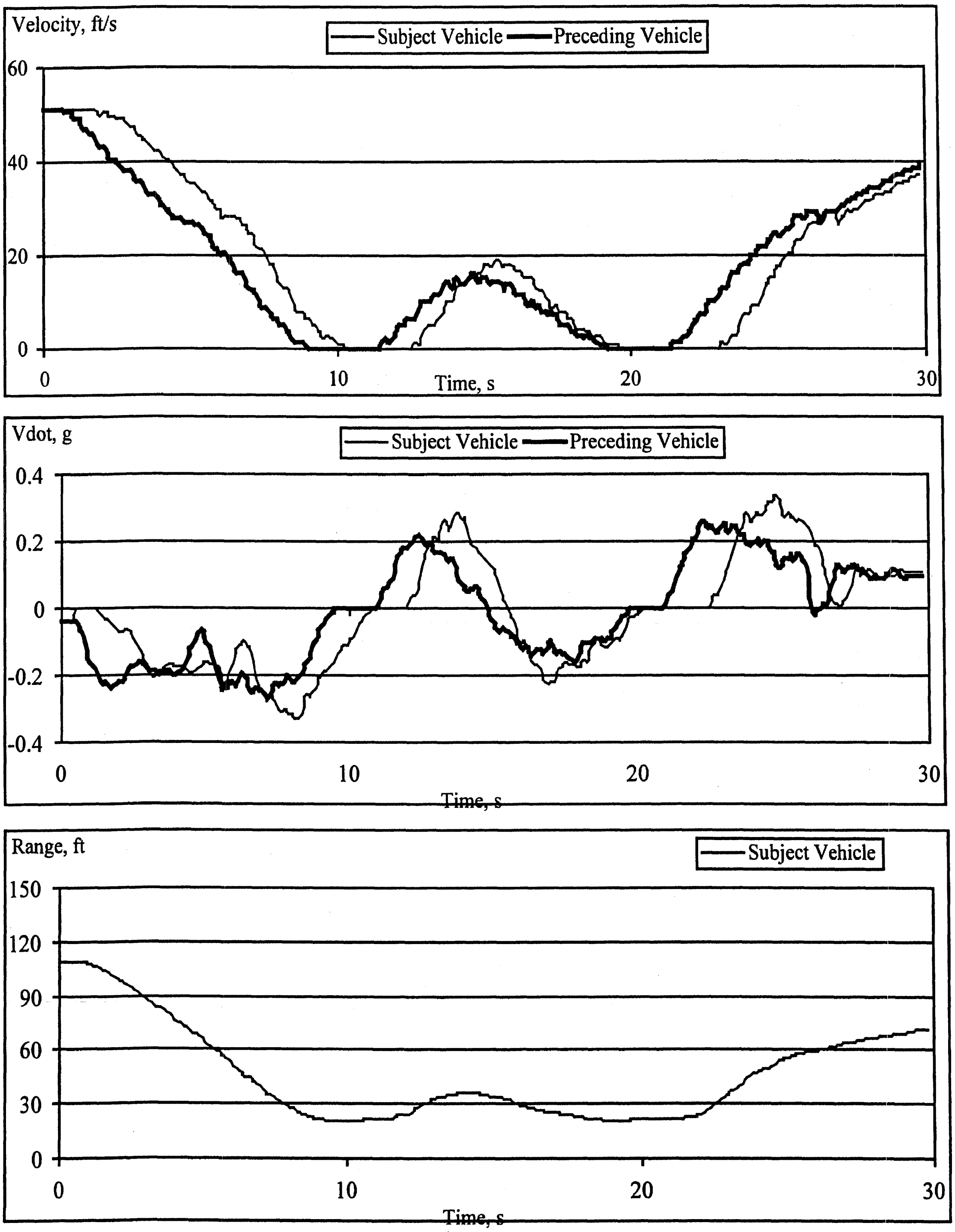

Figure 2. Two successive stop-and-go sessions

Figure 3 shows the time history responses for the test in which the subject brakes to a stop upon encountering the previously stopped confederate. The range signal shows, in this example, that the vehicle was detected by the range sensor only after braking by the subject was already underway, when the remaining range had fallen to within 300 ft (92 m). Please note that the late acquisition of the lead vehicle may have been influenced by the vertical curvature of the course over which testing was done —a factor having no significance in the earlier tests for which range was maintained to relatively short values throughout the stop. The Vdot data show that the subject tended to rather gradually increase deceleration in the mid-stop regime and then relaxed the braking level over the last 4 seconds or so.

3.2.2 Aggregated distributions and measures

Shown in Figure 4 are data taken from the 144 stops conducted as segment 1 tests (i.e., responding to lead-vehicle braking). Data are shown from only the first portion of these stops that is excluding the creep-ahead maneuver at the end of some of the tests.

In the top portion of figure 4 is shown a scatter plot of the results presenting the widely dispersed relationship between the subject's braking latency and the average deceleration. At first glance, one might suggest that there is no significant relationship between lead-vehicle deceleration level and latency. The next three plots, however, isolate the results according to three separate windows of the deceleration level in the preceding vehicle, plotting time latency against the initial range value at which the subject's braking was initiated. The three respective plots serve to segment the average deceleration of the preceding vehicle in successive tenths of a g. We note firstly that the initial range values, across the eight subjects, covered values from as short as 21 ft (6.4m) to as long as 250 ft (76m). The fitted linear regression lines, whose slopes are shown in the inset boxes, reveal that the latency in brake response is firstly determined by the range value at the moment of brake onset in the preceding vehicle and, secondly, by the level of deceleration that the lead vehicle generates. All three plots show that latency values tend to cluster tightly around 0.3 to 0.7 seconds whenever the initial range is short, say 30 ft (9m) or so. As range increases above that regime, the rate of influence of range on braking latency is strongly influenced by the deceleration level of the lead vehicle. Since the test subjects did not know which deceleration level would be invoked in any test, these very limited results tend to suggest that drivers are able to size up the rate of change of Rdot relatively early in the stopping sequence and to adopt the timing of their brake onset to the presented level of deceleration ahead.

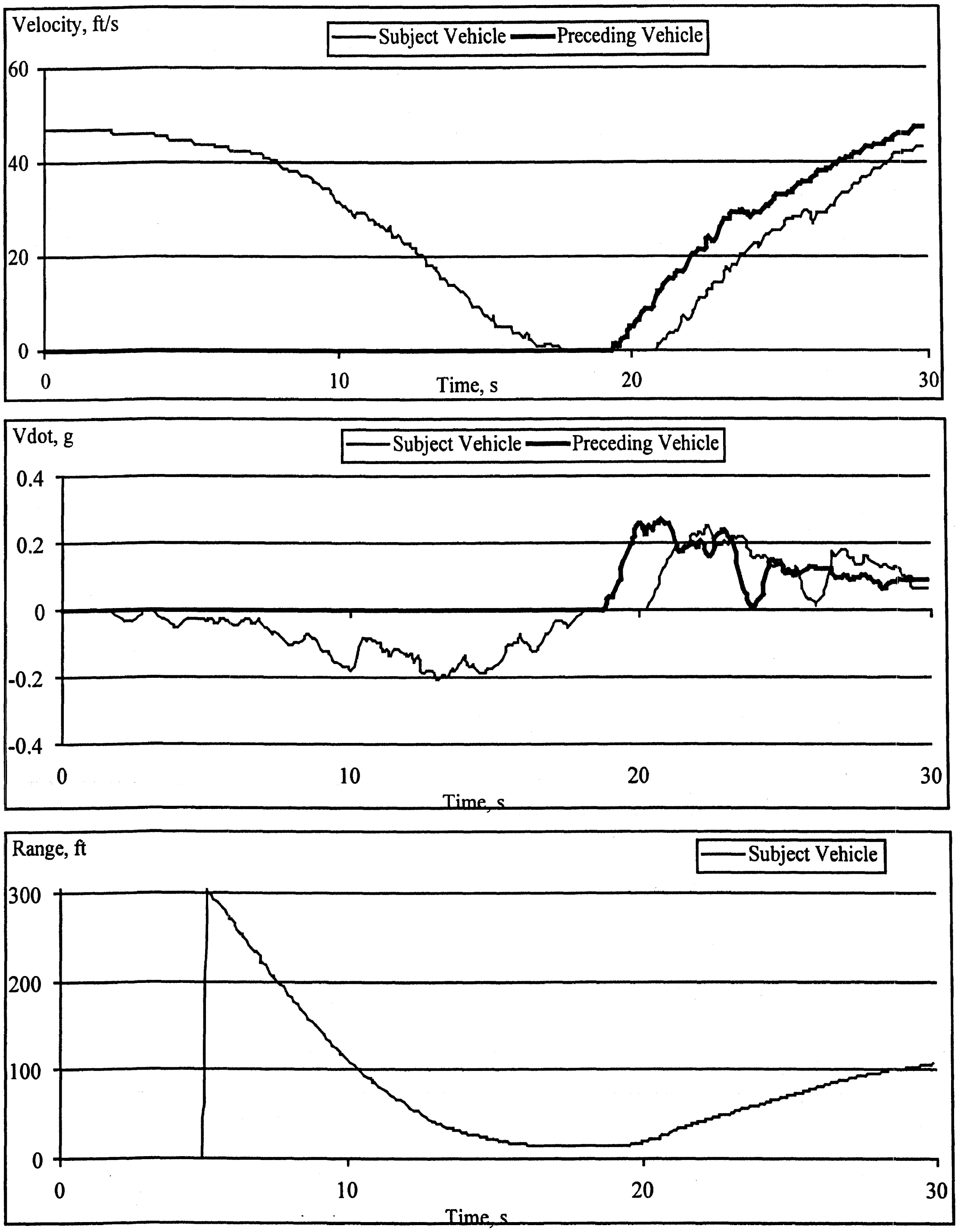

Figure 3. Brake to a stop upon encountering a stopped vehicle

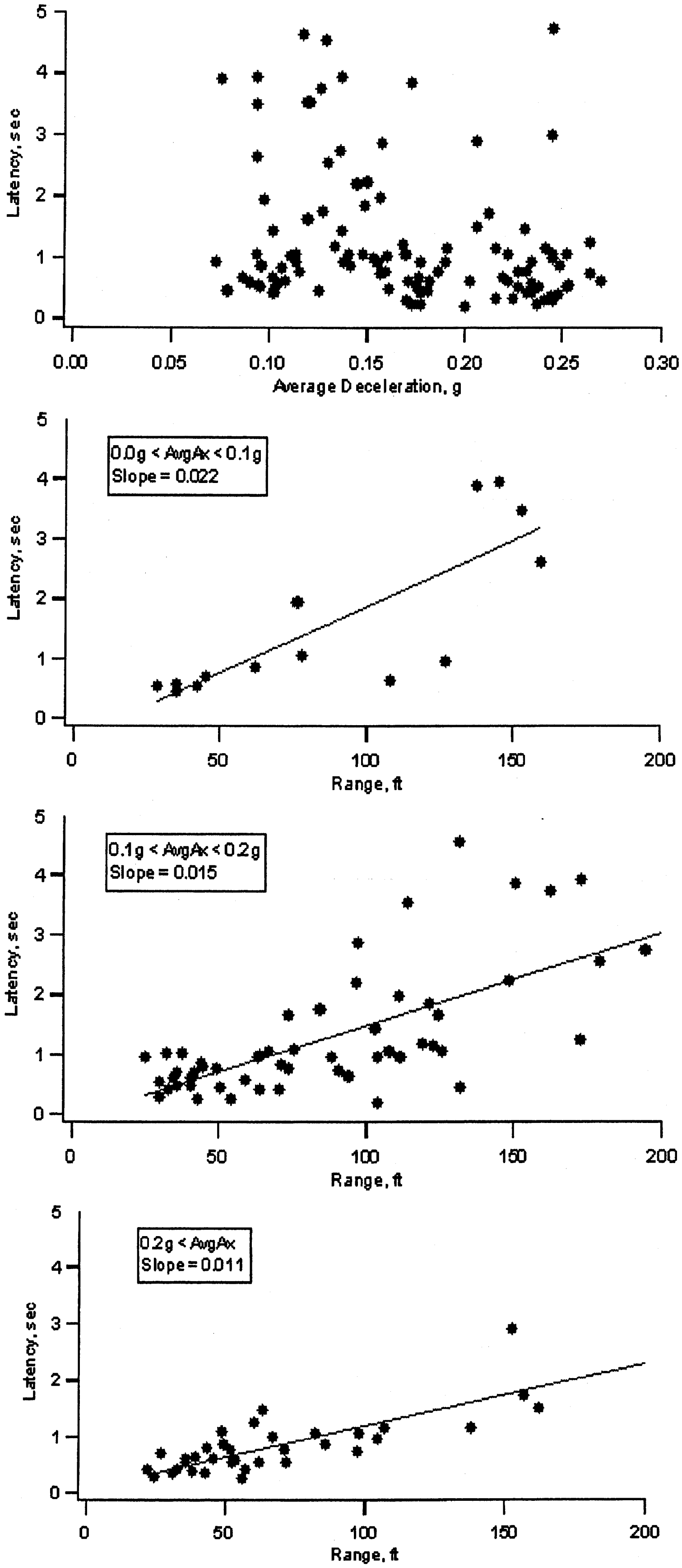

Figure 4. Latency results from segment 1 of the staged tests

One interesting issue that arises from the test encounter with a previously stopped vehicle involves the level of crash conflict tolerated by the approaching subject before the braking response begins. When initially detecting that a stopped vehicle is blocking the road, the subject is first observed to coast for a while, with throttle fully released. At some later point in the process, braking is applied and the vehicle is brought to a stop behind the lead vehicle. The moment of brake onset can be meaningfully described by the values of range, time-to-impact, and the deceleration-to-avoid-impact that prevail when the brake pedal switch closes. (Such data were the primary interest of the National Highway Traffic Safety Administration when they approved extending an UMTRI cooperative agreement to allow the usage of the government-owned FOT test vehicles in this project. Basically, NHTSA's interest traces to the prospect of a crash-warning function in which one simple argument of the warning algorithm is, "don't warn until the conflict with a stopped-vehicle-ahead has exceeded the threshold beyond which the great majority of drivers will already have begun braking. If the brake is not applied when such a condition develops, then trigger the warning." Thus, the NHTSA interest in the data was largely to identify the characteristics of the conflict, which if unaccompanied by braking, would quite certainly warrant a warning notice of some kind. Some discussion of the staged test data, below, addresses this proposition.)

Figure 5 shows that the range at which braking begins is distributed rather widely around the 250 ft (76 m) position, for this nominal range of initial speed. While ranges as short as 100 ft (30m) may at first seem surprising, this minimum value is typically associated with the response in which throttle release occurred very early in the sequence such that a more moderate time-to-impact value prevailed by the time the 100-ft range value was reached.

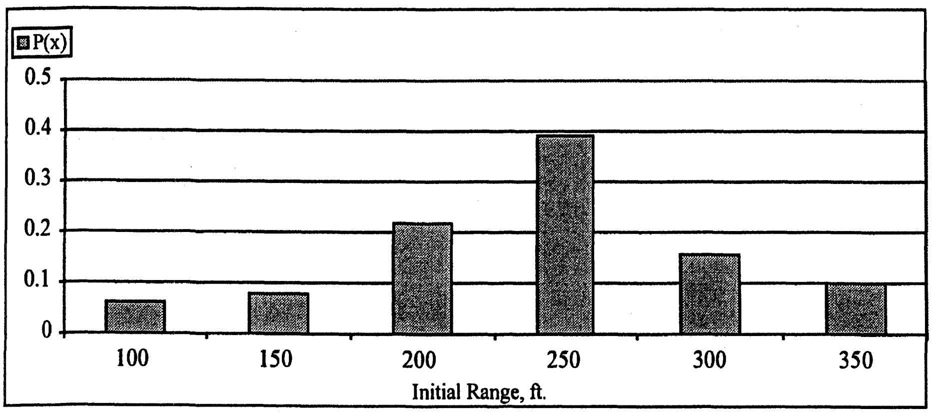

Figure 5. Distribution of initial range at brake on set while approaching a stopped vehicle

Figure 6 presents the time-to-impact distribution for the same set of stops. We see that while 5- and 6-second values are common, braking delays down to even a 3-second margin of time-to-impact occur in approximately 8% of the cases. By way of comparison, Figure 7 shows the corresponding distribution of time-to-impact values that were collected at the moment of brake onset from manual driving by 108 subjects during UMTRI's field operational test that was referenced earlier. Some 61,000 cases of brake application are represented in the data of Figure 7.

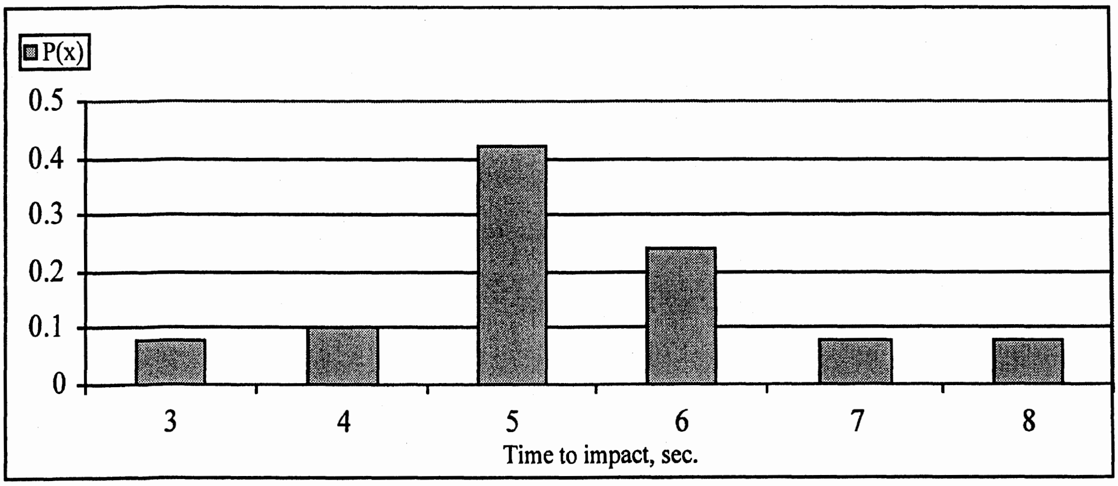

Figure 6. Staged-test results: distribution of time-to-impact value at brake onset while approaching a stopped vehicle

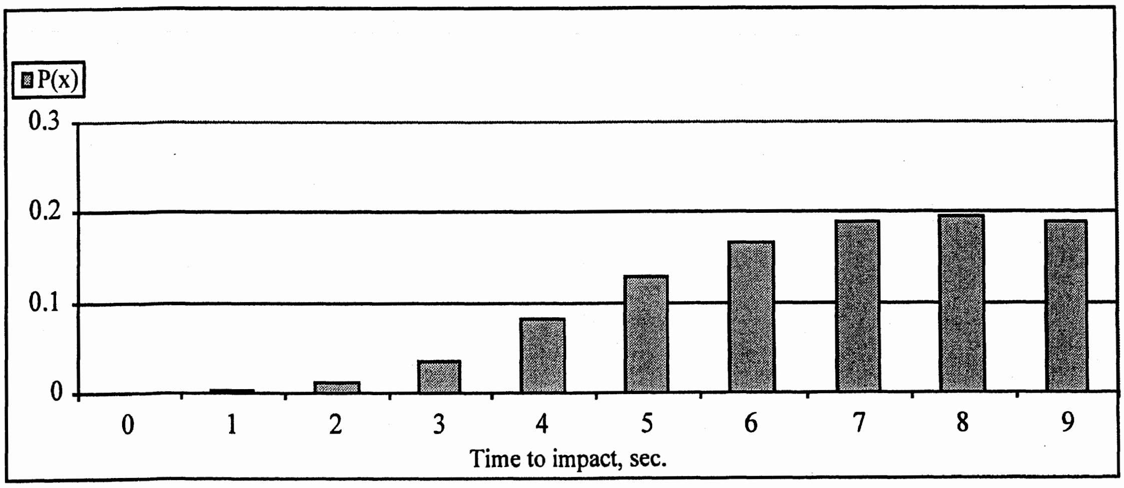

Figure 7. FOT results: distribution of time-to-impact values at the time of initial brake application (Vinitial > 25 mph)

In the FOT data, of course, a very broad array of actual and perceived conflict conditions had arisen to prompt braking by the subject, not simply the previously-stopped-vehicle scenario. Both plots show that brake applications with less than 2.5 seconds time-to-impact (i.e., the bin boundary separating the 2-second and 3-second results) are relatively infrequent—occurring in approximately 1.4% of the entire FOT data sample above 25 mph (40 km/h) and zero cases out of the 48 previously stopped, staged testing. Considering the NHTSA interest, however, failure to brake within some minimum time-to-impact value, by itself, would seem to constitute an insufficient criterion for warning. If triggered whenever the time-to-impact falls below 2.5 seconds without brakes being applied, for example, the warning would still occur in about 1 out of every 70 braking cases, which is approximately once every 50 miles of travel. This rate of occurrence would probably constitute a profound nuisance. At much shorter than 2.5 seconds-to-impact, however, normal human response delays would ensure a very low utility level for the warning.

Taking the discussion to the next step, a considerably better distinction between the previously stopped and the FOT manual braking results is observed when one considers the variable called *decel-to-avoid.* This measure expresses the deceleration level that would be needed, for the given closing condition—with negative Rdot—in order to just avoid a crash if the deceleration began immediately as a step function following brake onset and was sustained until the vehicle was stopped. Here, the comparison of Figure 8 and Figure 9 show that decel-to-avoid values above approximately 0.2 g's are extremely infrequent over the broad spectrum of braking events (in the FOT data) and occurred in only one of the staged tests with a previously stopped confederate vehicle. The FOT data yield a decel-to-avoid value exceeding 0.2 g's at the moment of brake onset only once in 1,300 stops (approximately once every 1,000 miles of driving.)

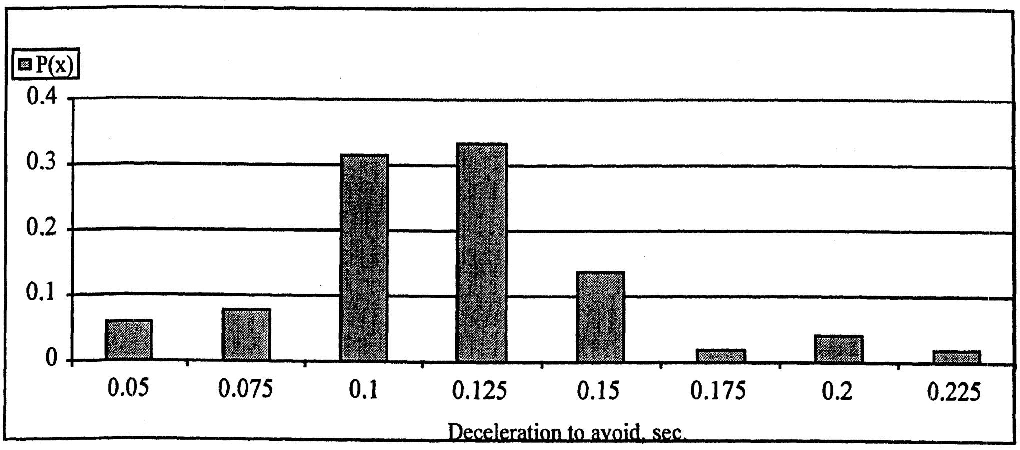

Figure 8. Staged-test results: deceleration to avoid (Rdot^2/2Range) values at the time of initial brake application (for Vinitial > 25 mph)

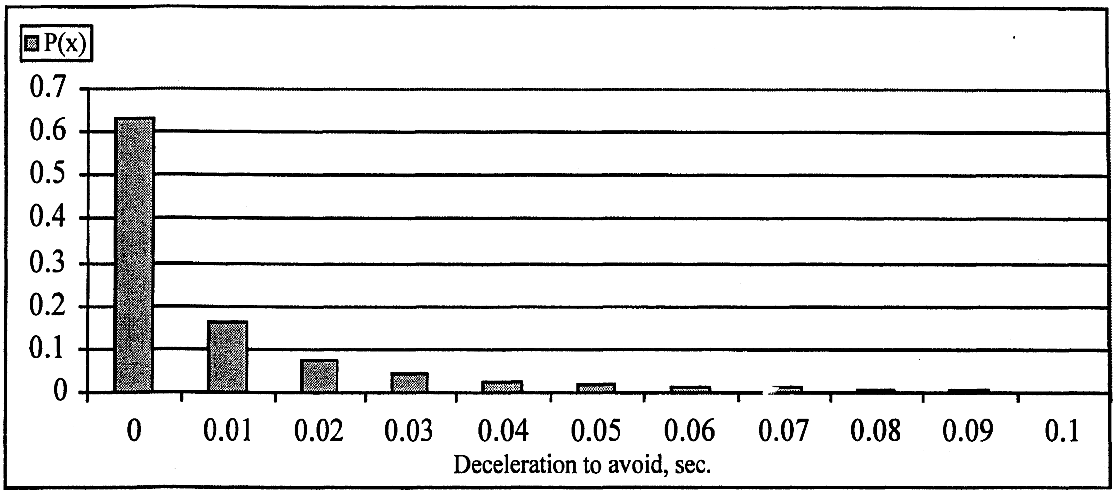

Figure 9. FOT results: deceleration to avoid (Rdot^2/2Range) values at the time of initial brake application (for Vinitial > 25 mph)

As a final consideration from braking tests responding to a previously stopped vehicle, Figure 10 shows the distribution of average deceleration values that prevailed across the 48 tests, overlaid on data from 1,900 cases drawn from FOT results in which the driver braked from the same nominal range of initial velocities to a complete stop. The FOT results represent braking behind impeding vehicles that were also engaged in stopping (i.e., they were not previously stopped when the subject first encountered them). The figure shows that the limited data from staged tests approaching a previously stopped vehicle yield a deceleration distribution that does not differ markedly from that observed in naturalistic data for stopping with impeding vehicles present, but not previously stopped. Indeed, average decelerations around 0.1 g tend to dominate braking distributions in the lower range of speeds, while a somewhat lower average (around 0.075 g) tends to dominate when braking at highway speeds.

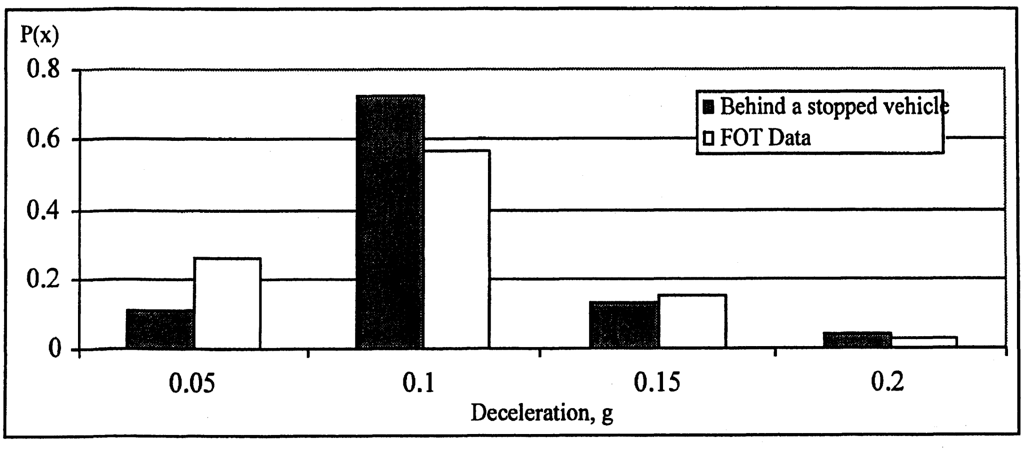

Figure 10. Distribution of average deceleration during a stop from 35 mph

3.3 Observations on Manual Stop-and-Go Control from Staged Tests

The principal observations that seem appropriate here involve the meaningfulness of the staged-test procedure. Two results seem to be somewhat anomalous. Namely, the distribution of initial headway values that were maintained during 18 segment 1 tests seem to include an unusual frequency of very short headways. Alternatively, the headway value remaining when the subject has stopped was often seen to be relatively longer than is normally seen when traffic stops in a queue. These observations would seem to imply that the non-naturalistic character of the staged tests was influencing behaviors toward some unnatural responses. On the other hand, it does not appear that the braking response, once it is deemed necessary, either initiates or is modulated in a way that is unnatural—except insofar as the terminal condition, once stopped, may leave a somewhat longer-than-natural static headway.

Moreover, these tests were seen as useful for planning the subsequent set of tests in real traffic by providing rudimentary samples of stop-and-go kinematics data for trial processing. They also served to explore lead-vehicle-decelerations up to 0.3g's, plus the previously stopped scenario, both of which certainly arise in the naturalistic environment, but not with the dense frequency of occurrence as could be cultivated in staged testing. Data samples from staged testing were also used as empirical evidence for developing a model of manual control, as is presented under section 5.1, below.

4.0 Concurrent Protocol Driving Tests

4.1 Test Method

Concurrent protocol testing sought to obtain data on stop-and-go driving in as naturalistic a situation as feasible. This was done in order to identify differences between how human drivers regulate their speed and range while following a vehicle, and how an ACC-type (i.e., headway-based only) control algorithm might do the same, although, only manual driving was being measured here. It is expected that observed discrepancies could be accounted for by identifying *other information* used by the human driver that is not available to a headway-only controller.

For example, the ACC-type control model is blind to most of the visual environment available to a driver. It bases its operation on measures of the host vehicle's velocity and acceleration and its range to the forward vehicle. Unlike an ACC system, a human driver is free to sample information from a variety of other sources. For example, visual cues arise from throughout the road scene (e.g., brake lamps ahead, traffic flow in adjacent lanes, traffic density, traffic signals, signs, road geometry, etc.).

Drivers may also employ situational strategies to optimize some aspects of their drive. For example, they may attempt to minimize drive time by searching for the fastest path through a congested area. They may attempt to conserve fuel by avoiding sharp accelerations. They may want to protect themselves against cut-ins by minimizing the range to the forward vehicle. They might increase safety by following at a greater distance, obtain smoother rides by avoiding potholes, maintain acceleration forces within a comfort range, or select lanes to maximize crash-avoidance options. They may, in fact, employ combinations of all these strategies in fluid, situation-dependent decisions about how to control the vehicle.

Given these possibilities, this study attempts to assess how well performance can be accounted for with a headway-control model alone, and looks for other environmental factors from a videotape record of the drive to account for discrepancies between the model and observed driving performance.

4.1.1 Task Description

1. *Subjects:* Eight drivers, between the ages of 29 and 51 (average age, 38), were asked to drive a predefined route through the Detroit metropolitan area and environs. There were seven male subjects and one female.
2. *Procedure*: The subjects were advised that they were participating in a study to investigate how people drive in stop-and-go traffic, and that data from their driving would be recorded. They were also told that the drive would specifically target Detroit morning rush-hour traffic. Subjects were encouraged to report driving strategies that they were aware of using, things they were looking at during the drive, and any thoughts they had related to the drive. A video camera was mounted in the vehicle to record the forward scene out the windshield throughout the driving session. It also recorded verbal reports subjects made during the drive. An experimenter accompanied six of the subjects; two subjects made the drive unaccompanied. During the drive, the experimenter periodically prompted subjects to make reports on their driving. Such prompting, however, was kept to a minimum to prevent the subject from becoming overly self-conscious of his driving, and to avoid creating an

impression that the subject's performance was being evaluated for correctness. Experimenters used a "Concern" button to mark events in the vehicle-record so that the videotape could be synchronized with vehicle data. All drives began at approximately 7:00 a.m. so that a roadway targeted for congestion could be reached at the projected peak rush hour.

3. *Driving route*. The driving route was selected according to the following criteria: a) The route included both principal arterial surface streets and segments of limited-access-highway traffic so that a variety of stop-and-go situations could be observed. Traffic on the surface-street portion of the route was regulated mainly by traffic-control signals (e.g., traffic lights, stop signs). Peak-hour traffic volumes principally induced the stop-and-go activity on the freeway (highway) portion of the route. The route was planned to permit observation of how such differences affect driving behavior. b) The incidence of highway stop-and-go traffic was a consequence of traffic volume, not road construction or accidents. This constraint was established for two reasons. Traffic accidents are random events that do not occur with any consistency from day to day. They also vary in the degree to which they disable traffic. We also avoided construction sites, since they create congestion by lane closure and may induce drivers to compete for position in particular lanes. Drivers are often forewarned about construction-related congestion by signs identifying the approximate forward location. Traffic congestion induced by excessive volume, on the other hand, is not marked in any way, and is thus not anticipated by the approaching driver. c) The highway stop-and-go traffic recurs regularly from day to day with a high probability. Since some highways in the metro-Detroit area are monitored for traffic volumes, and the resulting data are published electronically over the internet, it was possible to select a consistently congested section of freeway as the target for testing. d) The driving route took no more than two hours maximum time for a round trip. This constraint was motivated by the practical limits of some of the recording equipment, as well as by our sense of how long a reasonable drive session should be.

The adopted target route was an 83-mile loop shown in Figure 11. It contains an average of 3.68 miles of stop-and-go highway travel, 50 miles of ordinary highway traffic, and 33 miles of arterial surface street traffic. Stop-and-go highway traffic was largely confined to a 5-mile portion of the John C. Lodge Freeway near metro-Detroit. Other, less reliable incidents of stop-and-go traffic occurred at the merge point between I-275 and I-696. Stop-and-go arterial traffic was confined to Michigan Ave (US-12) from

Dearborn to Ypsilanti. This route contained a wide variety of traffic conditions including four areas of urban traffic (Dearborn, Inkster, Wayne, and Ypsilanti) controlled by traffic lights; some uncontrolled rural areas; varying numbers of traffic lanes (four to six); divided and undivided roadways; varying speed limits (25-40 mph); and sparse pedestrian activity.

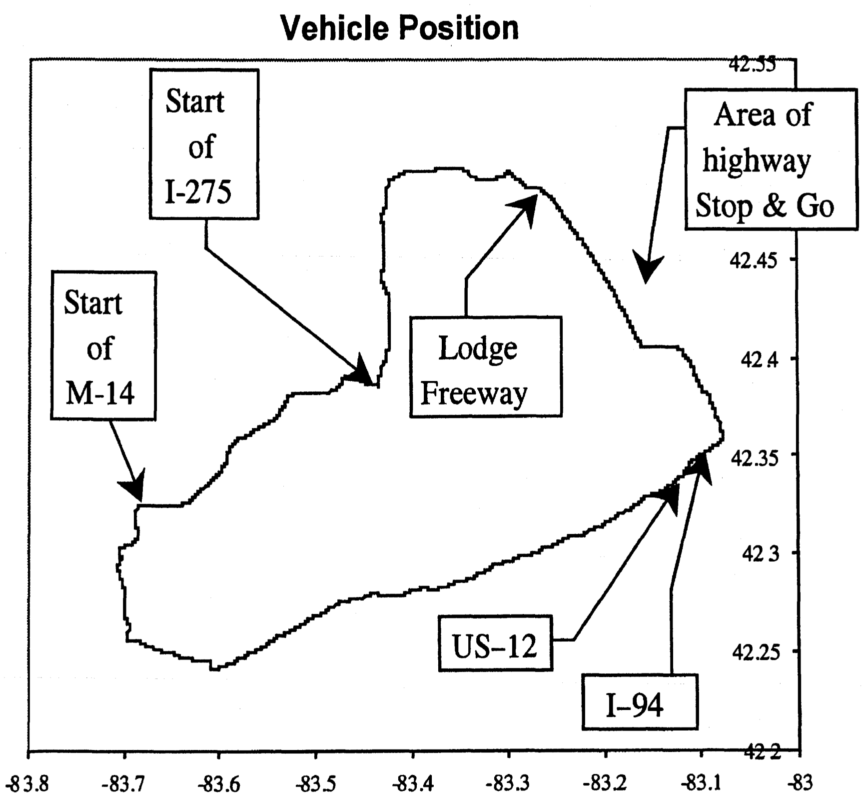

Figure 11. Schematic map of drive route

4.2 Results

4.2.1 Results drawn from the video records

Video Coding. An attempt was made to apply a coding scheme to some of the video data so that it could be incorporated into the analysis of vehicle data. The objective was to classify aspects of the driving situation which cannot be detected by ACC sensors, but which might be relevant to explain discrepancies between driver behavior and ACC-controlled behavior. Unfortunately, such coding proved to be extremely unwieldy. Apart from the laborious nature of the coding task, we found it difficult to faithfully capture the dynamics of the driver's strategy. Since this study is essentially an exploratory effort, it also seemed more efficient to direct our use of the video record to investigate specific discrepancies between the headway based-predictions and driver behavior. Consequently, coding data was produced from video recording for only one subject.

Subject Verbal Protocols. Subjects differed in the degree to which they made verbal reports while driving. Over the course of the drive, there was an average of 28 comments (range 43 to 15). Of these comments, 42% were statements related to driving strategy (e.g., "I don't like to get behind a tall van. [I pick a] lane based on roughness of the road"), and 55% were simple observations about the driving situation (e.g., "There are a lot of brake-pedal-tappers out this morning."). Most strategy comments focused on the following topics:

- Lane selection (e.g., avoiding potholes, merging traffic from entrance ramps, maximizing collision-avoidance options, maximizing speed, avoiding congestion)

  "...trying to get over a lane to get onto I-275N... make sure I don't get myself locked up here in traffic...there's a car riding along behind me, I want to get over a lane just in case he's trying to get past..."

  "...the lanes to my right are moving a little faster but looking ahead, there is nothing that would lead him to believe that the lane he is in is permanently stalled, so he doesn't have really any desire to change lanes...I think when we get through this bend, it will pick up speed...we may be doing 20, 25 mph soon!"

  "I'm caught behind this truck right now; this is not what I want..."
- Defensive measures (e.g., following distance, gap maintenance, avoidance of trucks and vans to maximize visibility)
  One driver changed lanes when he noticed someone pass him on the right (he explicitly commented on it).

  "...the reason I stay in this lane (he's in the center lane as he says this) is that if something happens, I have two ways to go...(I feel that you always need) an escape route..."
- Speed strategy (e.g., maintain traffic flow, minimizing variation in velocity, conservation of fuel by avoiding brake application, avoiding vans and trucks because they are slow)

4.2.2 Prominent differences observed, freeways versus streets

Basic driving characteristics. The drivers completed the drive in an average time of 117 minutes (range 111 to 123), averaging speeds of 42.3 mph (range 40.6 to 44.6). Table 1 summarizes the driving characteristics of each portion of the route. Notably, the average time spent on surface streets versus highway segments was approximately the same, although the surface-street-route distance was shorter (and traversed, predictably, at a slower rate). It is also notable that the Lodge Freeway, hosting the regularly predictable stop-and-go traffic, posted slower average speeds than the other freeway segments.

Each driver encountered highway stop-and-go traffic at approximately the same location on the Lodge Freeway, although there were differences between subjects in both the duration and extent of the traffic. The average time spent in highway stop-and-go was approximately 11 minutes (range 8 to 17 minutes), and the average distance traveled was 3.68 miles (range 3.1 to 4.7 miles).

Table 1. Route segment average length, speed, and duration

Type	Segment	Length (Miles)	Duration (Minutes)	Speed (MPH)
Surface Streets	Plymouth Rd	.77	1.90	25.15
	Michigan Ave	23.48	37.48	37.7
	River Rd.	.53	1.93	16.39
	Washtenaw Ave	4.24	10.09	23.07
	Huron Parkway	3.01	5.62	32.4
Total		32.03	57.02	33.70
Highway	M-14	14.21	12.23	70.06
	I-275	7.79	9.24	51.81
	I-696	9.24	11.67	48.81
	Lodge	13.02	20.00	39.63
	I-94	4.93	5.27	57.35
Total		49.19	58.41	50.53

4.2.3 Quantitative results

The data from the concurrent Protocol tests have been stored in computer files. These files have been searched for sections containing stopping and/or going (braking and/or accelerating) operations. There are now data files for numerous stops and start-ups on urban arterial streets. Figure 12 shows time histories for a typical stopping maneuver from long range on an arterial street.

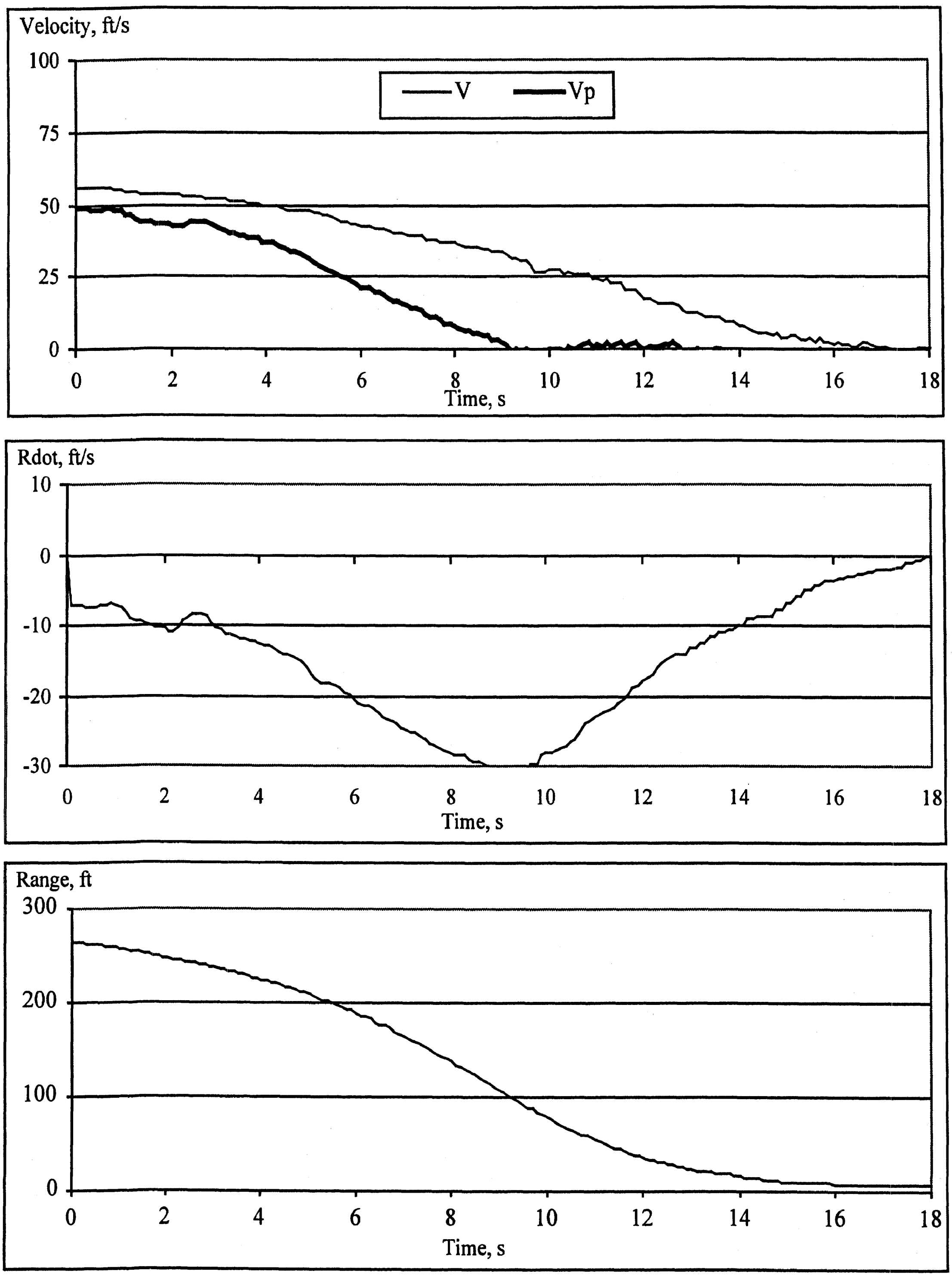

Figure 12. Stopping from long range on an arterial street

In addition, there are data sets pertaining to stop-and-go driving on an urban freeway. The example of stop-and-go freeway driving, as shown in Figure 13 indicates that there is a period of approximately 50 seconds between stops with the speed going from 0 to about

15 m/s (50 ft/s) and then back to 0 during the first 500 seconds (8 minutes) of congested freeway driving.

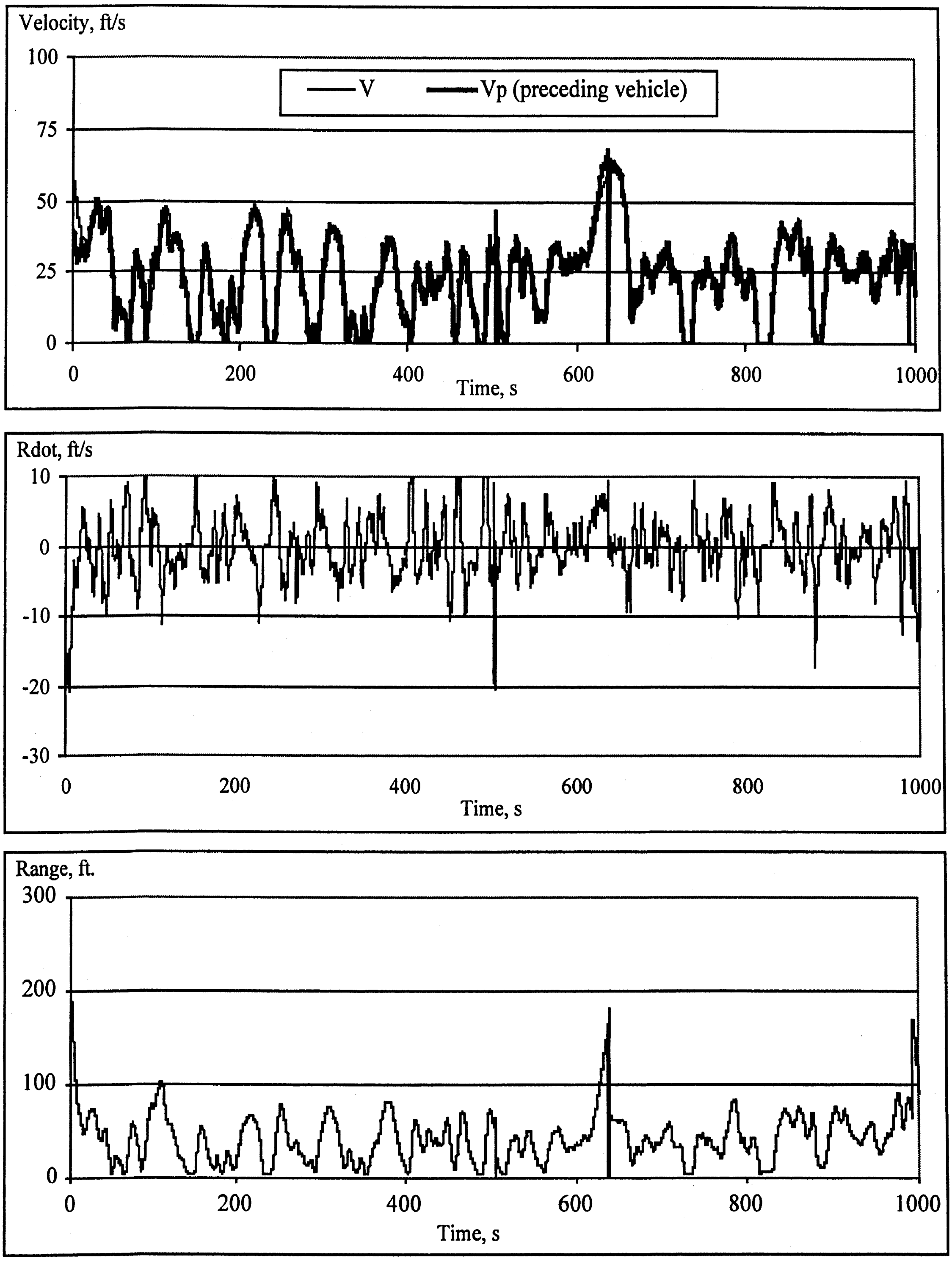

Figure 13. Stop-and-go driving on an urban freeway

Differences between freeway and surface-street, stop-and-go driving were expected, since the contexts under which the two types of driving occur are different. Surface-street stops predominantly occur in response to traffic signals. Such signals are usually clearly visible well in advance of stopping. They are located in predictable and expected places, although the *time* a light changes may occasionally be unexpected. Highway stop-and-go, in contrast, occurs in response to congestion—more cars are on the road. Here, stopping occurs in response to the braking behavior of the vehicle(s) immediately ahead. Driving is also more competitive—drivers might protect against cut-in by closing the forward gap. On the whole, stopping is less predictable in the freeway context than on surface streets. After all, the point of a limited access highway is to provide a rapid *(nonstop)* route from place to place.[1]

One way the differences in gap-maintenance strategy might be manifest in the drive data is to look at the distribution of time-headway data. We might expect to see that during low-speed (less than 35 mph or 56 km/h) segments of driving, the time-headway is, on average, smaller during freeway driving than during surface street driving, reflecting the tactic of guarding against cut-in by closing the headway.

To test for this pattern, three sections of the drive-route were analyzed for each subject, taking the average headway time for all speeds greater than 0 but below 35 mph (56 km/h). The speed criteria were applied to indirectly select for stop-and-go highway traffic and to eliminate higher-speed driving in which headway time declines. Of course, only data were used in which a preceding vehicle was detected.

Figure 14 shows that on the arterial street segment, headway times are longer for most subjects than on the freeway segments. An analysis of variance confirmed this result, $F(2,14) = 11.11, p < .01$. The mean values of time-headway for I-696 and the Lodge freeway were shorter (1.64, 1.84 sec) than for the M-12 surface arterial (3.46 sec). Thus, there is evidence that drivers tend to apply a different following strategy during low-speed highway driving, than they do on arterial surface streets. The result is consistent with the hypothesis that low-speed driving on highways is a consequence of higher traffic volume and that such a condition increases the probability that vehicles will cut into gaps between vehicles. To discourage cutting in, drivers close the headway gap reducing their headway times.

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1 To help mitigate some of the stop-uncertainty, drivers look at brake lights in adjacent lanes and on vehicles ahead of the immediately preceding vehicle for prior warning.

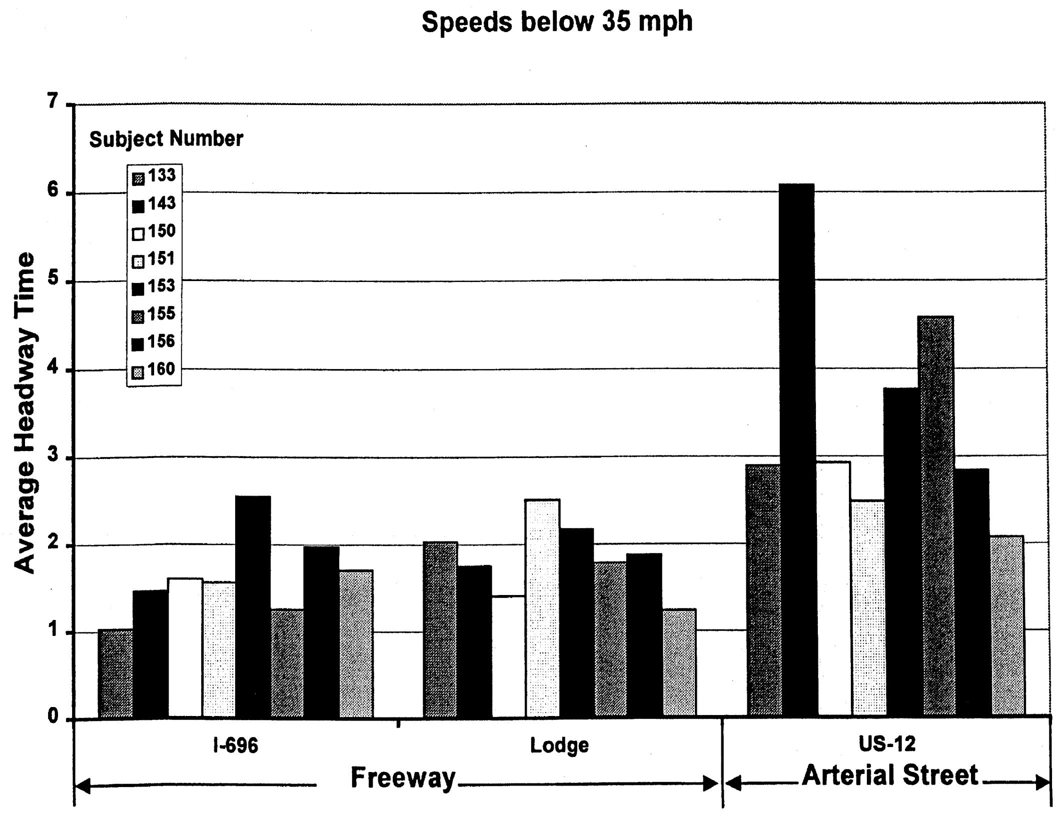


Figure 14. Average time headway for sections of roadway for each subject

Another possibility is that driver expectations of flow disturbance are partly responsible for differences in time headway. On highways, one expects traffic to flow continuously and at a relatively high speed. On arterial streets, one generally expects to be stopped periodically by traffic signals and by abrupt maneuvers conducted by other drivers, especially at intersections. Stop-and-go highway traffic is not normally anticipated. Drivers might close the headway gap in anticipation that traffic will return to posted speeds (up ahead) or simply out of frustration for having their route strategy thwarted.

Yet another possibility is that on surface streets, drivers approaching stop signs or stoplights no longer attempt to maintain the kind of time headway used in flowing traffic. Aware that they are required to stop, they perhaps see little advantage in maintaining small time headway. Instead, they try to decelerate gently and evenly, allowing large gaps and longer time headway to the preceding vehicle. Of course, a green or yellow traffic light might encourage the opposite behavior if the driver attempts to "get through" the light.

The summary data presented above cannot distinguish between these driver strategies, nor are the strategies mutually exclusive. A driver could reduce the time headway in stop-and-go highway traffic both out of frustration and as an attempt to prevent cut-ins.

4.3 Observations on Manual Stop-and-go Control from these Tests

Examination and iterative investigation of the quantitative results for stopping shows that there is a distinct qualitative difference between those stops initiated at long range and those initiated at relatively short range. This difference can be seen by comparing the data previously shown in Figure 12 with the data for stopping from a short range as shown in Figure 15. The qualitative differences between these situations have been interpreted as follows:

1) When the driver knows approximately the distance to the stopping point and is not particularly concerned with the range to the preceding vehicle (because the range is not small enough to pose a threat), the driver uses a control tactic based on the available stopping distance.
2) When the driver is concerned that the range to the preceding vehicle is smaller than desirable, the driver chooses to use a control tactic in which range is maintained at approximately its current value until the speed of the following vehicle is nearly equal to that of the preceding vehicle and until the range is acceptable for the speed for travel.

With regard to the development of driver models, these observations are used as clues, which serve as the basis for lines of thinking (called "leads"). These leads have been pursued in developing control tactics suitable for use in a model representing the behavior of drivers in stop and go situations. The structure of that model is explained in section 5.0. The results of the modeling activity are very encouraging. Comparisons between the model and operational data are also presented in section 5.0.

Further iterative investigation into data pertaining to periods of stop-and-go driving has led to the following observation:

When the following vehicle is at relatively short range and the preceding vehicle is accelerating or decelerating, the driver chooses a control tactic such that the velocity of the following vehicle matches the velocity of the leading vehicle with good fidelity except for a slight time lag. Clearly, this observation might have been anticipated because a following vehicle is more or less forced to mimic the operation of its preceding vehicle in stop-and-go driving. If the driver of a following vehicle does not promptly mimic the operation of the preceding vehicle, another driver in an adjacent lane is likely to cut into the resulting gap.

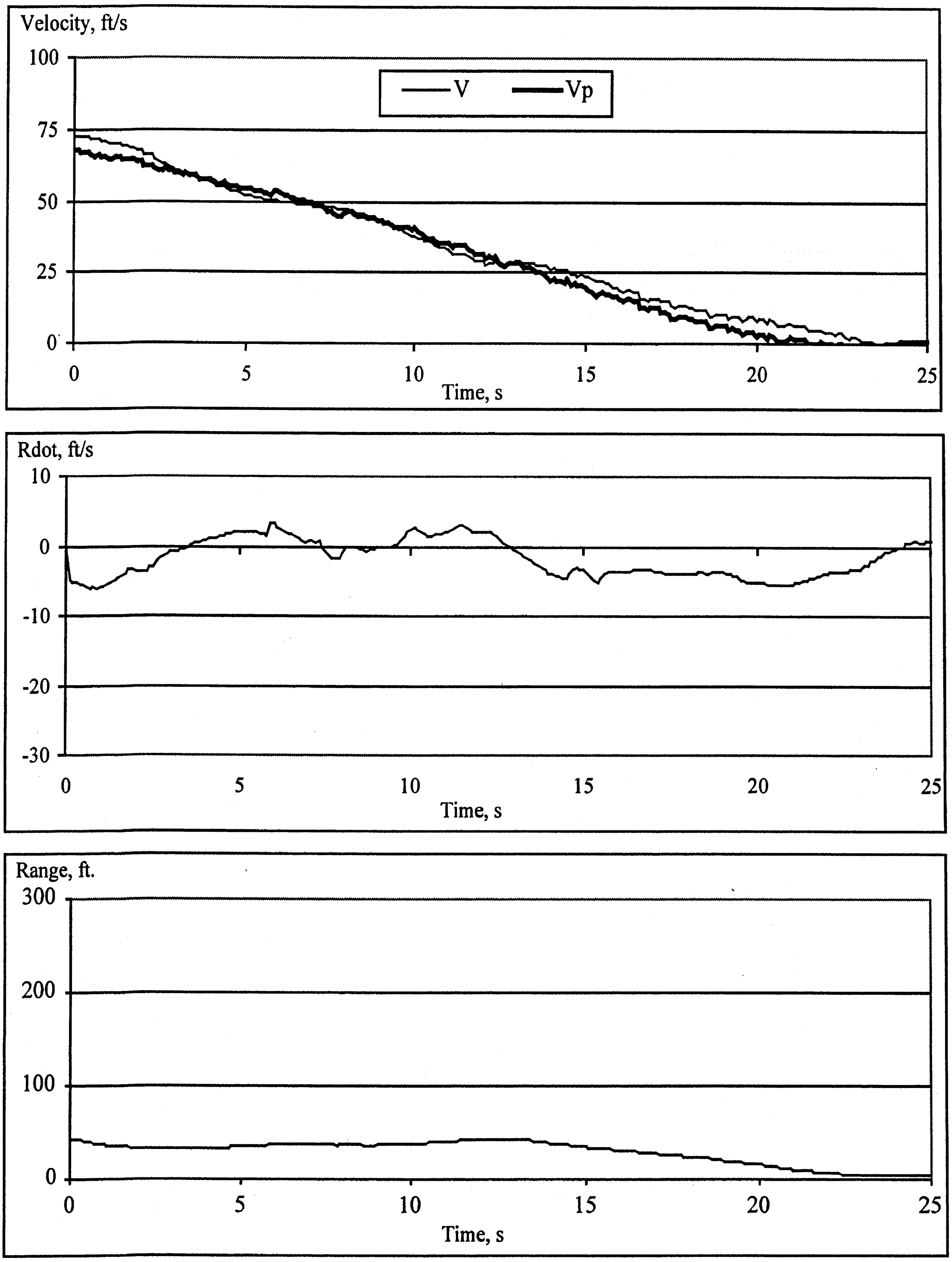


Figure 15. Stopping from short range on an arterial street

Again this control tactic has been incorporated into a model for emulating driving behavior in stop-and go driving. And again the modeling results are presented in Section 5.0.

Interestingly, this observation implies that drivers have some means for deducing the acceleration (increasing or decreasing speed) of a preceding vehicle. In the past, we have viewed the driver as being capable of sensing and perceiving only range, range rate, and velocity. Since we believe that the driver has no sensor for directly measuring the acceleration of a remote object, we find (assert) that the driver has a capability that is somewhat like differentiation for determining and estimating the acceleration of a remote vehicle.

5.0 Modeling Manual Control of Stop-and-Go Driving

UMTRI's model of the manual control of headway is based on ideas pertaining to vehicle dynamics, control systems, and human factors. Rasmussens's paper entitled *Skills, Rules, and Knowledge; Signals, Signs, and Symbols, and other Distinctions in Human Performance Models*, [16] has had a large influence on the form of our model and our approach to modeling driver behavior. Slotine and Li's book entitled *Applied Nonlinear Control* [15] has provided us with insights concerning techniques referred to as "feedback linearization" and "sliding surfaces." We have extended and adapted these nonlinear control concepts to aid in building driver models that incorporate skills, rules, and knowledge levels in representing the performance and behavior of skilled human operators.

In the context of this modeling effort, a skilled driver is a person who knows how to manipulate the brake and accelerator pedals to make the vehicle respond as desired. In this sense the skilled driver understands the vehicle's dynamic response to control inputs. This means that the driver essentially has the skill to convert a desire for a certain type of motion into control actions that will achieve that desired motion (at least to an acceptable, that is, satisficing level of performance in most situations). This understanding of the input-output characteristics of the vehicle is a learned capability, which becomes nearly automatic to the extent that the driver has great confidence in his or her ability to control vehicular motion even though the driver cannot explain in detail how such control is executed.

Various ideas concerning vehicle dynamics, control systems, and human factors are combined in this section to form a driver model. The result is a model that uses information concerning the current driving situation to determine how the driver manipulates the brake and throttle controls.

An essential aspect in making a realistic model is to infer from physical evidence what the driver is trying to do. Since we have no direct means of measuring what the driver is thinking, we need to examine the qualitative results and the quantitative data to see if we can ascertain the rules that the driver is using. In order to solve this puzzle concerning the driver's rules we have methodically followed leads like those described in section 4.3. We have iterated on interpretations of these leads until a relatively clear mental image of the driver's control rules has emerged.

Armed with this mental image, we have built a computerized model so that we can use it to test our theory of driving against the physical data recorded during real driving. Computer predictions have been compared to observed data from actual stop-and-go driving, leading to further refinements and improvements in our model. We now believe that the resulting computerized model is useful not only as a means for emulating driver performance but also as the basis for a prototype stop-and-go ACC system.

5.1 Model developed during this study

The model developed in this study is an extension and refinement of the driver modeling approach described in TRB paper *Evolving Model for Studying Driver Vehicle System Performance in Longitudinal Control of Headway* by Fancher and Bareket [14]. The driver characteristics identified in the FOT final report [3] have been considered during the development of the following model.

5.1.1 The Model Structure and Rationale

Figure 16 taken from the FOT report shows the skills, rules, and knowledge levels of driver behavior as they fit into a block diagram of the driving situation. At the skills level the driver does routine tasks associated with manipulating the brake and accelerator pedals. At the rules level, the driver is looking for signs indicating whether to change tactics in response to a changing situation. Essentially, there are different rules for different situations. At the rules level, the driver decides which set of rules to use. The knowledge level, operating at the highest level of cognition, is concerned with knowledge of the overall system. The inputs to the knowledge level are "symbols" denoting items concerning the status of the overall system. In the context of longitudinal control of headway, the knowledge level is where supervision takes place. It is where strategic plans are made based on goals and motivations and factual knowledge.

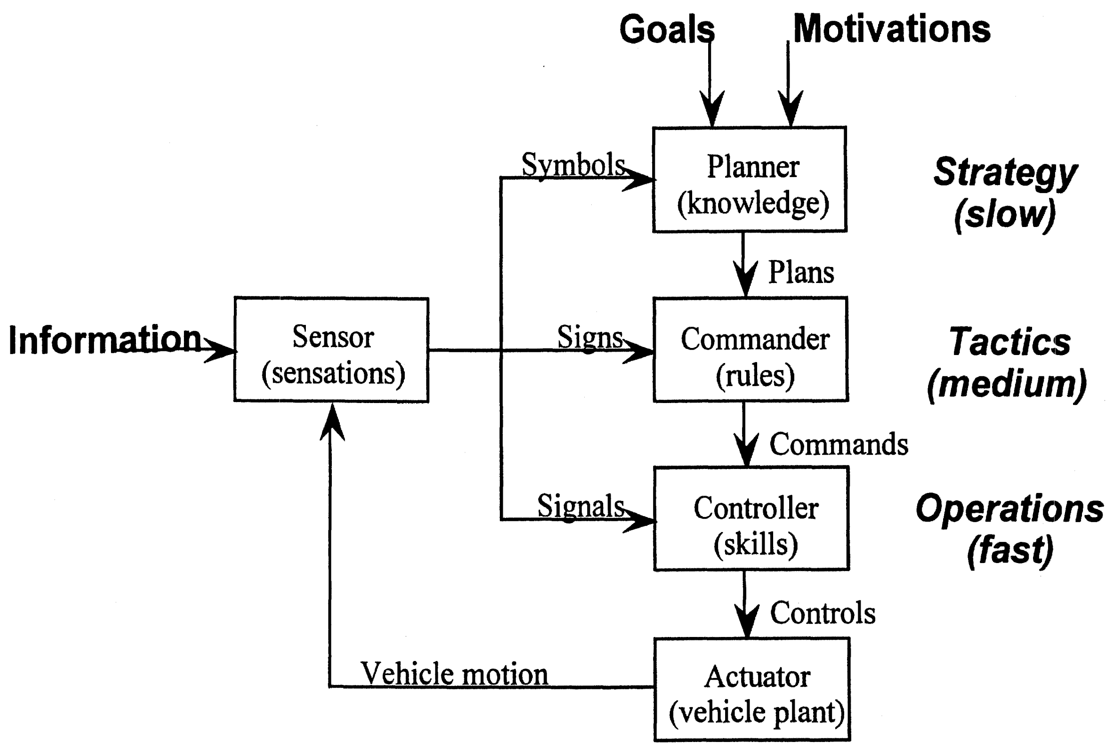


Figure 16. Skills, rules, and knowledge levels of driver control

In our mental images of the driver, the rules and skills levels of behavior can be represented fairly directly using concepts borrowed from nonlinear control theory. Figure 17 is a control system type of diagram indicating the flow of information between different elements of the system.

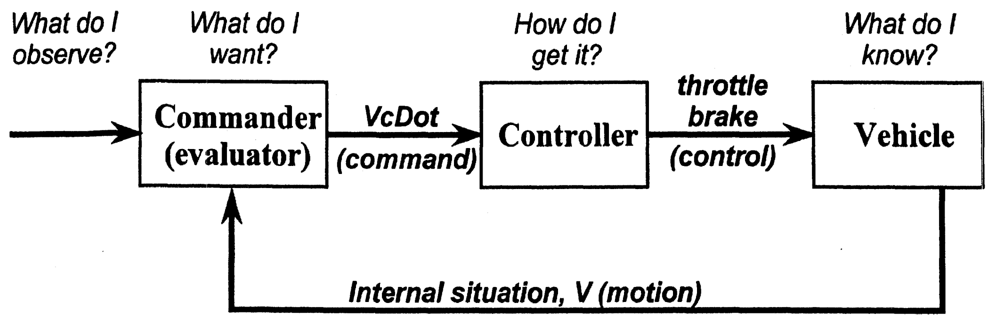


Figure 17. Flow of control information in the driver-vehicle system

The rules reside in the commander element. These rules utilize observations of range, range-rate, and velocity to determine the desired level of acceleration or deceleration for coping with the current driving situation. The commander also contains the relationships employed in deciding which rules to use in particular situations. In this context, psychological signs correspond to the results of examining pertinent inequalities, which identify different driving situations such as closing from long range, following at nearly constant speed, too close to the preceding vehicle, etc.

The commander sends an acceleration/deceleration command to the controller as shown in Figure 17. The controller accepts this command with little or no critical evaluation. Rather the controller's purpose is simply to manipulate the brake and accelerator pedals in a manner that will cause the vehicle to perform in accordance with the desired acceleration or deceleration command.

In achieving its purpose the controller performs an operation which is essentially the inverse of the operation described by the vehicle's equations of motion. The net effect of this arrangement is that the controller-vehicle combination becomes approximately an integrator. Hence, the desired acceleration command is integrated to obtain a velocity that approximates the desired velocity signal.

Note that this arrangement has very powerful practical implications with regard to deducing the control rules built into the commander. We can look at the headway situation and deduce acceleration/deceleration commands without having to concern ourselves with the vehicle's equations of motion. Although the vehicle's equations of motion determine the tracking rules built into the controller, they have little influence on the structure of the commander.

The point of this discussion is to establish a particular perspective on the development of driver assistance systems. The first half of this perspective applies to the controller. It may be summarized as follows:

Movements of the vehicle's controls (in this case brake and accelerator pedals) produce forces that determine the motion of the vehicle. These forces are equivalent to certain levels of acceleration per the equations of motion. By developing a controller, which converts acceleration commands to movements of the vehicle's controls, we can convert the controller-vehicle combination into a subsystem with a commanded acceleration as its input and a velocity that is the integral of the commanded acceleration as its output.

We will portray these features algebraically in the next section. The purpose here is to explain the concepts behind the structure of our model for representing longitudinal control of headway.

The other half of this perspective deals with the commander and the perceptual aspects of recognizing the driving situation. For addressing this portion of the control synthesis, we have found a range versus range-rate phase space to be a useful construct. For example, we believe that the driver is concerned with the range being too small as well as with rapid closure as indicated by a negative range-rate. Suppose there are perceptual boundaries approximately as indicated in the following range versus range-rate diagram, Figure 18. These boundary lines define six zones as depicted in Figure 19, with the horizontal line near the center of the diagram representing the desired comfortable range for the present speed condition.

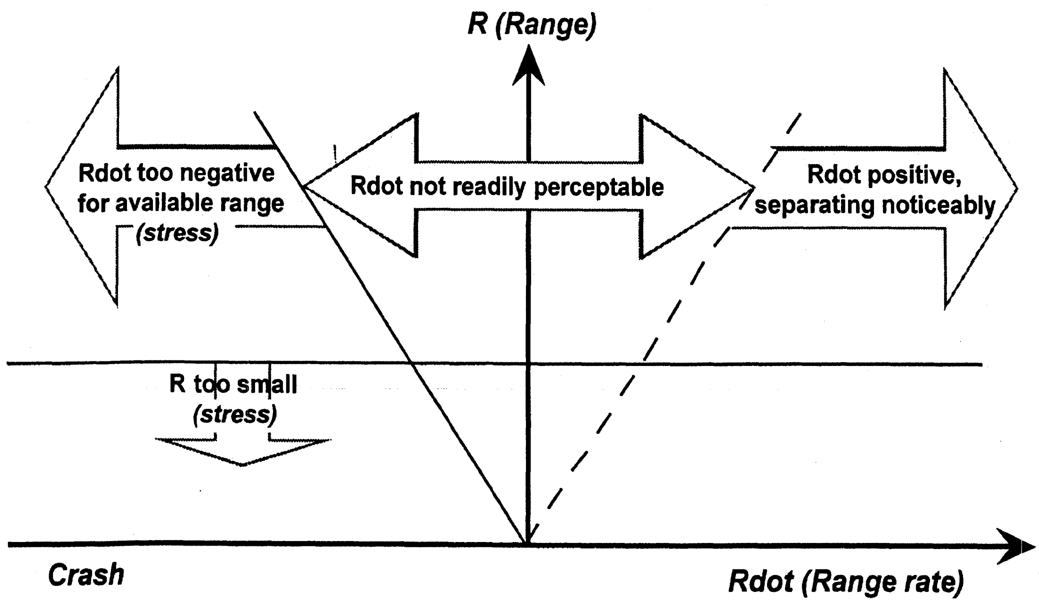


Figure 18. Perceptual boundaries in range-versus-range-rate space

It appears reasonable to postulate that zone 1 is the most stressful zone such that the driver may be willing to brake hard if the situation is characterized by an range, and range-rate, coordinate in this zone.

In zone 6 the driver is not too close but the range-rate is of concern. The driver is expected to commence slowing in this zone. See appendix D and references [3] and [14].

Zone 2 is a transition region between Rdot < 0 (closing) and Rdot > 0 (separating). In this zone the driver has difficulty perceiving range rate but knows that the range is too short. Examination of test data indicates that drivers tend to brake in this region but they usually get off the brake as soon as they detect that Rdot > 0. There is a tendency to sustain any control action that had begun in zone 1, if zone 2 is entered from zone 1.

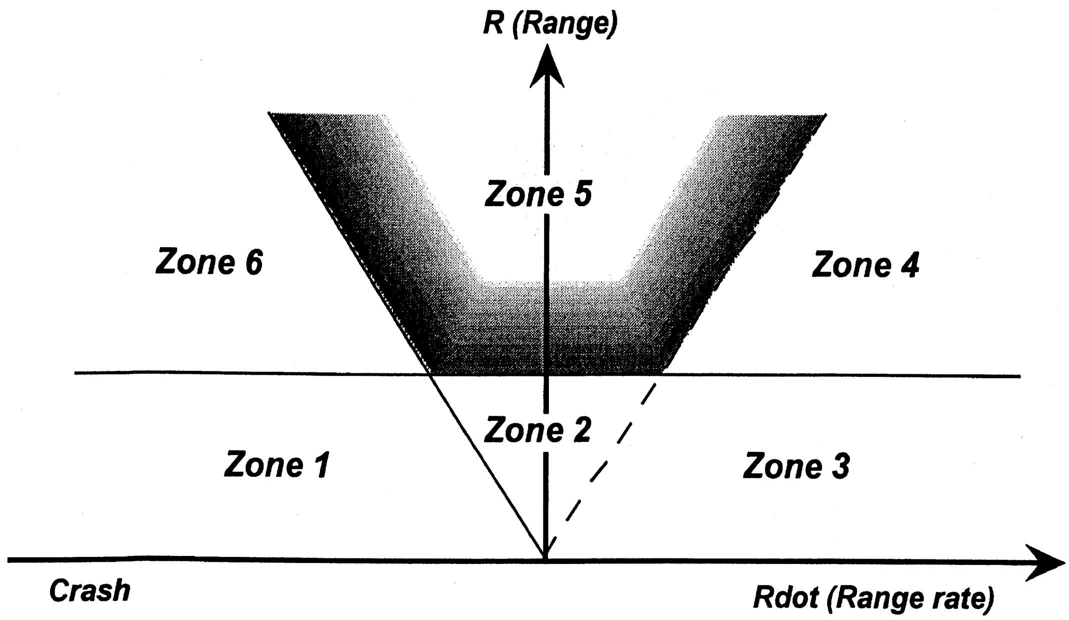


Figure 19. Controller zones in range-versus-range-rate space

With regard to situation trajectories, which are time indexed (time ordered) sets of (Rdot, R) points in the phase plane, trajectories on the left side (Rdot < 0) must go down and trajectories on the right side (Rdot > 0) must go up, because of the obvious influence of Rdot on the trend in R. Horizontal tangents to the trajectories are only physically possible for Rdot = 0, otherwise, a horizontal tangent represents infinite acceleration. (Of course, due to measurement inaccuracies, measured trajectories may cross the Rdot = 0 axis with non-zero slopes.) The point here is illustrated by the observation that zone 2 cannot be reached from zone 4, for example. Further reasoning of this type indicates that zone 2 is usually entered from zone 1.

Proceeding counter-clockwise, we need to postulate how the driver chooses to change speed in zone 3. The driver is too close in zone 3 but the vehicles are separating. The driver knows that the range will increase if speed is simply maintained or reduced slightly. If the lead vehicle accelerates rapidly, the driver may even consider speeding up to close the otherwise expanding gap before another driver attempts to take it.

In zone 4 the driver is not too close and is able to perceive the rate of separation of the lead vehicle. In this zone it is reasonable for the driver to speed up and try to catch the lead vehicle if it is not going too fast.

It appears to be problematical to develop a simple qualitative rationale for describing driver behavior in zone 5. The driver is not threatened by short range or by closing too fast. In this zone other factors may be more important to the driver than closeness or closing threats. For example, the reason for keeping range small might be to keep another vehicle from cutting-in. Other considerations could include the intent to exit (turn off) soon or anticipation of a traffic light ahead, thereby allowing plenty of distance for stopping.

Finally there is need for a seventh zone in which R is so large that the driver is simply unconcerned with the range to the preceding vehicle. In this zone the driver modulates the throttle to get the desired speed of travel (corresponding more or less, to the set-speed value when in ACC operation).

However, the above considerations do not exhaust the need to distinguish zones of behavior because there are limits on the accuracy with which drivers can perceive range. These limits are believed to be approximately ± 10 percent. For example, in perceiving a range value of 30 m (100 ft), variations between 27m (90 ft) and 33 m (110 ft) would look almost the same to the driver as the 30 m (100 ft) value. The addition of these perceptual boundaries yields the R-versus-Rdot diagram shown in Figure 20, where Rh is the desired range value for the operating conditions.

The shaded control region (the trapezoidal "box") corresponds to a driver dead zone in which the driver cannot readily determine accurate values for range or range rate. In a sense, the principal goal of the headway-control system is to get into the box.

A diagonal line through the corners of the box has been constructed in Figure 21 to create a vector field that will cause trajectories in the phase plane to converge toward the box. Clearly this is a creative step in the sense that it will allow us to make a computerized system that behaves like a driver in certain situations.

The diagonal line constitutes a sliding surface. It serves as a simplifying abstraction of reality in that trajectories in zone 3 are based on trying to get to the line (within the limits of the maximum allowable acceleration or deceleration. Through this process we have created a vector field, which has the property that trajectories in the phase space will lead to the box in zone 2. Clearly one could create other vector fields that would do practically the same thing.

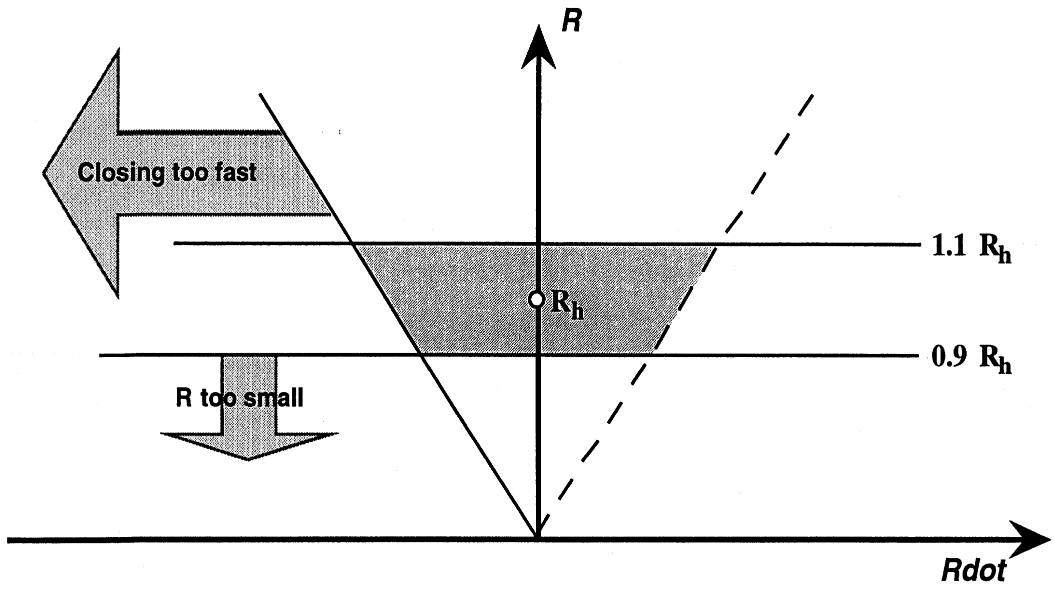


Figure 20. Perceptual limits

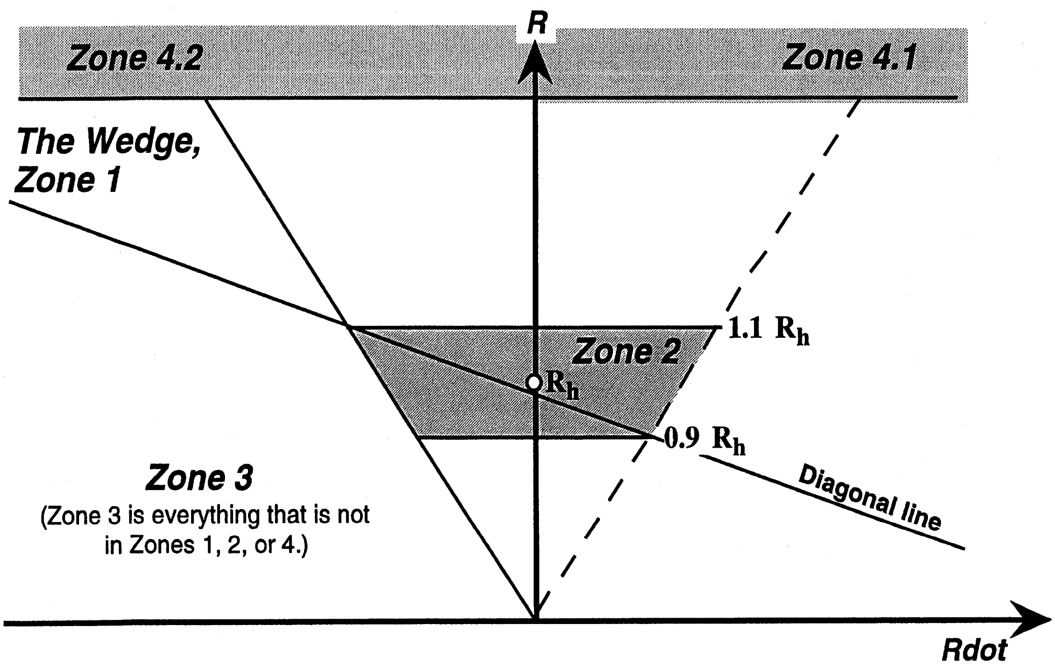


Figure 21. Sliding surface and control zones

The wedge, the name given for zone 1 in this figure, is an operating sector in which stopping distance rules are used to determine the commanded deceleration.

Zone 4 has two parts: 4.1 and 4.2. In zone 4.2, the driver is assumed to hold velocity constant. In zone 4.1 the driver gradually increases speed toward that of the preceding vehicle. Zone 4, altogether, is the sector in which the driver's choice of control actions does not depend conceptually upon the preceding vehicle. However, in zone 4.1 we use the speed of the preceding vehicle as if it were a reasonable estimate of the set speed value. (This works out well for most situations in which the leading vehicle tends to travel at a reasonable "free" speed when the opportunity presents itself.)

There is one matter left with regard to explaining the structure of the model. That is, we need an explicit means for determining the desired range value Rh. During the development of ACC systems, there has been considerable discussion of this matter. We have sometimes used Rh as a function of the velocity V of the ACC vehicle and at other times we have used Rh as a function of the velocity of the preceding vehicle, Vp. For stopping situations we have found that either way works. However, for starting from a stop, we observe that Rh needs to be a function of Vp if the following vehicle is going to "go" at all. Furthermore in the context of stop-and-go driving, we have found that Rh must "bottom out" at some minimum range value and must also be adjusted according to the acceleration of the lead vehicle Vpdot. Although work continues to determine an appropriate expression for Rh. It has been described by an equation of the form:

$$R_h = R_f + T_h Vp \tag{1}$$

and

$R_h dot = T_h V_p dot$, which is approximated using (2)

$$V_p dot \approx \tilde{V}_p\, dot \tag{3}$$

where: R_f is the minimum range,

T_h is the headway time for Vp = a constant, and

$\tilde{V}_p\, dot$ is the estimated acceleration (deceleration) of the preceding vehicle.

There is a subtle point here. If, according to the model, the driver of the following vehicle tries to accelerate faster than the preceding vehicle, the preceding vehicle will be an impediment such that the range will stay relatively short. However, if the preceding vehicle chooses to accelerate more rapidly than the driver of the following vehicle expects, a relatively large range gap may develop. Sometimes the expectation built into the model may be different from a particular driver's expectations in a specific situation at a certain time and place. This factor will sometimes cause range discrepancies in comparisons between model predictions and measured behavior during the positive-acceleration phases of stop-and-go operation.

5.1.2 Implementation of Relationships Describing the Model

The model of manual control of headway is implemented in SIMULINK®, which is a commercial simulation package that is part of MATLAB®. In order to develop a computerized model of this type, one formulates differential and algebraic equations, inequalities, and logical expressions describing the system to be represented by the computerized model. The process of implementing the relationships describing the system is graphical in that a special type of information flow diagram is constructed by interconnecting sets of elements representing standard mathematical and logical operators. Using the graphical approach in SIMULINK®, we have constructed a computerized representation of the system to be studied. This representation is a type of analogy. It allows us to experiment with models; both in the sense of (1) trying different features in the model and (2) predicting what the driver-vehicle system will do in new or different driving situations.

A recent set of information flow diagrams for this model is included in appendix B to this report. The mathematical and logical expressions used in the model are presented and discussed here for various sections and subsections of the model.

Driver's (ACC) World

First consider a section of the model called the driver's (or ACC's) world. In this section, the situation outside of the driver's vehicle is included in the model. The principal independent variable in this part of the representation is the velocity of the preceding vehicle Vp. We either use measured time histories of Vp as the input to the simulation or we artificially generate Vp time histories that are representative of interesting events such as impeding (lead) vehicle braking.

Since the driver may suddenly become aware of a particular preceding vehicle, the initial conditions of range and velocity may be important inputs to certain computer runs simulating these types of driver-related events.

The basic equations representing the outside world are:

$$\text{Rdot} = \text{Vp} - \text{V} \tag{4}$$

$$R = \int Rdot\ dt \tag{5}$$

Where V is the velocity computed in the vehicle section of the model. Expressions (4) and (5) are very simple since the model only considers the driving characteristics of the single preceding vehicle—hence, the name "ACC world." Traffic signals, other vehicles, entrance ramps, poor visibility, slippery roads, etc. are not included in the simplified model.

Commander

The commander section employs expressions pertaining to (1) perception and recognition, (2) decision/selection processes, and (3) rules for generating acceleration commands.

The primary inputs to the commander section are range, range rate, and velocity. There are a number of parameters used in this section, and their values determine the type of behavior represented by the model.

The sensors for gathering range, range-rate, and velocity information are not represented explicitly, but perceptual capabilities are included in the expressions representing the commander. Accordingly, the expressions do not distinguish between actual range and sensed range. This pragmatic abstraction of reality considerably simplifies the expressions used in the commander.

Certain expressions used in the commander employ an estimate of the acceleration of the preceding vehicle. This estimation process is described by the following equation

$$\text{Tc} \cdot \tilde{\text{V}}\text{pdot} + \tilde{\text{V}}\text{p} = \text{Vp} \tag{6}$$

This is a first-order system with a time constant, Tc. Experimenting with the model has shown that the model functions satisfactorily for $1\,\text{s} < \text{Tc} < 2.8$ s. (A wider range for Tc might be acceptable. However, we haven't tried a wider range.)

To solve equation (6) in the computer we need to include an integrator, in this sense equation (6) becomes:

$$\tilde{\text{V}}\text{pdot} = \frac{\text{Vp} - \tilde{\text{V}}\text{p}}{\text{Tc}} \tag{7}$$

and

$$\tilde{\mathrm{V}}\mathrm{p} = \int \tilde{\mathrm{V}}\mathrm{pdot}\ \ dt \tag{8}$$

We see the need for further investigation as to the computation of the desired range, Rh. In most of the results presented here, the desired range is determined as follows:

$$Rhdot - Th \cdot Vpdot = \frac{-(Rh - Rf - Th \cdot Vp)}{Teh} = -\frac{e_h}{Teh} = e_h dot \tag{9}$$

and

$$\mathrm{Rh} - \mathrm{Th} \cdot \mathrm{Vp} = \int (\mathrm{Rhdot} - \mathrm{Th} \cdot \mathrm{Vpdot})\mathrm{dt} \tag{10}$$

where Rf is the desired range at a stop when Vp = V = 0, Th is the desired headway time, and Teh is a factor that determines the importance of the term containing Vpdot.

A typical average value for Rf is 3m (10 ft). Th has been found to be dependent on driver characteristics with a representative value around 1.4 s in these driving exercises. We have used Teh = 0.5 sec with reasonable success in matching simulation results to actual driving behavior, but the exact value does not appear to be critical. In addition, it is not clear how best to estimate the value of Teh. Nevertheless, we currently think that an effect like that represented by equation (9) needs to be included in the model.

The desired range, Rh, forms the basis for sets of inequalities defining zones of different types of behavior within each of which specific rules are employed for determining the commanded acceleration. The psychological signs by which a driver selects different sets of rules correspond to whether the following inequalities are true or false.

An Rdot, R point that satisfies all of the following inequalities is in zone 2 (i.e., the central box):

$$\left.\begin{array}{l} \mathrm{R} < (1 + \mathrm{A}) \cdot \mathrm{Rh} \\ \mathrm{R} > (1 - \mathrm{A}) \cdot \mathrm{Rh} \\ \mathrm{R} > -\mathrm{B} \cdot \mathrm{Rdot} \\ \mathrm{R} > \mathrm{B} \cdot \mathrm{Rdot} \end{array}\right\} \tag{11}$$

If all the inequalities (11) are satisfied, the logical variable COM2 is made equal to 1, and the command variable Vcdot2 is selected as the command to the controller. (The expression for Vcdot2 will be presented later on in this section.) Experience gained by experimenting with the model has led us to select parametric values such that A=0.13 and B=8 sec.

An Rdot, R point that satisfies the following expression is in the wedge (Zone 1):

$$\left.\begin{aligned} &R < -B \cdot Rdot \\ &R > (1-A^2) \cdot Rh - A \cdot B \cdot Rdot \end{aligned}\right\} \tag{12}$$

If (12) is satisfied, COM1 is made equal to 1 and Vcdot1 is selected as the command to the controller.

Zone 4 (for both 4.1 and 4.2) is defined by the following inequality (with R expressed in meters):

$$R > Rh + 24 \tag{13}$$

If (13) is satisfied, COM4 is equal to 1 and the rules for Zone 4 are used.

The logical expression for selecting the rules for zone 3 is:

$$COM3 = \langle \text{not } COM1 \rangle \text{ and } \langle \text{not } COM2 \rangle \text{ and } \langle \text{not } COM4 \rangle \tag{14}$$

When COM3 is equal 1, Vcdot3 is sent to the controller.

The rules for the acceleration commands for the various zones are as follows:

$$\text{Zone } 2: \ Vcdot2 = \tilde{V}pdot + Rdot / T2 \tag{15}$$

(Note that this rule is based on the need to satisfy the relationship T2 Rdotdot + Rdot = 0 where Rdotdot = Vpdot – Vdot)

$$Zone\ 1: \ Vcdot1 = \frac{V^2}{-2Ds} \tag{16}$$

where:

$$Ds = R - Rf + \frac{\tilde{V}p^2}{-2\tilde{V}pdot} \tag{17}$$

(Note that Ds is an estimate of the stopping distance available to the driver.)

$$Zone\ 3: \ Vcdot3 = \tilde{V}pdot\left(1 - \frac{(1-A^2)}{A \cdot B} Th\right) + \frac{Rdot}{A \cdot B} + \frac{e}{A \cdot B \cdot T3} \tag{18}$$

where

$$e = A \cdot B \cdot Rdot + R - (1 - A^2) \cdot R_h \tag{19}$$

and it is assumed that $Rhdot \approx Th \cdot \tilde{V}pdot$ (i.e., $e_h dot = 0$)

(Note that e is a measure of the distance from the diagonal line that serves as the sliding surface, defined by $A \cdot B \cdot Rdot + R - (1 - A^2) \cdot R_h = 0$)

$$Zone\ 4: \ For\ \ Rdot < 0\ , \ Vcdot4 = 0 \tag{20}$$

(This rule means do not change speed.)

$$For\ \ Rdot\ \ \geq\ 0,\ \ Vcdot4 = \frac{(Vp - V)}{10} \tag{21}$$

(This rule means that speed will be changed until V = Vp, or until Rdot becomes negative, or until the trajectory leaves zone 4.)

These rules (as described by expressions (4) through (21)) may seem to be complicated. They contain linear and nonlinear equations and there is logic and switching involved. However, these provisions afford flexibility to the method employed. We have taken the open-loop equations for the vehicle's response and systematically converted that open-loop system into a closed-loop system that satisfies our goals and objectives as indicated by expressions (4) through (21). We have converted the original vehicle system into a system that performs what we need for representing driver control.

This process is like that of feedback linearization used in nonlinear control theory, except that feedback linearization is usually used to convert a nonlinear system (the plant) into a chosen form of linear system. However, there is no reason why the same technique cannot be used to convert an original system into a nonlinear system of our choosing or preference. This allows us to include nonlinear relationships such as those associated with the stopping distance calculations. It allows us to use algebra to synthesize the system, given sensors for measurement of the quantities needed for our equations. We simply use the sensed quantities to solve for the acceleration commands. In this case, since there was no sensor for Vpdot, we used an approximate differentiator. Otherwise, even though it may appear that there are many differential equations involved, we are only solving algebraic equations in the process of converting the system into one that satisfies our objectives.

5.1.3 Comparison of Model Predictions with Measured Results

The model of driver behavior has been exercised extensively. We have comprehensively compared simulated results versus measured results for 61 stop-and-go driving events. These events involved five different drivers, driving on different days, but on the same route. For each driver, the longest stop-and-go driving episode, covering a number of successive stops, occurred on the same section of freeway regardless of the day or the driver.

Sixty-one sets of graphs have been prepared for comparing simulated with measured results. A complete compendium of these graphs is included in appendix C. Figure 22 (a and b) (run 133.103) is an example that shows reasonably good agreement between model predictions and measured results. The input to the simulation is the measured time history of Vp as shown in the graph presented in the left column next to the top of the figure.

The top left plot of figure 22a shows good agreement between Vdata and Vsim for the same motion of the preceding vehicle. This qualitatively good fit between measurement and simulation of the velocity of the driver's vehicle is typical of almost all of the cases studied. If V data and Vsim are not very much alike, range data (Rdata) and range simulated (Rsim) will be greatly different.

In this case with Vsim ≈ Vdata, inspection of the time histories for range data and range sim shows that they are reasonably similar. We have chosen to use the root-mean-square value (RMS) of the difference between Rsim and Rdata to quantify the goodness of fit for this run. The value is 1.5 m (5 ft.) for this case. Experience gained by trying many driving situations and model features indicates that this RMS value represents a good fit for this model.

(Since the events (situations) simulated are not for equal periods of time, care needs to be exercised in comparing the results of different simulation runs. Nevertheless, RMS values less than 3m (10 ft) appear to represent a good fit. Between 3m (10 ft) and 6m (20 ft) is considered a fair fit. Poor is between 6 m (20 ft) and 12 m (40 ft) on this scale, and RMS values exceeding 12m (40 ft) are judged to be bad.)

Figure 22a also includes time histories for Rdot, Vdot, throttle angle, and brake pressure as well as a range-versus-range-rate diagram. The details of these graphs have been used in trying to improve the model conceptually and also to improve the fit to measured data. Up until now, we have focused mainly on the velocity and range variables. However, we have observed that an apparently good fit in the range-versus-range-rate diagram means an excellent fit overall. After all, range and range-rate need to show good agreement in their individual plots for the (range-rate, range) trajectories to match well in the phase plane.

Figure 22b (133.103B) shows an expanded presentation of the velocity, range, and range-rate data for this example of a single stop-and-go event. In this run, the parameter, Th, is based upon that part of the situation in which the driver is decelerating above 0.08 g. It is postulated that during the braking part of the stop-and-go maneuver the driver's choices are largely constrained by the behavior of the impeding vehicle. In the accelerating part, the driver may or may not be constrained by the motion of the preceding vehicle. If the driver wants to accelerate faster than the preceding vehicle, the preceding vehicle presents an impediment (an impeding vehicle). On the other hand, if the preceding vehicle accelerates faster than a following driver wants to accelerate, the follower is not constrained much by the preceding vehicle and may use other factors in deciding on an acceleration level. In the case when the driver's desired acceleration is actually constrained by the acceleration of the preceding vehicle, the preceding vehicle serves literally as a leading vehicle (i.e., determining the pace of progression). In any event, since Th is based on the deceleration phase of the situation, one might in general expect a better fit to the deceleration part than to the positive acceleration part of the range time history.

Figure 23a (run 133.40) shows results for an example of stop-and-go driving. There are stops occurring at roughly every 50 seconds in this case. The maximum speed reaches nearly 15 m/s (50 ft/s) between stops. As with single stop-and-go events, the match between Vdata and Vsim appears to be very good. Upon completion of the initial transient into stop-and-go motion, range data and range sim are nearly alike, with the forced oscillations going between a maximum of approximately 21 to 24 m (70 to 80 ft) and a minimum of 3 m (10 ft).

Figure 23b (run 113.40) provides a close look at the very good fit between simulated and measured values of velocity, range-rate, and range for this example. Even though the event goes on for 500 s (until it is interrupted by a sudden change in the Rdot signal), the RMS value of the difference in range is only 4.5 m (15 ft).

Model 153, Th = 2.2, Tc = 1.4, T2 = 1.4, T3 = 2.2, Driver: z133.103

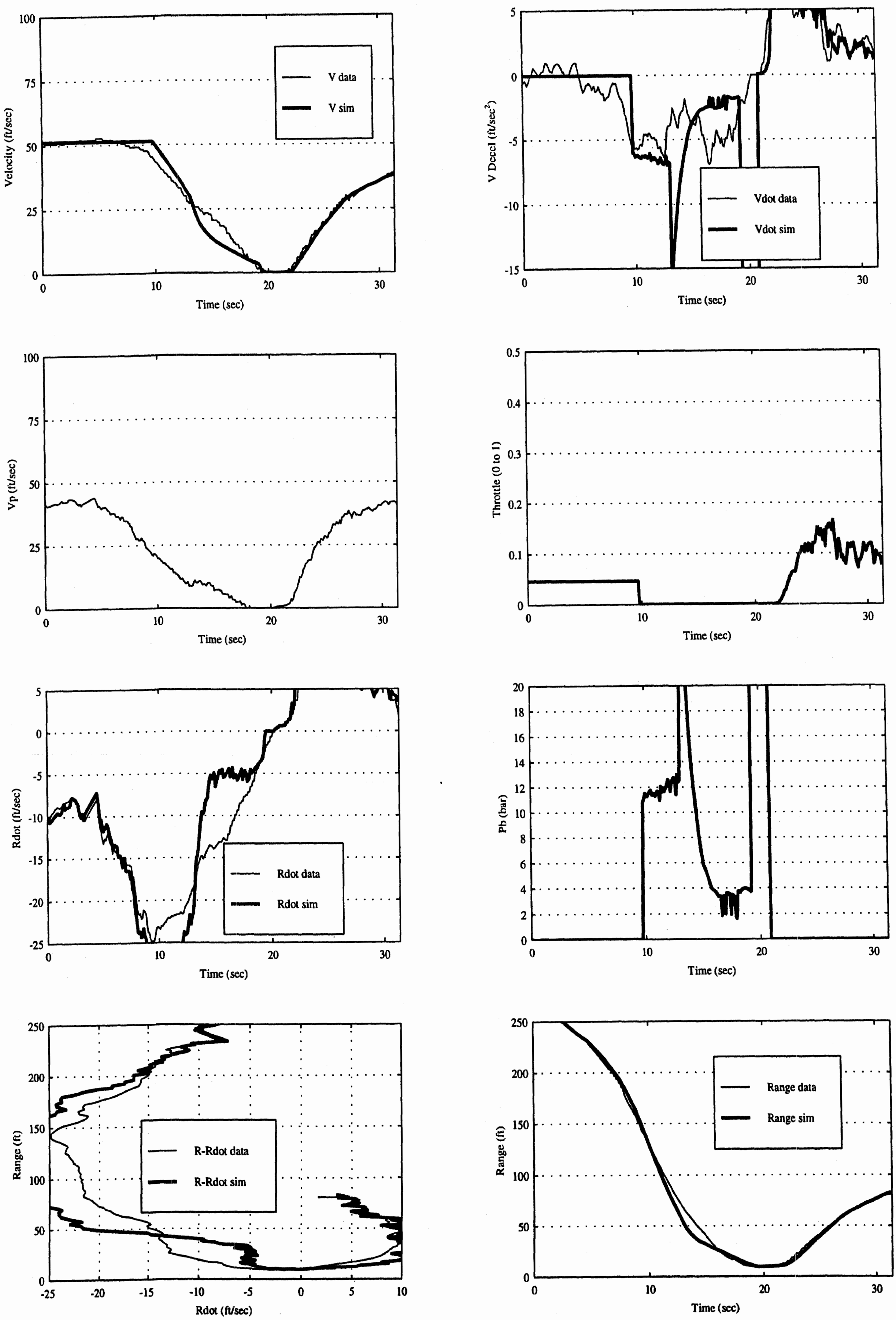


Figure 22a. Single stop and acceleration, comparing model and measured results

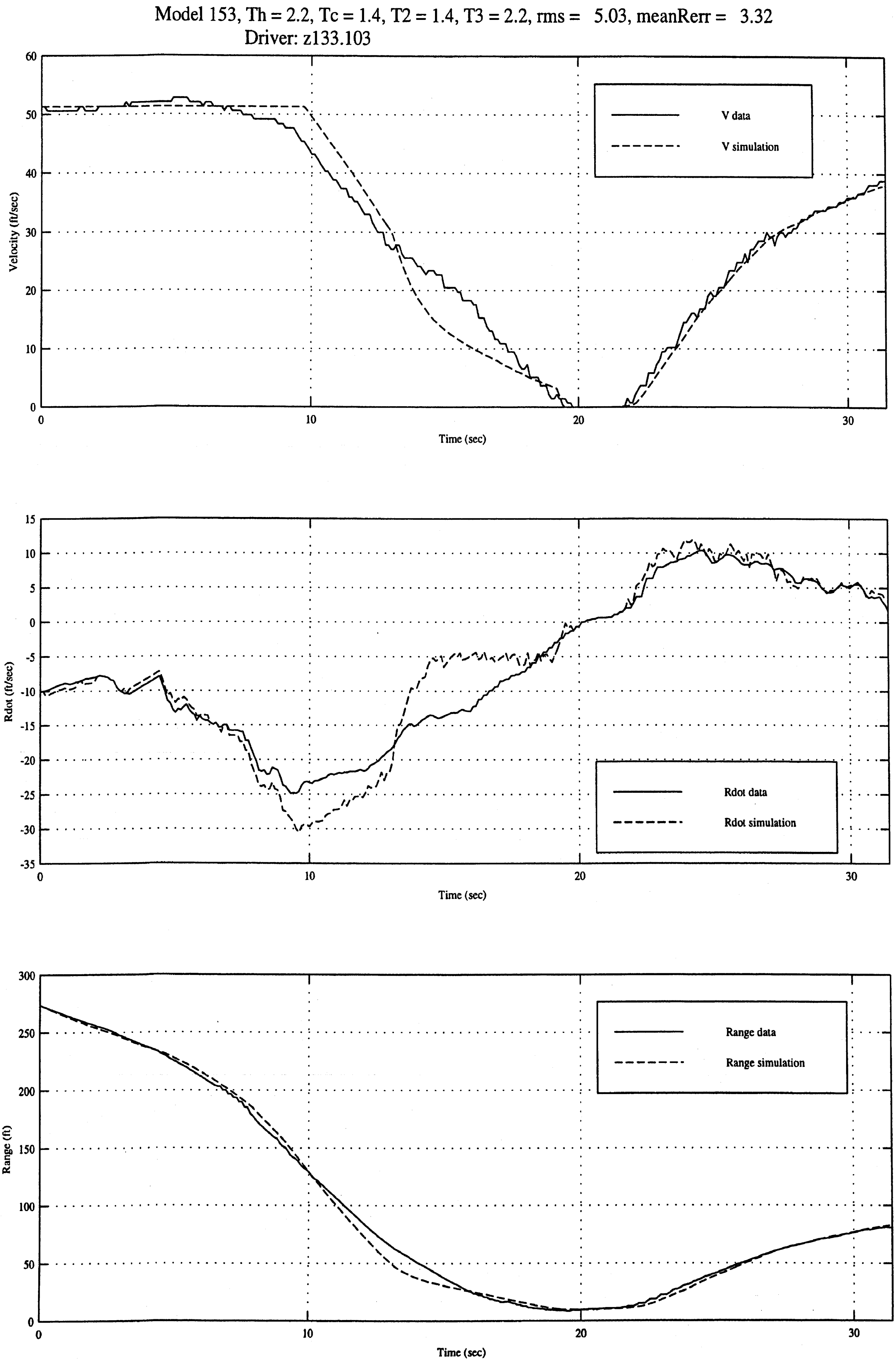


Figure 22b. (continued). Expanded V, Rdot, Range comparisons

Model 153, Th = 1.6, Tc = 1.4, T2 = 1.4, T3 = 1.6, Driver: z133.40

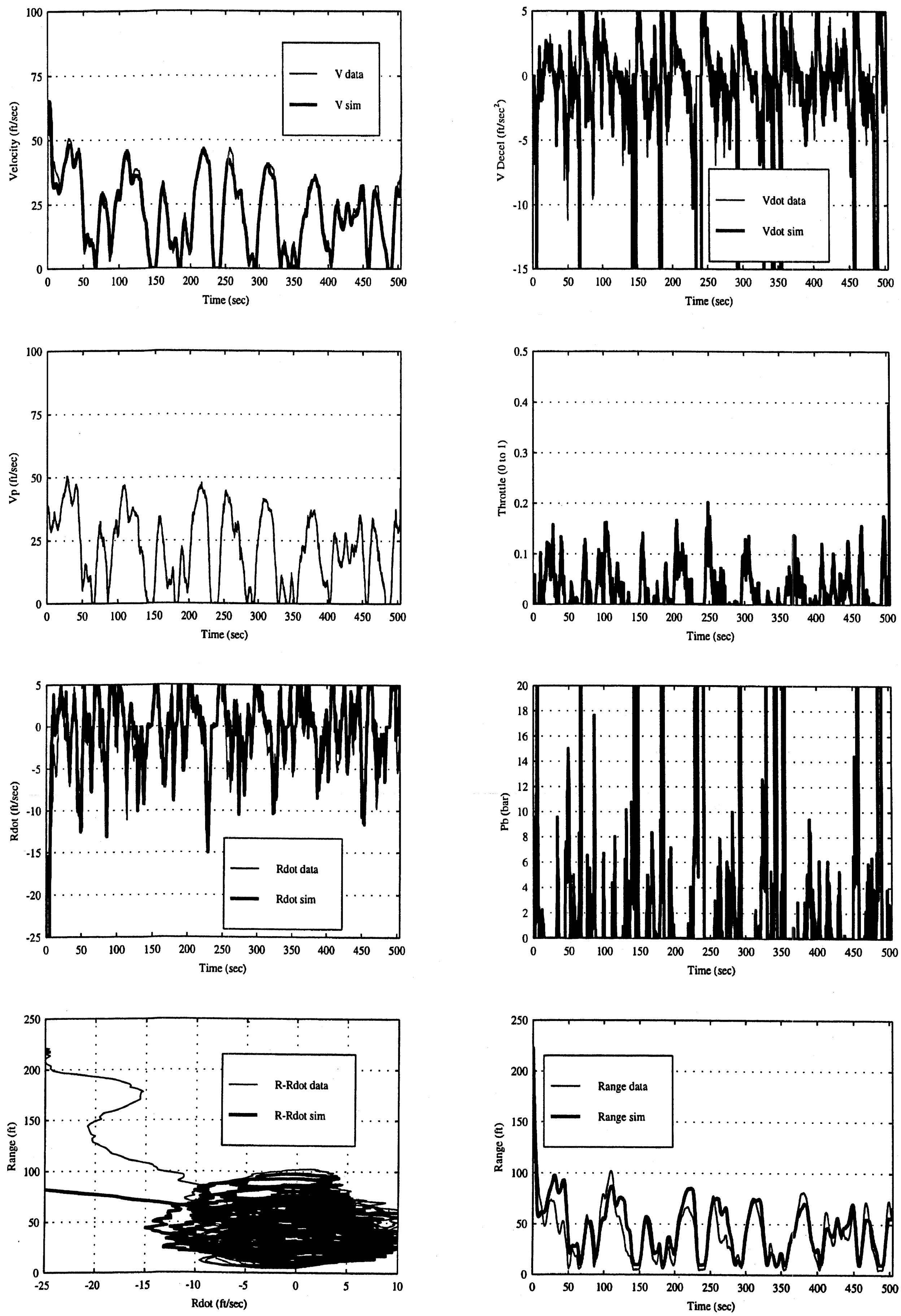


Figure 23a. Stop-and-go driving, comparison of model and measured results

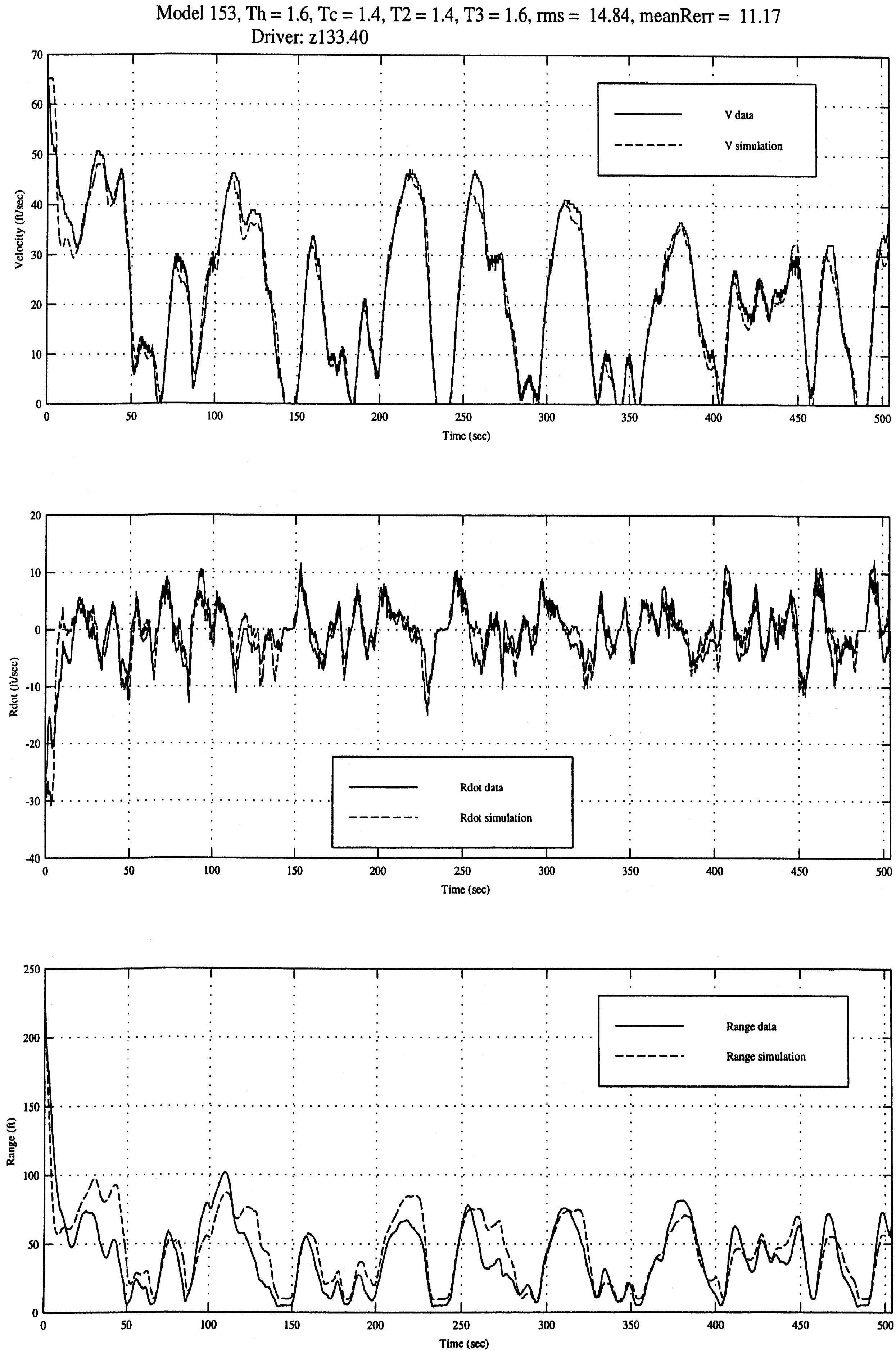


Figure 23b (continued). Expanded V, Rdot, and Range comparisons

Frankly, this is a better fit then we had any reason to expect based upon our original knowledge and understanding of stop-and-go driving. However, the process of methodically following "leads" into the observed phenomena appears to be useful as long as we focus on trying to understand what the data (physical evidence) tells us about the possible control mechanisms that underly these phenomena.

Clearly figures 22 and 23 pertain to examples for which the model works well. Figure 24 presents a case for which the model does not work well. The preceding vehicle suddenly reduced speed by 40 percent and then promptly resumed speed. After that, the preceding vehicle executed a stop-and-go cycle. On the one hand, the model showed roughly the same velocity excursions as did our subject driver. (Compare the Vdata with Vsim traces at the upper left of figure 24a and at the top of figure 24b.) However, the differences between Rdot data and Rdot sim are substantial, with Rdot sim not over shooting as much as Rdot data. This results in a rather large difference in the range-time histories, shown at the lower right of figure 24a. Given that there are cases with large RMS differences in range, there is reason to pursue clues that might lead to a better understanding of the phenomena involved. Nevertheless, from the perspective of using this model in an ACC-system control algorithm, one could argue that the model's smoothness attribute makes it in some ways better than the driver's behavior.

Model 153, Th = 1.2, Tc = 1.4, T2 = 1.4, T3 = 1.2, Driver: z133.126

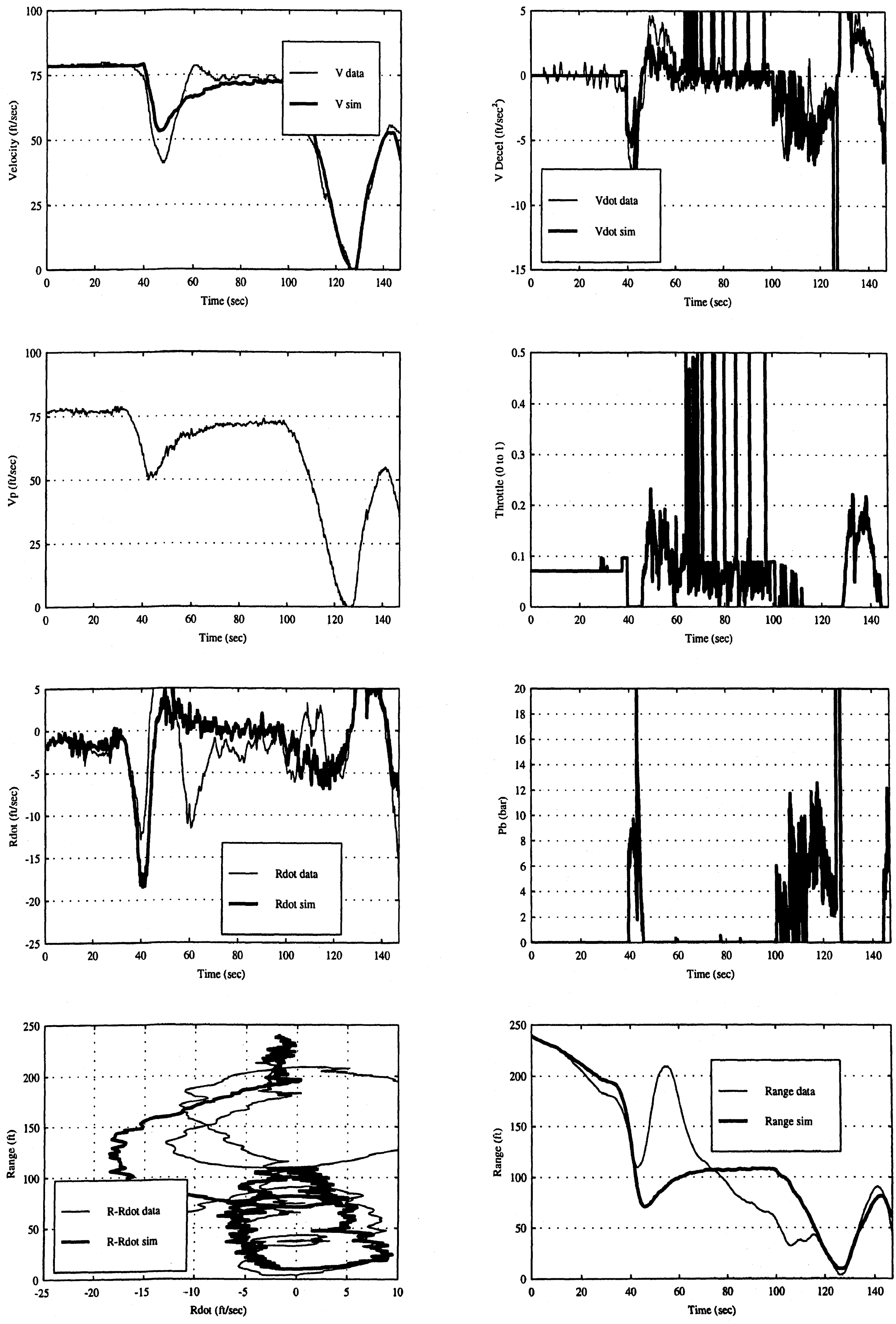


Figure 24a. Example where driver actions do not correspond to a headway control model.

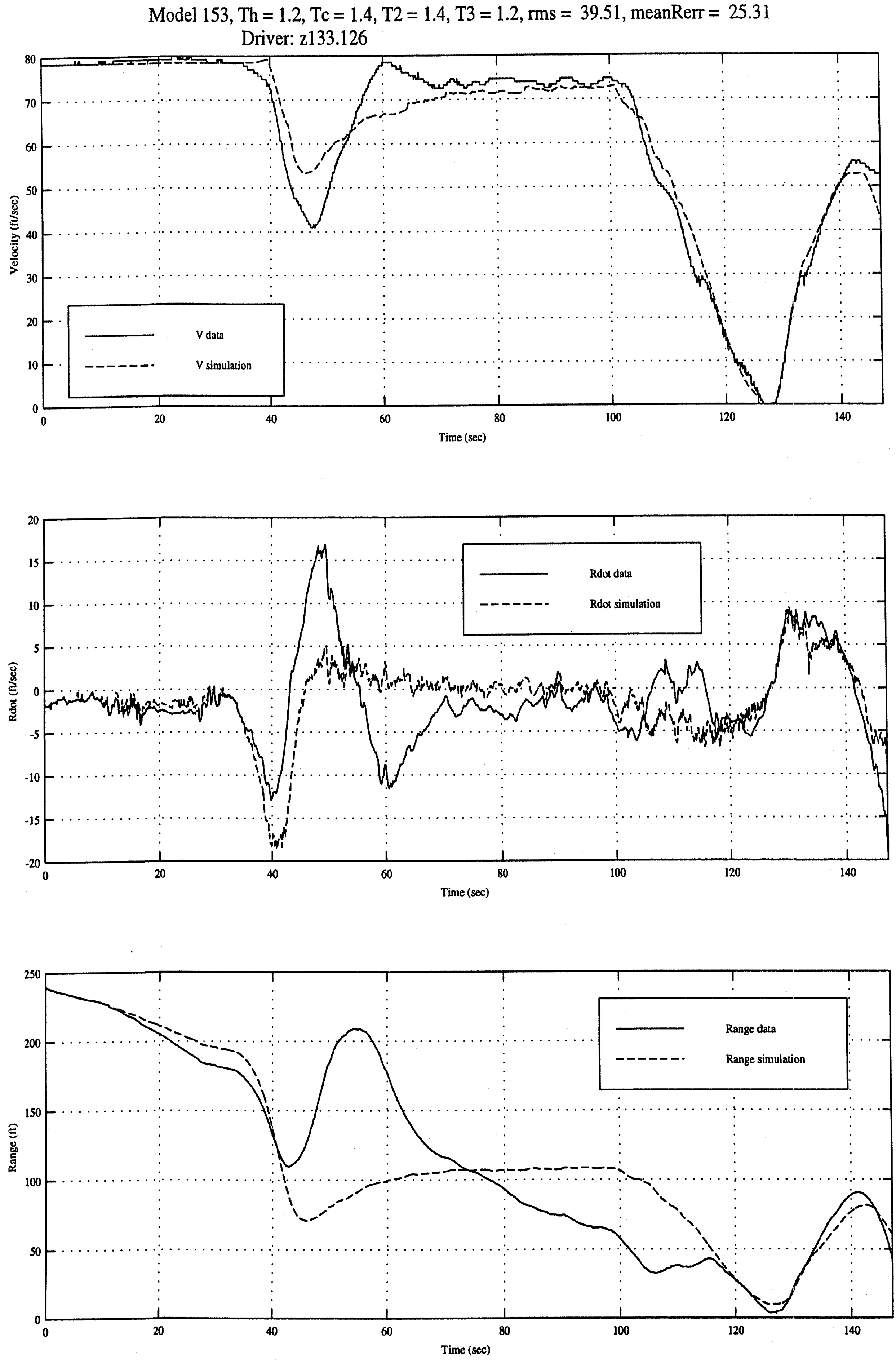


Figure 24b (continued). Expanded V, Rdot, and Range comparisons

Since Th is a major factor in determining the desired range, Rh, and since the rule (equation) for Rh ultimately determines how the model responds to the motion (Vp) of the preceding vehicle, parametric sensitivity to Th was explored over a range of values from 0.8s to 2.0s, for all of the 61 stop-and-go events. The results expressed as RMS differences in range are tabulated in Table 2 and displayed in a scatter plot in Figure 25. The runs presented previously in figures 22, 23, and 24 are specially indicated in Table 2 and Figure 25 by their assigned "plot index" numbers, 1, 7, and 14, respectively. Please note that four data points (one for each value of the Th parameter) appears at each value of the plot index in the figure. Clearly, the RMS results for data files Z133_103 and Z133_40 are good while the results for file Z133_126 are bad for any value of Th. In the table, Rf, is the mean of the range values that prevail between the vehicles when the lead vehicle is stopped. If no such data points exist in a particular file, an arbitrary number of 99.9 is displayed in the table (clearly, however, this is not the value of Rf that was used as a parameter in the simulation.)

Table 2. RMS Values for BMW stop-and-go model

S & G	File Name	Final Range, Rf, ft.	RMS values for values of Headway Time (Th, sec.)				Plot index	Notes
			0.8	1.2	1.6	2		
1	z133_103	10.6	14.3	10.7	8	5.8	1	Th = 2.2 sec (figure 22)
2	z133_104	6.6	14.7	8.5	10.4	17.4	2	
1	z133_109	5.7	20.8	9.2	5.7	7.5	3	
1	z133_110	8.1	31.1	27.8	31.9	38	4	
2	z133_115	11.9	7.8	15.5	23.1	29.5	5	
1	z133_123	9.8	27.7	17.8	11	8.7	6	
1	z133_126	5.5	44.8	39.6	43.1	55.7	7	Th = 1.2 sec (figure 24)
1	z133_132	9.5	13.4	8.2	19	31.5	8	
1	z133_141	7.3	14.4	13.6	15.2	15.6	9	
1	z133_144	11.6	27.5	27.5	28.7	53.9	10	
2	z133_155	6.8	19.5	12.9	25	38.3	11	
1	z133_170	5.7	23.2	20.7	23.8	32.8	12	
2	z133_175	10.3	27	24.4	30.3	38.6	13	
yes	z133_40_	6.1	16.7	12.3	14.7	20.3	14	Th = 1.6 sec (figure 23)
1	z133_9__	6.5	19.9	17.9	19	24.2	15	
1	z143_101	99.9	25.8	22.3	19.9	17.4	16	
2	z143_111	11	22.4	13.8	8.1	8.1	17	
1	z143_126	9.7	19.7	33.4	49.2	71.6	18	
1	z143_155	5.2	11.3	24.7	35.7	47.3	19	
1	z143_21_	5.1	6.2	12.9	21.6	28.7	20	
1	z143_40_	16.8	9.6	7.4	6.6	8.7	21	
1	z143_45_	13.1	10.9	20.7	32.4	43.1	22	
yes	z143_56_	6.6	8.1	14	21.8	29.5	23	
1	z143_72_	10.5	11.5	12.4	16.3	23.3	24	
1	z143_97_	10.1	15.6	17.5	21.7	27.9	25	

S & G	File Name	Final Range, Rf, ft.	RMS values for values of Headway Time (Th, sec.) 0.8	1.2	1.6	2	Plot index	Notes
1	z150_117	7.4	46.1	37.4	28	17.9	26	
2	z150_122	99.9	9.9	22.4	35.3q	48.9	27	
1	z150_124	9.8	28.7	31.3	40.3	48.1	28	
1	z150_125	6.5	22	14.2	25.4	40.8	29	
2	z150_128	7	27.3	10.5	15.5	30.9	30	
1	z150_138	9.5	10.7	14.5	17.8	23	31	
1	z150_139	5.9	20.8	9.5	14.8	22.8	32	
1	z150_141	8.8	20.5	22.7	26.8	30.4	33	
1	z150_143	99.9	47	31.6	25	35.1	34	
2	z150_147	12.3	18.4	17	26.7	40	35	
1	z150_154	99.9	72.7	55.6	39.2	34.6	36	
yes	z150_157	5	24.3	15.6	21.8	34.4	37	
2	z150_179	7.8	27	32.8	43.8	58.7	38	
0	z150_51_	99.9	21.4	19	42.1	56.9	39	
yes	z150_56_	7.4	10.4	13.5	19.5	25.8	40	
yes	z150_90_	8.3	12.3	19.6	34.8	51.3	41	
1	z151_40_	8.4	58.9	46.5	36.3	28.9	42	
yes	z151_42_	6.9	38.1	24.3	14.8	15.9	43	
2	z151_57_	11.5	51.6	40.1	32.1	24.4	44	
yes	z151_59_	5.7	30.2	21.8	31.6	44.7	45	
2	z151_63_	99.9	45.3	41.3	45	56	46	
1	z151_70_	7.8	27.3	22.1	45	66.9	47	
1	z151_80_	10.7	66.2	46.5	35.6	39.3	48	
0 (2)	z151_89_	99.9	7.1	13.5	20.1	26.7	49	
2	z151_91_	6.9	18.4	14.8	26.9	39.3	50	
1	z151_95_	6.8	13.5	15.8	25.9	37.3	51	
yes	z153_105	9.3	60.1	49.9	42.5	35.4	52	
1	z153_111	99.9	27.7	20	20.4	17.4	53	
2	z153_114	8.7	45.9	38.1	35.6	36.6	54	
1	z153_116	6.9	17.3	26.1	40.5	56.8	55	
2	z153_152	9	55.8	45.4	36.8	31.1	56	
1	z153_156	99.9	22.4	15.6	9.4	6.9	57	
1	z153_160	13.7	48.3	42.5	34.2	26.1	58	
1	z153_21_	7.5	15.5	20.1	29.5	39.7	59	
1	z153_67_	11	29.8	25.9	33.9	46.1	60	
yes	z153_78_	8.9	25.9	15.2	11.3	17.4	61	

Work continues for examining ways to determine meaningful parameter values in the model. In that sense we are only part of the way towards developing a finished model of this type. With regard to the headway time, Th, we have come to appreciate its importance for matching test results. This importance can be seen by examining the entries in Table 2 and the corresponding points in Figure 25. In most cases there is at least one value of headway time Th that corresponds to an RMS value less than 6m (20 ft). However, there are a number of cases for which the RMS difference is much larger than 6 m (20 ft) regardless of the headway time selected. This evidence supports the view that headway control does not always predominate in the driver's strategy and tactics, even during a concentrated sequence of stop-and-go driving.

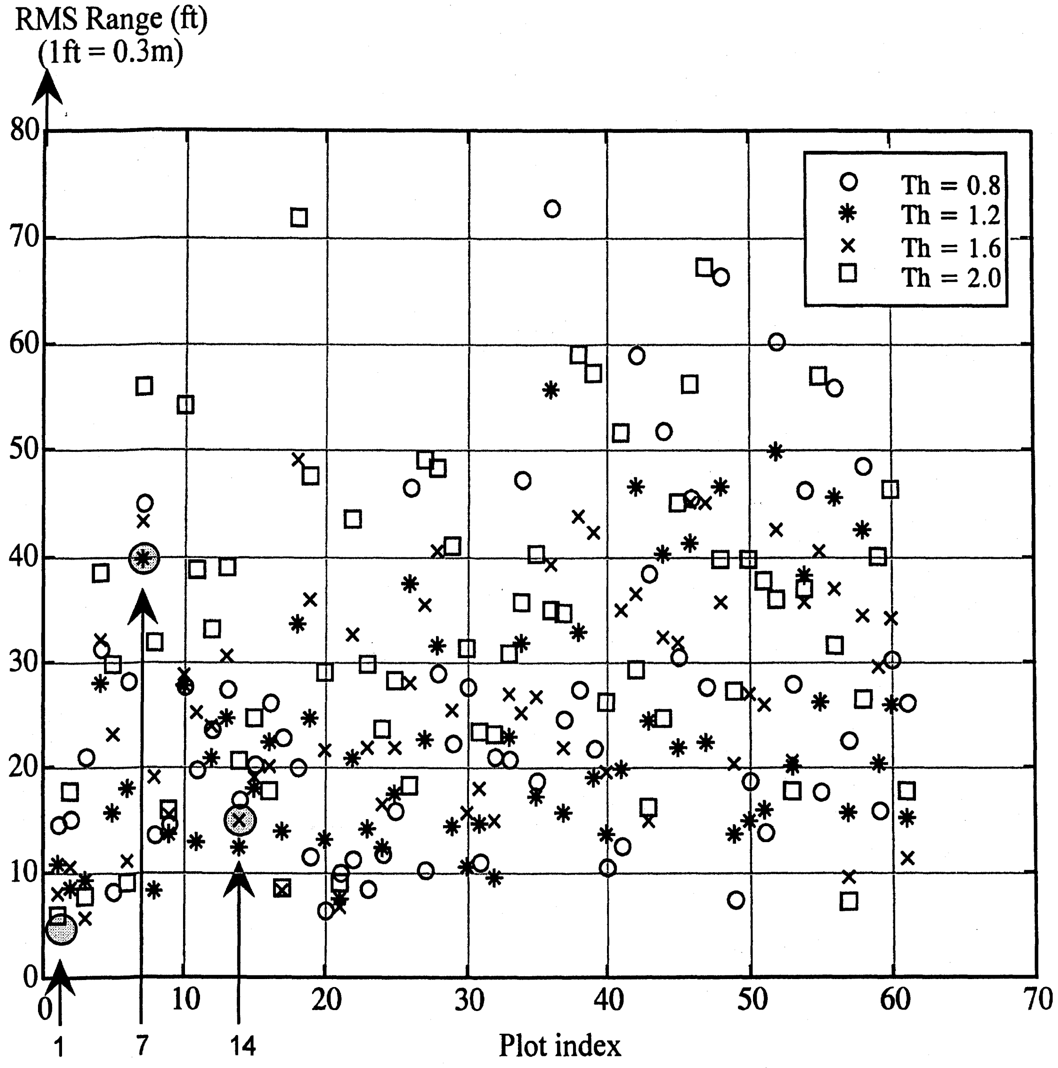


Figure 25. Influence of Th on RMS measure of fit

With regard to considering the development of a stop-and-go ACC system based upon the driver model, it appears that a driver-adjustable headway-time feature may be desirable for reasons of driver comfort and convenience.

Further efforts to develop an understanding of the influence of the headway time, Th, have been pursued empirically using a least-squares approach for fitting Th with a linear equation. For example, in all the test data for which $Vp > 10$ ft/sec, $R > 10$ ft, and the brake is on, we find that the following equation fits the data:

$$Th = 1.422 + 0.03\ R - 0.047\ Vp \tag{22}$$

When examining accelerating, following and, braking individually, we obtain the following results:

For accelerating, (Vpdot > 0.1 g):

$$Th = 1.12 + 0.017\ R - 0.023\ Vp \tag{23}$$

where $r = 0.81$

For following, ($-0.1g \leq Vpdot \leq 0.1g$):

$$Th = 1.17 + 0.012\ R - 0.016\ Vp \tag{24}$$

where $r = 0.92$

For decelerating, (Vpdot < -.1g):

$$Th = 2.06 + 0.027\ R - 0.055\ Vp \tag{25}$$

where $r = 0.88$

Hence we can see that accelerating and decelerating phases of the stop-and-go cycle are indeed being handled differently and, as we might have expected, drivers are more conservative when deceleration is taking place. There is much more that could be pursued here. In general, we can say that an understanding of how to determine Th and Rh is crucial to developing a better model.

Another point with regard to the development of a stop-and-go ACC system has to do with control near the end of a stop at very short range. The model needs some work here if it is to represent the basis for a prototype ACC system. As can be seen by examining the model results in figure 22a, there are periods of very high levels of brake pressure at approximately 14 and 20 seconds in this example situation. These results nevertheless indicate that the model needs improvement when range approaches Rf (the final minimum range). We believe that adjustments to the Rh command circuit and to the rules for zones 1 and 3 will alleviate the problem, although fidelity in sensor outputs at very short range is an obvious implementation issue as well.

In summary, we find that the model accounts for much of driver behavior in stop-and-go situations. The ability to fit test data appears to be fair to good in most cases. Nevertheless there is considerable room for improvement. Methods for determining parametric values for use in the model have not been developed to the point where they constitute nearly routine procedures. In particular there is a need for further examination of how to determine the driver's desired range and the headway-time parameters such as

Th and Teh. Even so, we believe that we can modify the form of the driver model and use engineering judgment to create a prototype stop-and-go ACC system that will operate reasonably well in a vehicle. We recommend the development of such an ACC algorithm and its use in an ACC-equipped vehicle as a next step in this research effort.

By examination of Table 2 (and Figure 25) one can readily identify the situations that are distinguished by large RMS values of the difference between the headway control model and the measured data. These cases warrant special attention because the behavior of the driver-vehicle system is not explained by headway-control considerations alone. The study of information from such cases provides the opportunity to learn about additional factors that influence the speed and range values that are sought by the driver. Such considerations are the subject of the next section.

5.1.4 Use of Model-difference to Isolate *Altercontrol* Tactics

The driver's actions in longitudinal control are clearly governed both by the reality of the immediate headway constraint, such as the ACC function offers to address, and by a host of other considerations that may be quite unrelated to the prevailing headway. Thus we might say that all longitudinal control can be divided into operational zones covered either by headway-only terms of control or by the sum of all other terms for control. Here we shall adopt the term H_{only} to represent the domain for ACC-like control of headway (and maximum cruise speed) and the term *altercontrol* to represent the entire domain of "other" control tactics by which drivers address the situational complexities that lie outside of the headway dimension. We will first lay out the conceptual basis for finding transitions to altercontrol from actual driving data and then we will present crude illustrations of applying this concept, revealing example altercontrol tactics in manual stop-and-go driving.

Conceptual Basis for Isolating Altercontrol

As shown in figure 26, the scope of concern of the H_{only} controller is confined to the immediate headway space and essentially represents that which an ACC controller is tasked to manage (albeit with the possibility of human-like features for dealing with lane constraints, transition to a new headway target, stopping dynamics, and the like.) Altercontrol must deal with everything else. Altercontrol includes, for example, all circumstances in which throttle and/or brake are modulated to enable passing maneuvers, to respond to traffic signals and signs, to anticipate out-of-lane conflicts such as a pending cut-in or the converse case in which a preceding vehicle is anticipated to vacate its currently impeding position by turning right or left when traffic clears. Altercontrol also includes a host of other cautionary tactics such as arise when the driver is uncertain about another vehicle's movements, when downrange vision is occluded by nearby vehicles, when construction zones violate lanemarking conventions, etc.

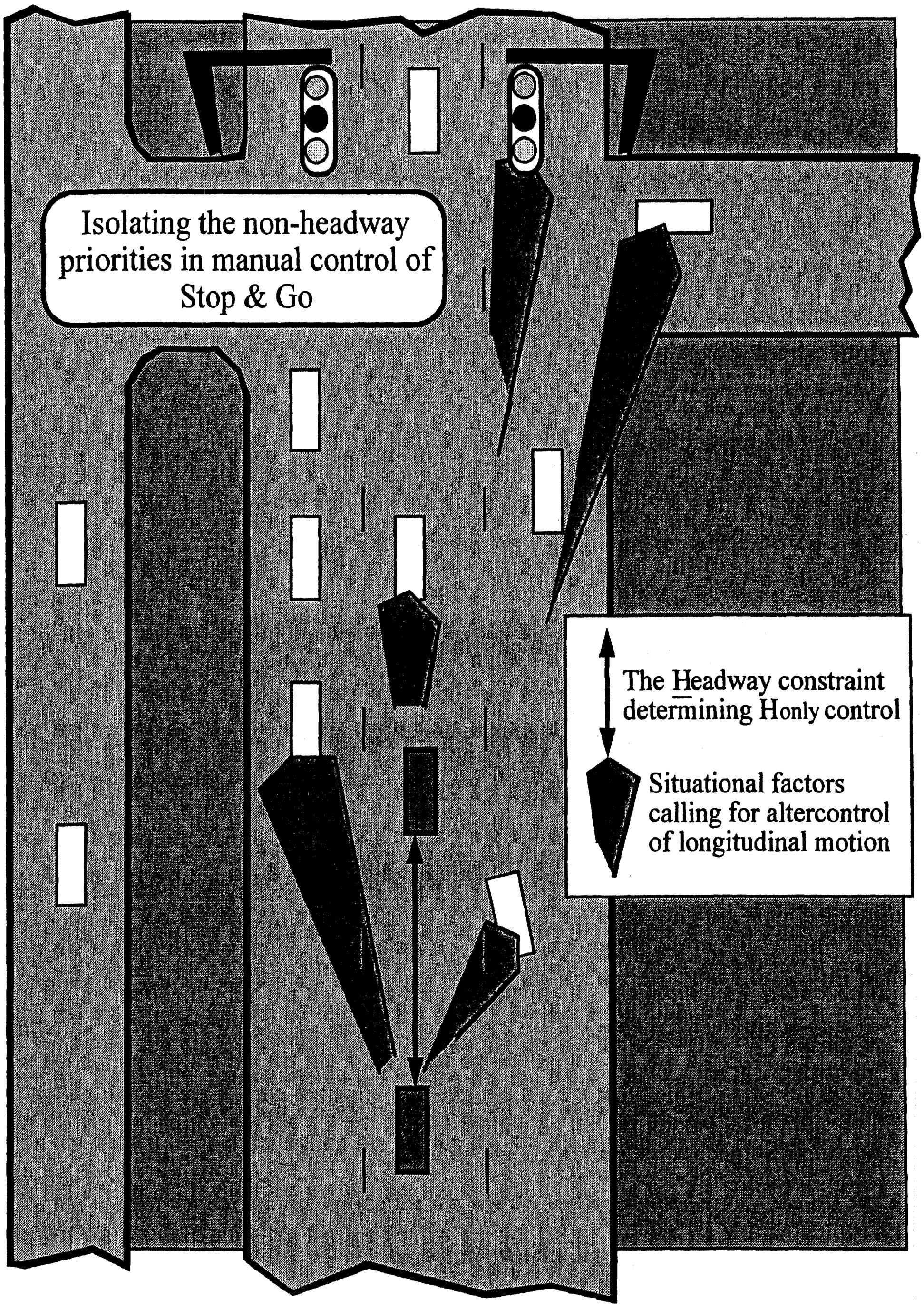


Figure 26. Headway and nonheadway considerations in manual driving

The importance of discriminating the situations in which H_{only} versus altercontrol prevails is that the boundaries between them define temporal events that will have distinct importance for determining ACC system acceptance. That is, if ACC is assigned as the H_{only} controller, its boundaries with the domain for altercontrol will coincide with either driver intervention events or moments of subjective judgment on system acceptance, even if manual intervention on ACC does not occur. If, as an investigative method, the ACC developer can carefully map out the entire manual driving experience according to its H_{only} and altercontrol topography, he will thereby gain a distinct upgrade toward a methodical approach for ACC development and performance evaluation.

Here, we must recognize that the manually-executed version of H_{only} control may differ in significant ways from the H_{only} control characteristics of an ACC system. On the human side, despite the extent that H_{only} control is individualized by the idiosyncrasies of a specific driver, there are underlying constraints simply posed by stereotypical human capability such as temporal response bandwidths, the resolution on human visual perception, the psychological appraisal of headway risks, and the psychomotor consistency/reliability of the human actor as a headway servomechanism. There are also intentional factors—satisficing theory for example suggests that a substantial degree of control sloppiness arises from the person's sense of disutility in doing it better.

On the machine side, the ACC-provided form of H_{only} control is flexible in its definition, limited only by the technological scope of the system and the investment made in sensing and computing. What might be labeled as altercontrol space in the human context may be partially bitten off by a more extended ACC functionality.

Clearly, once an ACC controller is installed, its role is to accomplish its version of H_{only} control in a way that somehow complements the driver's exclusive role in accomplishing what's left as altercontrol. But in the stop-and-go environment, the complexity of demands for altercontrol can be high. It is believed that the driver will perceive benefit from an ACC controller that manages the headway regime while situating the driver for seemless transitions back into altercontrol. The strength of these perceptions will largely determine the acceptability of any stop-and-go ACC system. Thus, if by definition the ACC controller is unable to accomplish altercontrol tasks, the mere identification of the temporal boundaries that distinguish altercontrol versus H_{only} control constitutes an important step toward the methodical development of stop-and-go ACC.

If a reasonable model exists for describing manual control of headway (that is, a model of the human H_{only} controller such as that presented earlier), the opportunity exists to use such a model for methodically isolating events in manual driving during which altercontrol is being applied. The straightforward context for isolating such events is by means of manual driving experiments using an instrumented vehicle. With the full complement of basic headway-related data then on hand, one can simply compute the continuous difference between the range response that a human driver actually did employ in the test (viz., R=f(m), using m to denote the comprehensive manual controller, and the headway range that the manual H_{only} model computes (viz., the range response, $R=f(H_{only})$), given the speed profile of an impeding vehicle.

As diagrammed in figure 27, exact correspondence between $R(H_{only})$ and R(m) lying along the 45° line would derive under all driving conditions for which a simple ACC controller is judged to be fully satisfactory. When the range value that is maintained under H_{only} control is longer than the manual driver would actually prefer, such that the operating state lies in the lower right portion of the graph, the driver would experience frustration with the impediment that H_{only} control imposes and would apply more throttle in order to close up the range gap. When the range value under H_{only} control is shorter than the manual driver prefers, such that the operating state lies in the upper left portion of the graph, the driver experiences discomfort and perhaps apprehension over the crash potential, thereby calling for more braking.

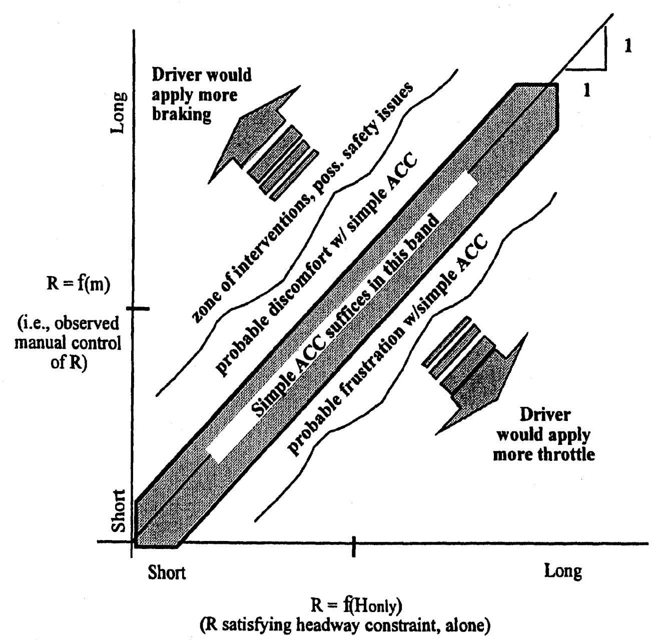


Figure 27. Range as controlled in manual driving vs. range as would be controlled by an H_{only} control model (or an actual ACC system).

Shown in figure 28 are example scenarios in which the continuous difference between the actually measured range resulting from a manual driving test, R(m), and the computed model result, R(H_{only}), is plotted as a function of time. Four scenario segments are shown, beginning at the left as follows:

- R(m) begins to grow longer than R(H_{only}) — that is, the difference value grows positive — as the actual driver elects to coast after observing a traffic signal turning amber. Clearly, the altercontrol tactic is to begin managing speed in response to the traffic control device, thereupon departing from simple (H_{only}) control.
- The difference value grows abruptly more positive as the driver begins to brake for a red light, even though the preceding vehicle goes through the intersection. A stiff phase of altercontrol has set in, placing the operating point in the safety-critical, upper-left corner of the diagram that was shown above in figure 27.
- The difference value grows positive as the driver shows a precautionary coasting response due to having noticed braking in the adjacent lane. A great variety of such throttle-release episodes is thought to dominate the altercontrol space. The failure of simple H_{only} control to afford almost any of these coasting responses will likely influence the net level of comfort perceived in any crude form of stop-and-go ACC system.
- The difference value goes negative as the driver accelerates toward an impeding vehicle which is clearly, from the driver's broad appraisal of the scene, about to vacate the lane ahead by turning off of the roadway. Failure of simple ACC to provide a comparable response may tend to frustrate some drivers and thereby discourage utilization. The situationally driven tightening of headway gaps, in order to discourage cut-in behavior, is another classical context in which negative differences in [R(m) - R(H_{only})] would arise.

Clearly the previously mentioned computation of the RMS difference between measured and modeled range variables provided one means of detecting an extended segment (or stream) of driving data in which altercontrol may have dominated the driving tactics. Another detection method would simply involve the finding of threshold exceedances, for some defined tolerance band on the [R(m) – R(H_{only})] difference variable such as is in figure 28. By whatever computational scheme, the ability to detect moments of transition from H_{only} to altercontrol in data from a manual driving sequence offers the possibility of a synchronized video appraisal such that the altercontrol domain may become catalogued, graded, and assessed according to the severities and the probabilities of its contents. With such rigor, the possibility of cognitive modeling could be ushered in, seeking to represent the decision-making and vigilance tasks that are embedded in manual driving, thereby establishing the baseline from which for ACC-assisted driving will be executed. Insights from cognitive modeling may then stimulate innovative approaches in ACC system design that make its usage in stop-and-go driving less frustrating and less risky.

In the short section which follows, two example cases of computed model difference, as obtained from manual-driving data are presented for isolating video segments showing transitions to altercontrol. It remains for later work to mechanize such methods and to begin the great chore of cataloguing, grading, and assessing the probabilities in the altercontrol domain.

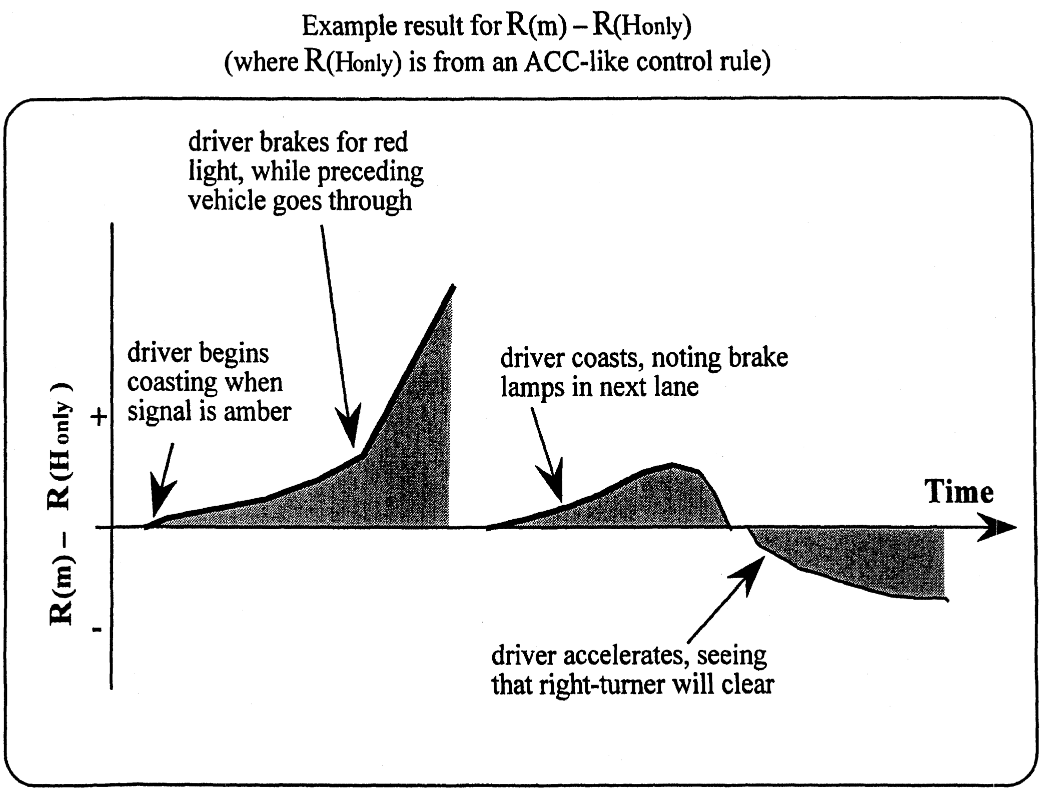


Figure 28. Typical scenarios to show variation of actual and computed result

Test Examples Illustrating Transitions to Altercontrol

All vehicle data measured from manual driving were partitioned into sequences of following activity call *streams.* Typically, a stream starts when the host vehicle first gets behind another vehicle. This can happen as a consequence of a cut-in, lane change, or simple merge. The stream continues until the host vehicle stops following the lead vehicle, as indicated by an abrupt change in the sensed forward range. For the purposes of evaluating the stop-and-go model of manual headway control, we attempted to model only streams that contained full stops of the host vehicle.

Comparisons were made between the velocity and range predicted by the model and the recorded driver behavior. Where large discrepancies in the RMS difference were evident, we consulted the videotape record to determine whether other factors (beyond the domain of measured headway variables might be influencing the driver's behavior. The following two cases provide an admittedly ad-hoc means of illustrating the general idea for isolating such factors from recorded data.

Driver 133, Stream 110

Figures 29a and 29b present quantitative model versus data comparisons and the corresponding video segment for driver 133 and stream 110. The stream begins when the host vehicle moves laterally into the lane, taking a position behind a lead vehicle at a relatively high speed (~45 mph or 73km/h). The model predicts that the driver would first attempt to lengthen his range to the preceding vehicle. Instead, measured data show that the driver maintains a much shorter range than was predicted. There are two possible reasons for this:

- In the audio track of the videotape, shortly after lane entry, the driver comments that the traffic light up ahead is green. Perhaps he is tolerating a shorter range in order to slip through the light before it turns red.
- Although no rearward video was recorded, it is also possible that the host driver has just merged into a relatively small gap between two vehicles. If so, proper driving etiquette might prescribe that he not decelerate in the normal manner that the model dictates, lest he annoy the driver behind him.

As the stream continues, we see the driver's response conforms to that of the model down to the stopping point. (The driver failed to make the green light.) When the traffic light changes to green again, the response of the host driver deviates in another way from the model predictions, this time allowing a much *larger* gap to accumulate between him and the lead vehicle. In this case, it appears that the driver lags behind in order to move into position for a lateral maneuver into the right lane behind another vehicle.

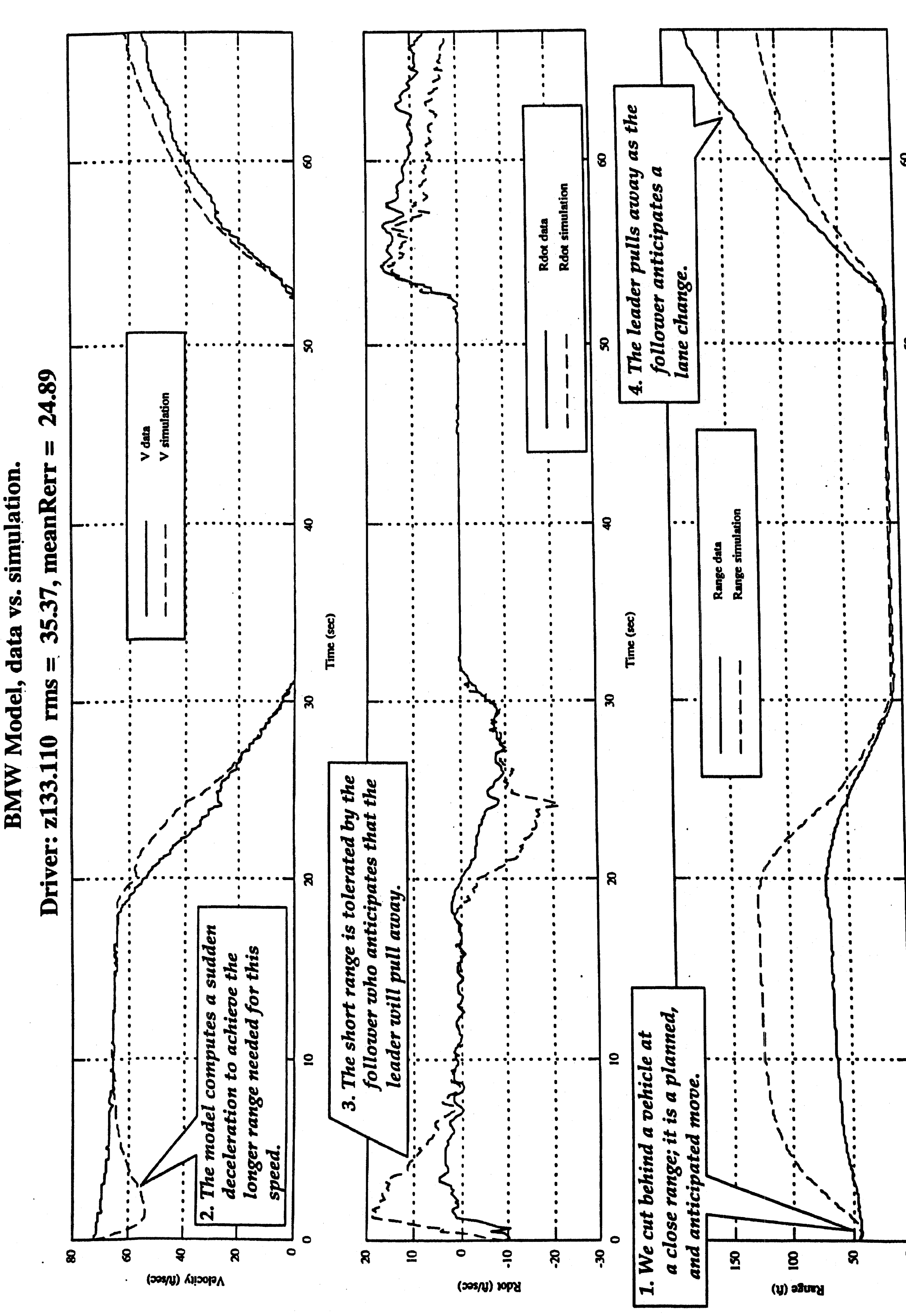
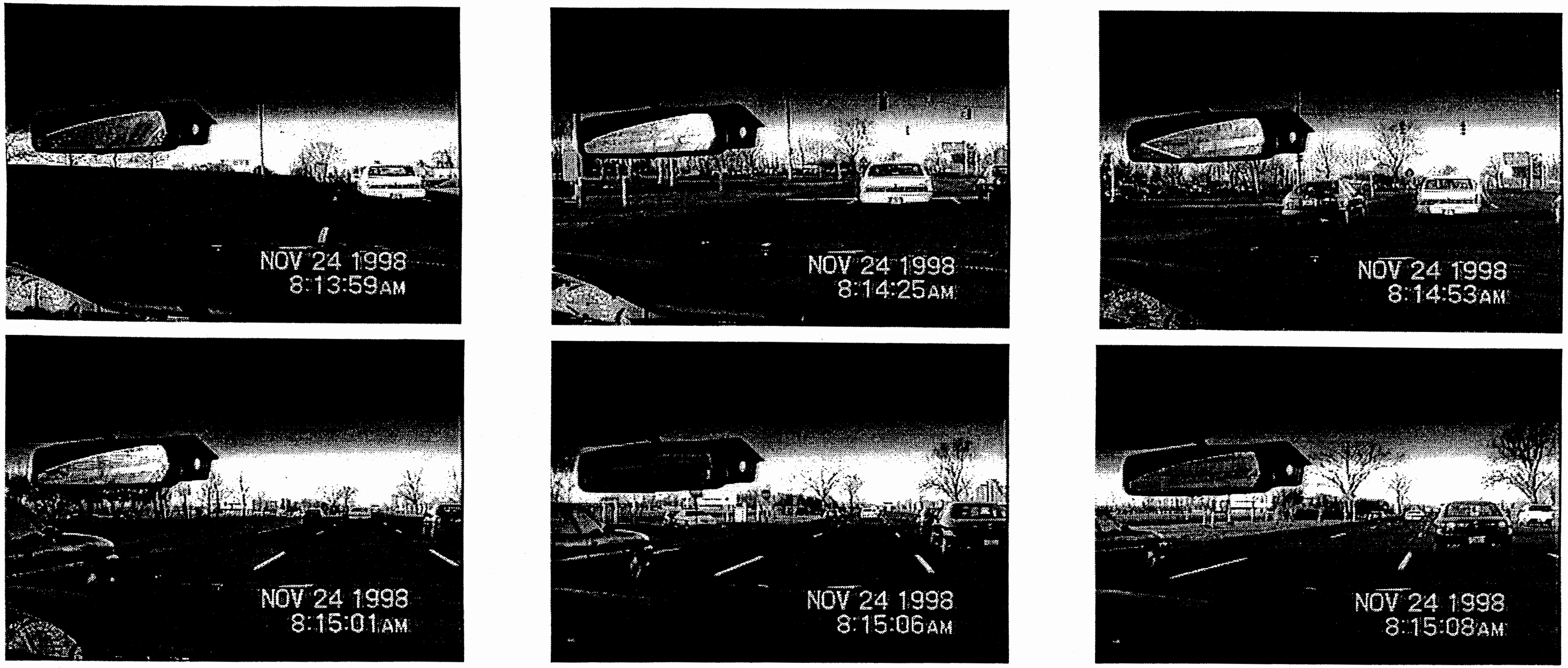


Figure 29a. Annotated time history of a stop-and-go event for driver 133



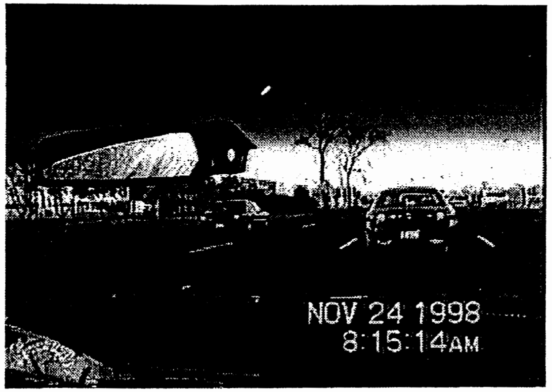


Figure 29b. Video sequence for Driver 133, Stream 110.

The sequence (from left to right) shows the starting merge (frame 1) behind the light colored vehicle. After the traffic signal turns green (frame 3) considerable range opens up between the host vehicle and the preceding one. As explained in the text, this may be accounted for by the merge to the right behind the dark vehicle (frame 5,6, and 7).

Driver 143, Stream 155

Like figure 29, figure 30 (parts a and b) shows time-history data (actual and modeled) and video results for driver 143 stream 155. Here the driver merges behind a black pickup truck and follows it at a relatively close range. The driver's initial time-headway is approximately .5 sec and rises to about .8 sec. This headway gap is unusually short. It may have been a consequence of the host driver anticipating a change to the right lane, which is clear of traffic. Interestingly, both the host vehicle *and* the lead pickup truck initiate the same lane change at the same time, thwarting the host driver's goal to move to a clear lane. Both vehicles then come to a stop at a traffic light. When the light changes to green, we see the pickup truck briskly break away from the other vehicles in adjacent lanes, trailed closely behind by the host driver. The host driver then changes into the left lane when he is far enough ahead of the left-lane traffic, so that he can pass the pickup. The driver, in this case, seems to be searching for a clear lane to move into and appears to be willing to temporarily compromise range safety to achieve this goal. The model, having no such motivation, does not behave in this fashion.

In these cases, we see evidence that drivers may modify their following behavior to support other strategic goals: to move into clear lanes, to fit into gaps, to clear past traffic in other lanes, etc. It is likely that many more altercontrol strategies of this kind are employed.

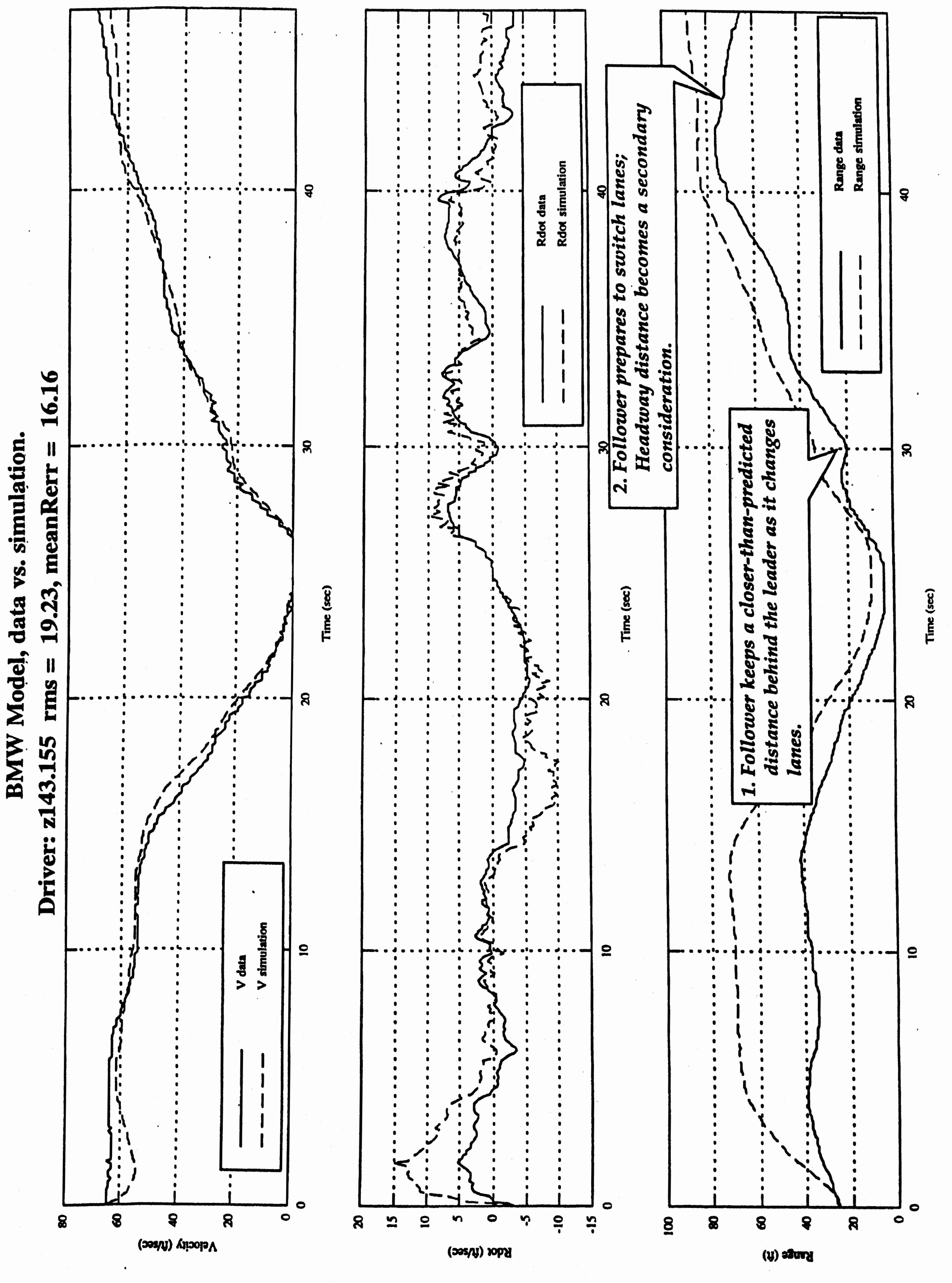
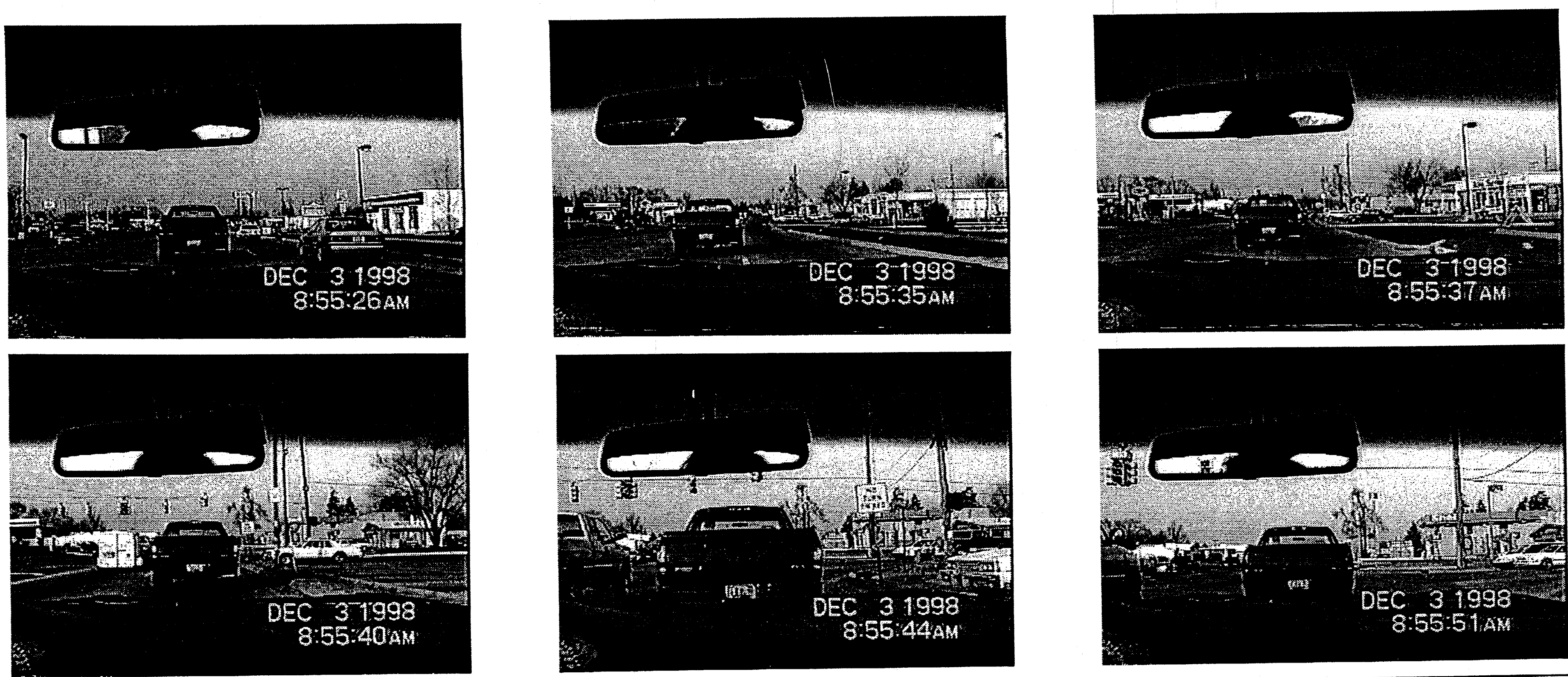


Figure 30a. Annotated time history of a stop-and-go event for driver 143



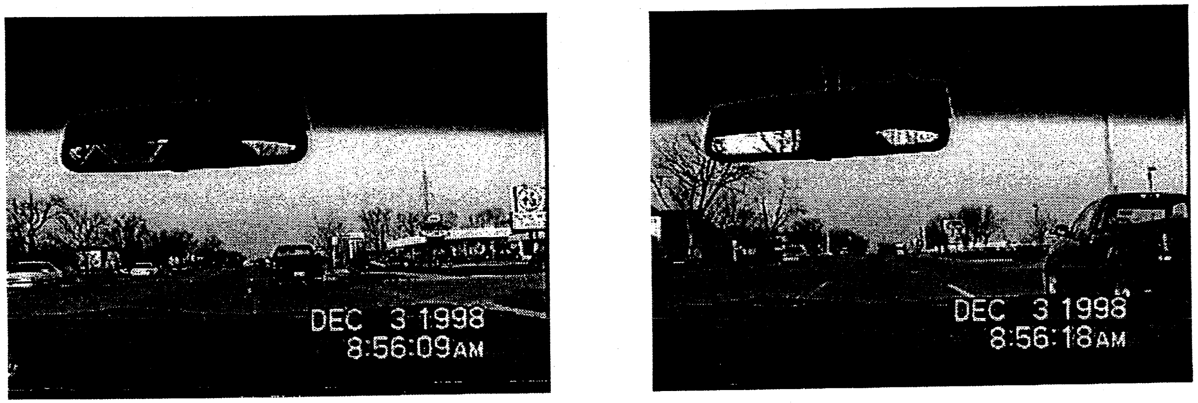


Figure 30b. Video sequence for Driver 143, Stream 155.

In this sequence (from left to right) we see the host driver change to the right lane along with the black pickup truck (frames 1, 2, 3, and 4). After the stop at the traffic light (5), the host driver shadows the fast accelerating pickup (6,7) and finally switches to the left lane to pass (8).

5.2 Considerations of the applicability of ACT-R and SOAR for driver modeling

It is clear from the preceding results that driver behavior is both dynamic (i.e., it adapts to different driving situations) and goal-oriented (i.e., a strategy is chosen by the driver to momentarily achieve some desired outcome). A model that does not take into account the specific driving context will find it difficult to accurately model driver behavior. Perhaps control-theoretic formalisms used to model driver behavior could be supplemented by the use of models that are more directly attuned to modeling behavior. In particular, we investigated two cognitive modeling systems: ACT-R and Soar.

Both ACT-R and Soar are types of production systems used over the last fifteen years to model human information processing. In a nutshell, a production system is a method of organizing a large collection of decision-making elements called productions. A production is a data structure containing a conditional part and an action part. When a stimulus is presented to a production system, it is encoded into some form of internal representation in the system's *working memory.* A production whose conditional part matches working memory *fires,* that is, its action is executed. The action changes working memory so that new conditions are instantiated. Other productions matching the new conditions then fire and the process continues until either no further matches can be made between the productions and conditions, or until a stop condition is reached.

Over the years, Soar has been used to model planning behavior (Akyürek, 1992), multitasking in driving (Aasman & Michon, 1992), concept acquisition (Miller, 1993), short-term memory (Newell, 1990), syllogistic reasoning (Polk & Newell, 1988), sentence comprehension (Lewis, 1993), and tactical air-combat simulation (Rosenbloom et al., 1994). Likewise ACT-R has been used to model a wide variety of human behavior ranging from perceptual-motor skill, memory, learning, cognitive arithmetic, to analogical reasoning (Anderson, 1998). Given the amount of exposure these models have received over the years, it seems reasonable to look to them to provide a framework in which to help organize the various conditions that may affect human driving behavior.

Use of either Soar or ACT-R as a modeling framework requires extensive training in each system. Such training is provided to the user community through annual workshops, published tutorials, training materials, user guides, reference manuals, and books. The amount of such training material is not only indicative of the amount one needs to know to effectively use these systems, but also of the extent of the growing user communities.

Assuming it is helpful to organize driving behavior into a systematic framework, how should we select which of these frameworks to adopt? Both Soar and ACT-R are, at heart, Turing machines. Each can be "programmed" to achieve similar outcomes. The differences between the two systems lie in the degree to which each attempts to mirror human information processing. Although Soar began as a model of human problem solving, and has been promoted as a *unified theory of cognition* (or, UTC) (Newell, 1990), since Newell's death in 1992, the status of Soar as a psychological theory has diminished. Instead, much of the current research and development using Soar has been focused on simulation of intelligent agents in tactical air-combat situations (Rosenbloom et al., 1994). Little further work seems to have been done to further promote Soar as a UTC. Indeed, there has been strong criticism of Soar as a UTC (e.g., Cooper and Shallice, 1995) which has been left unanswered. Evolution of the Soar framework itself has not always been justified in terms of a psychological model. Some changes appear to be motivated by concerns about computational efficiency and technical elegance.

In contrast ACT-R, through the careful stewardship of John Anderson, is somewhat better positioned as a cognitive model. Anderson is a cognitive psychologist and has made great effort to relate all of ACT-R's architectural features back to psychological principles. As a consequence, it is more likely that success in modeling driving behavior within the constraints set by ACT-R may lead to more compelling insights into driving behavior.

ACT-R is a computer-based system for modeling cognitive behavior. There is now a version known as ACT-R/PM that includes perceptual and motor functions as well as cognitive functions. It seems that at some point in the future we might be able to use ACT-R to study driver control of headway. However, there is a lot to learn and understand before one is able to use ACT-R with confidence in a new application. Nevertheless, there appear to be fundamental psychological principles and understanding of constraints on human cognition that are built into ACT-R. For now we can strive to see if we can deduce what these principles may be and to use them in our models to the extent possible.

The notion of a production system appears to be a fundamental feature of ACT-R. In simple terms this means that the rules for producing actions or answers are the results of "if, then" statements. These rules are compiled from factual and/or perceptual knowledge that is held in declarative memory plus procedural knowledge that is held in procedural memory. In a certain sense, a person can reflect on and acknowledge the items in declarative memory but is not consciously aware of the items in procedural memory. There is also a goal stack and a current goal that is part of the system for deciding which procedure to use in a given situation. The decision process depends upon considerations that, at least at first, seem complicated and complex. Some of the complexities considered are:

- conflict resolution between alternative rules
- ways of making retrieval requests in declarative memory
- how new rules are formulated
- how skills are learned
- the speed of retrieval of information
- the latencies in completing productions
- goal structures
- expected gain
- probability of achieving a goal
- the cost of solving a problem
- activation-based retrieval of information

Even though the process is complex, each production "firing" may be summarized as consisting of three stages:

- conflict resolution in selecting a production that matches the goal
- declarative retrieval of the knowledge chunks used in the production
- production execution including motor involvement

With regard to the model presented in this report, there may be some correspondence between Anderson's views as expressed by ACT-R and Rasmussen's hierarchy of skills, rules, and knowledge. Very loosely, we have resolved the conflicts by assigning rules to each situation that we have considered. We use mainly factual information that the driver perceives ahead. And we assert that an experienced driver has finely honed skills that facilitate the execution of the commands produced by the rules. It seems that an ACT-R approach could aid studies that sought to address complicated issues such as:

- the ability to treat situations in which drivers choose productions (altercontrols) that are based on more than just considerations of headway control
- the ability of drivers to learn how to supervise ACC systems
- driver decisions to intervene on ACC and drive manually
- the risks drivers may be willing to tolerate during ACC driving

Just as in all human decision-making, a basic question is whether the outcome will be worth the effort. In summary, is the cost of learning to become fluent in ACT-R worth the time it would take to do it?

6.0 Outlook for a Methodical Approach

There are elements of a methodical or at least systematic approach in what we have been doing in this research effort. In this section we attempt to generalize from the current stop-and-go ACC context to driver-assistance systems in general.

A main postulate of the envisioned methodical approach is:

Designing a control device to assist the driver will require one or more models (either conceived in the mind of the designer and/or computerized) of how the driver manually performs the nominal function that the driver assistance system seeks to address.

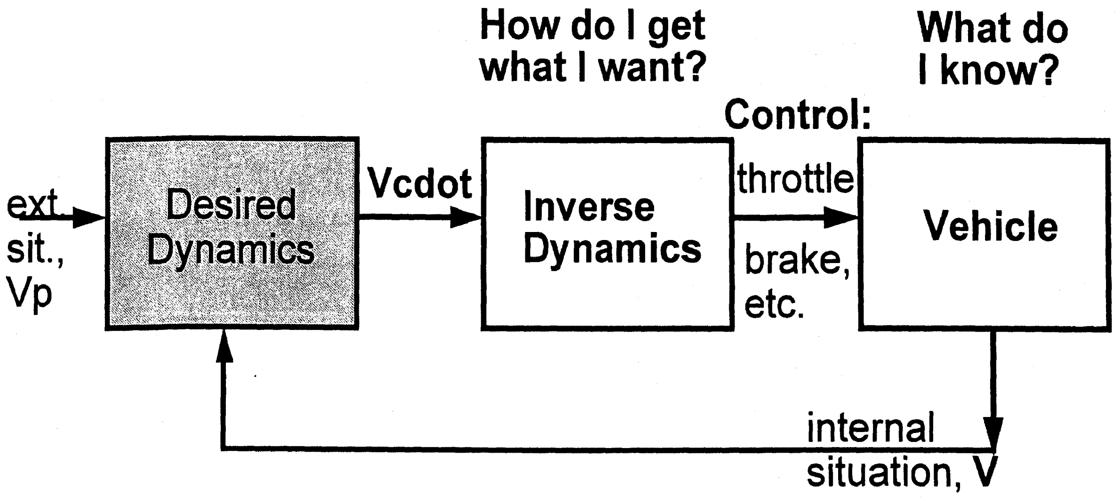
In this regard, an initial step in model formulation is to gather physical evidence of human behavior in driving situations that are pertinent to the driver assistance function desired. For example, for stop-and-go ACC we have measured range, range rate, and velocity in headway-control situations in manual driving, with a sample of subjects.

The next step after gathering physical evidence would be to develop a basic form of model covering the constraints in human performance that apply to sensing, perceiving, recognizing, deciding, and responding. One needs to follow up on leads derived from clues found in the physical evidence. Human factors, psychology, control systems, and vehicle-dynamics literature and techniques need to be examined and studied to aid in penetrating to an understanding of what the data (physical evidence) reveal about the underlying principles or mechanisms that explain (predict) human control.

In this context the system designer obtains valuable knowledge concerning the types of sensing that are needed. In addition, the designer develops the basis for evaluating how a proposed driver assistance system would match human performance in the domain of the targeted function, or otherwise complement the human role that may be undertaken as the system supervisor.

Given the experience obtained in developing a model of manual stop-and-go driving, we recommend organizing the model around skill-based, rule-based, and knowledge-based behavior. This will yield a model that has the planner, commander, and controller functional elements derived in this study.

With regard to developing a controller element that performs at the skills level, we would use vehicle-dynamics expertise to develop an appropriate inverse dynamics model of the vehicle. This will, at least to first order, mean that the combined vehicle model plus controller element acts like an integrator. In the ACC-type application this integrator receives a desired force (that is, desired acceleration) command. Figure 31 and the equations shown in the figure provide an example of how this approach was applied to the skills-level controller in the stop-and-go ACC study.



Inverse Dynamics reasoning:

$$F(\mathbf{Control}) = M\ Vdot + Fd$$

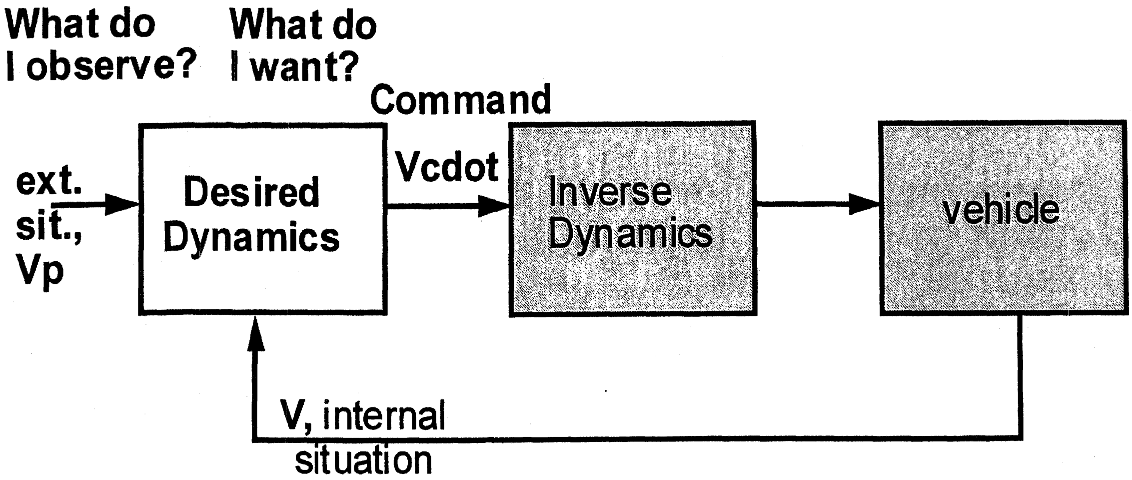
$$\mathbf{Control} = F^{-1}(M\ Vdot + Fd)$$

But if $\mathbf{Control} = F^{-1}(M\ Vcdot + Fd)$,

$$\mathbf{V} = \int \mathbf{Vcdot}\ dt, \text{ which is what I want.}$$

Figure 31. Emphasizing the inverse dynamics role in the system

To provide the command input to the skills-level controller, we would develop rules and associated signs used for recognizing pertinent situations. Figure 32 illustrates an example case taken from this study of stop-and-go ACC. The equations in the figure delineate the development from a desired sliding surface (based upon Rh) to an acceleration command Vcdot to be used when the signs call for tracking a preceding vehicle.



Desired Dynamics reasoning:
T Rdot + R = Rh,   Rdot = **Vp** - **V**,
T Rdot + R - Rh = e,
edot + e/Te =0
Vcdot = Vpdot + (Rdot -Rhdot + e/Te)(1/T)

Figure 32. Emphasizing the role of the desired dynamics relationships in the system

Once the model of manual driving becomes functional and useful for making predictions, it provides the basis for creating the design for a proposed driver assistance system. This design will incorporate ideas concerning sensor requirements and the control algorithm. The formalism and rigor associated with developing the computer model for manual driving will have aided in developing a quantitative means for trying and evaluating such ideas. The modeling effort should even prove useful in predicting how the driver will supervise the driver-assistance system. It may also aid in developing ideas for driver interfaces involving information displays, controls, and feedback assurances.

This brings us to the present state in the study of stop-and-go ACC. As we have recommended in section 5.1.3, the next step is to build a working prototype and gather some more physical evidence. We need new information and feedback from supervisors of this new functionality. We need to develop a better understanding of how people cope with the special responsibilities and situations presented under stop-and-go ACC control and the situations that cause them to arise. We need to understand the time margins that drivers desire in order to be comfortable with their supervisory skills. We need to discover when drivers will simply turn the system off and drive manually.

In addition to creating a model of the corresponding manual driving functions and then developing and learning from a stop-and-go ACC prototype, we also anticipate that a methodical approach will draw value from the model-difference technique for highlighting events that provoke altercontrol. Especially with stop-and-go ACC as the functionality in question, we tend to believe that the complexity of the application environment will cause the suitability of any system solution to be heavily determined by the system's compatibility with transitions to altercontrol. Our view of the methodical approach thereby includes some use of the model difference method. Below we have listed three applications of the basic technique that might aid in understanding the boundaries between the system's H_{only} control domain and the driver's exercise of altercontrol.

1) First, one can exercise a manual H_{only} control model to highlight model differences from manual driving data, in the same manner that we have discussed and very briefly illustrated in Section 5.1.4. That is, one would continuously subtract the modeled range history, $R(H_{only})$, representing human control of headway, alone, from the complete range history, R(m), that was measured during manual driving throughout each tracking stream. The purpose of this exercise is to help mechanize an orderly cataloguing of normal manual altercontrol situations, according to their type, severity, and frequency.

2) Next, one could implement, in place of the manual H_{only} model, the designed model representing a candidate stop-and-go ACC controller to again highlight model differences from manual driving data. Comparison of these model differences (i.e., R(m) minus R(ACC)) with those found under application 1, above (i.e., R(m) minus $R(H_{only})$) should reveal how well the candidate ACC algorithm will mimic manual headway control, or by implication, yield the same manually expressed boundary with altercontrol.

3) A companion test scheme is also envisioned for helping the researcher detect and perhaps gain a better intuitive understanding of the altercontrol domain. By this technique, one would embed either the manual H_{only} model, or a candidate ACC range controller as a real-time computation on board a manually driven, but ACC-sensor-equipped, vehicle platform. The continuous model difference, also computed on board, would be used to modulate an audible feedback tone, perhaps whose tonal frequency varied continuously according to the magnitude of the model difference. Although the tonal feedback scheme may require a substantial dead zone around the zero-difference level in order to subdue the annoyance factor, we anticipate that the alerting value of the feedback, while a researcher is

actually engaged in the driving process could be instructive. (Please note that we are imagining a research tool here and not a product feature.)

Once the appropriate manual model has been constructed, the prototype system has been developed and tested in an exploratory way, and the altercontrol boundaries have been mapped out and understood, the methodical approach could then consider the warrants for an enveloping model of the closed-loop human-and-ACC control system. Such modeling would only proceed together with new empirical data taken from increasingly naturalistic testing of a system prototype with lay subjects. Additionally, meaningful measures must be formulated for characterizing driver/vehicle compatibility as it is observed during naturalistic operation.

At this level, one must deliberately seek to understand feedback paths between ACC system manifestation and the driver's processes of a) learning system operation and b) executing system supervision and interventions. Whether cognitive modeling tools prove useful in the future for representing such processes remains to be seen. At this juncture, our expectation is that while the study of cognition models has helped to illuminate the scope of the overall problem, only minimal representation of cognitive processes at the knowledge level of our controller are likely to be practicable in the near term.

7.0 Conclusions and Recommendations

This project has involved a cursory examination of manual stop-and-go driving. The fact that the effort was so productive, in terms of data collection using instrumented vehicles, database compilation, processing of driving data, and the development and validation of a manual control model, was due to the availability of preexisting research tools that enabled each of these efforts. These tools were, for the most part, created earlier at UMTRI under sponsorship from the National Highway Traffic Safety Administration, whose gracious support is hereby acknowledged.

The basic conclusion from this work is that a rather broad exploration of the stop-and-go driving context has yielded the draft version of an ACC control algorithm that reasonably approximates manual headway management in this driving regime. The project has also made progress on methods for documenting concurrent driving experience and for delineating the headway-only versus altercontrol phases that prevail in such driving.

Useful products from the effort include:

- a modest database documenting the stop-and-go driving time histories of eight drivers over a 2 1/2-hour route
- a MATLAB/SIMULINK® code representing the manual control of headway and speed in the stop-and-go environment
- an appendix of experimental results comparing model prediction with actual driving behavior over 61 driving segments that include a complete stop

Consideration has also been given to literature that helps assess the modeling steps by which higher-level cognitive decisions would factor into the driver model. At this point it seems more advisable to consider the overlay of a modest set of decision processes onto the mechanistic model developed here than to adopt anything like the production system models, ACT-R or Soar.

It is recommended that the next step in this research include the implementation and trial operation of an ACC-controlled vehicle whose high-level algorithm is basically that of the manual driver model developed here. It is also recommended that the domain of altercontrol be catalogued at least in an introductory way so that an orderly scoring of the ACC driving experience can be related to the headway-determined versus altercontrol phenomena that are observed within manual driving.

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APPENDIX A

Classical Sensory Psychophysics and Visual Components of Driving

Cavallo, V., Mestre, D. & Berthelon, C. (1997). Time-to-collision judgments: visual and spatio-temporal factors. *Traffic Transport Psychology.* 97-111.

Estimations of time to collision are not based solely on tau, but appear to involve several sources of information concerning the driving environment (distance, apparent size, and egospeed). The source of information used in estimating the time to collision is likely to be task dependent. However, exactly which sources, and rules for combining them, are not yet understood.

Crundall, D. E. and Underwood, G. (1998). Effects of experience and processing demands on visual information acquisition in drivers. *Ergonomics, 41*(4), 448-458.

Experienced drivers select visual strategies, distributing their visual attention under various levels of cognitive load, according to the complexity of the roadway. The strategies of novices are frequently too inflexible to meet the changing demands of a complex driving scenario.

Hoffman, E. & Mortimer, R. (1994). Scaling of relative velocity between vehicles. *Proceedings of the Human Factors and Ergonomics Society 38th Annual Meeting.* 847-855.

A driver's ability to detect changes in headway is limited by a threshold value of approximately a 0.003 radians/sec for changes in subtended angular velocity. Scaling is performed in non-linear manner, however a linear approximation gives a relatively good fit to the data.

Kaiser, M. & Hect, H. (1995). Time-to-passage judgments in non-constant optical flow fields. *Perception & Psychophysics.* *57*(6), 817-825.

Lee, D. (1976). A theory of visual control of braking based on information about time-to-collision. *Perception.* *5*(4), 437-459.

Meyer, F. (1994). Time-to-collision from first-order models of the motion field. *IEEE Transactions on Robotics and Automation, 10*(6), 792-798.

Regan, D., Hamstra, S. & Kaushal, S. (1992). Visual factors in the avoidance of front-to-rear-end highway collisions. *Proceedings of the Human Factors Society 36th Annual Meeting.* 1006-1010.

Research results suggest that it is important for a driver to look directly at a lead vehicle in order to adequately judge time to collision and optimally control braking. Sensitivity to closing rates falls off dramatically in the peripheral field of view.

Rockwell, T. (1988). Spare visual capacity in driving-revisited. New empirical results for an old idea. Vision and Vehicles II, Gale et al. (Editors). Elsevier Science Publishers, 317-324.

The major conclusion from vision research conducted over a six-year period is that glance durations are a reasonably consistent measure of driver " in car" visual performance. Glance duration is impacted more by the demands of the driving task than by the visual characteristics of " in car" targets. Glance frequency, rather than glance duration, is considered to be a more sensitive measure of visual workload imposed by the usage of in-car elements.

Summala, H., Lamble, D. and Laakso, M. (1998). Driving experience and perception of the lead car's braking when looking at in-car targets. *Accident Analysis and Prevention*, *30*(4), 401-407.

Detection of the lead cars brake lights is substantially impaired in daylight when the following driver is looking at the dashboard. Brake lights do not contribute at all to the detection of the lead car's braking when the following driver is looking at areas inside the vehicle such as the console. Different levels of driver experience did not affect the detection of closing headway in the peripheral regime of one's vision.

Ecological Psychology and Driving

Gibson, J. J. and Crooks, L. E. (1938). A theoretical field-analysis of automobile-driving. *The American Journal of Psychology*, *51*(3), 453-471.

Grimm, H. G. (1986). *The need to consider ecological and cognitive approaches in traffic psychology.* Fachbereich Sozialwissen enschaften der FH Karlsruhe.

This article describes a field of traffic psychology. It has not taken full advantage of recent developments particularly in the areas of ecological and cognitive psychology. The author concludes that the general taxonomy of objective conditions in traffic is required; that a detailed analysis of motorist's cognitive representation is essential; and that better interaction between related fields is critical to advancing our knowledge of traffic psychology.

Schiff, W. and Arnone, W. (1995). Perceiving and driving: where parallel roads meet. *Local Applications of the Ecological Approach to Human-Machine Systems, Volume 2*, Hancock, P. (ed.), Laurence Erlbaum Associates, Hillsdale, N.J., 1-35.

Mental Workload and Mental Modeling of the Driving Task

Ranney, T. (1991). Laboratory and closed-course measures of driver decision making. *Proceedings of the Human Factors Society 35th Annual Meeting.* 1144-1148.

Inter-correlations among driving-related tasks were strongest between moving-vehicle tasks, suggesting that controlling a moving vehicle is more strongly influenced by individual differences in performance than from the cognitive requirements of the decision task. Tasks responding to stimuli outside of the vehicle at a distance were associated with higher variability than tasks using stimuli near the subject.

Ranney, T. (1994). Models of driving behavior: A review of the literature. *Accident Analysis and Prevention, 26*(6), 733-750.

The paper reviews models that emphasize the cognitive components of driving behavior. It is concluded that hierarchical control structures and theories of automaticity and errors provide the potential tools for defining alternative criterion measures, such as safety margins, and for developing and testing theories of driving behavior and crash causation. Two examples of models are described.

Robinson, G. H. (1975). Toward measurement of attention as a function of risk and risk preference in man-machine systems. *Human Factors, 17*(3), 236-242.

Rouse, W. B., Edwards, S. L., and Hammer, J. H. (1993). Modeling the dynamics of mental workload and human performance in complex systems. *IEEE Transactions on Systems, Man, and Cybernetics, 23*(6), 1662-1671.

A model of the dynamics of the relationship between subjective workload and human behavior is proposed. Simulation experiments showed that for linear workload models the proposed identification model performed surprisingly well, despite the fact that the underlying "ground truth" has substantial nonlinear and heuristic components.

Stanton, N. A., Young, M. and McCaulder, B. (1997). Drive-by-wire: The case of driver workload and reclaiming control with adaptive cruise control. *Safety Science. 27*(2/3), 149-159.

This study shows the reduction mental workload, within a secondary task paradigm associated with operating adaptive cruise control, contrary to previous research results. More research is needed related to the driver interface of adaptive cruise control systems in order for drivers to develop appropriate mental representations of the systems capabilities and limitations. The authors state that automation at some level does reduce driver workload, but that driver performance is degraded in critical situations.

Stene, T. (1991). Task analysis: driver workload and information needs. *ISATA International Symposium on Automotive Technology and Automation, 24th.* 695-702.

Young, M. S. and Stanton, N. A. (1997). Automotive automation: Investigating the impact on drivers' mental workload. *International Journal of Cognitive Ergonomics. 1(4)*, pp. 325-336.

While automation at some level does lower the driver's mental workload, there remains the possibility that, should a device fail, a driver would be faced with more attentional demand that he could cope with. Contextual action theory (CAT) can explain the perceived imbalance between attention demands and the available resources. The authors suggest a dynamic-allocation-of-function approach to motor vehicle automation in order to provide stable levels of attention demands, thereby maintaining driver performance.

Driver Braking and Steering Behavior in Response to Obstacles or Events

Adams, L. (1994). Review of the literature on obstacle avoidance maneuvers: braking versus steering. *The University of Michigan Transportation Research Institute Report No. UMTRI-94-19.*

A review of the literature has found the drivers are more likely to brake than to steer in response to obstacle. However, the optimal maneuver is more frequently steering alone, or steering combined with braking. While it is unclear why drivers choose their strategies in emergency situations, there appears to be a lack of knowledge regarding alternative maneuvers as well as handling capabilities of their vehicles. Informing drivers about which maneuvers might maximize their success may decrease the number of accidents.

Groeger, J., Grande, G. & Brown, I. (1991). Accuracy and safety: effects of different training procedures on a time-to-coincidence task. *Vision in Vehicles III*, 35-43.

Kopf, M. (1997). Driver-vehicle interaction while driving with ACC in borderline situations. *Proceedings from the Fourth World Congress on Intelligent Transport Systems.*

Three versions of adaptive cruise control were tested; differing mainly in the maximum level of deceleration which could be applied. The goal the experiment was to study borderline situations that might result from a mismatch between the driver's mental model of the system and actual system performance. It was shown that drivers were able to learn adaptive cruise control system behavior, thereby reducing driver workload associated with the intervention decision process. The results can be used to design adequate man machine interfaces, reducing the frequency of borderline situations, by supporting driver's prediction capabilities.

Lieberman, D., Ben-David, G., Schweitzer, N., Apter, Y. & Parush, A. (1995). A field study on braking responses during driving. I. Triggering and modulation. *Ergonomics*, *38*(9), 1894-1902.

A study of emergency braking concluded that the visual angular velocity during optical expansion of the lead vehicle image may be used by drivers to continuously modulate braking behavior, while the onset of brake lights, by itself, may be enough to trigger a "ballistic" preventative response. In addition, the experiment showed that shorter following distances predisposed individuals to react faster, independent of the driving speed.

Nilsson, L. (1995). Safety effects of adaptive cruise controls in critical traffic situations. *Proceedings from the Second World Congress on Intelligent Transport Systems*. 1254-1259.

Schweitzer, N., Apter, Y., Ben-David, F., Lieberman, D. & Parush, A. (1995). A field study on braking responses during driving. Minimum driver braking times. *Ergonomics*. *38*(9), 1903-1910.

Sohn, S. & Stepleman, R. (1998). Meta-analysis on total braking time. *Ergonomics*. *41*(8), 1129-1140.

A meta-analysis revealed that only two characteristics were influential on the mean of total braking time: the awareness level of the driver and country in which the experiment took place. For variance of total braking time, four characteristics were influential: the distance from the brake stimulus, the awareness of the driver, the type of brake stimulus, and country in which experiment took place.

Taoka, G. (1989). An analytical model for driver response. *Transportation Research Record. 1213*, 1-3.

This research showed that a lognormal function could be used to model the probability density function of the surprise response times of drivers. The median driver should respond within 1.2 seconds, the mean driver within 1.4 seconds, in the fifth percentile driver within 1.9 seconds, under surprise braking conditions.

Van der Horst, R. (1991). Time-to-collision as a cue for decision-making in braking. *Vision in Vehicles. 3*, 19-26.

Van Winsum, W. and Brouwer, W. (1997). Time headway in car following and operational performance during unexpected braking. *Perceptual and Motor Skills. 84*, 1247-1257.

Van Winsum, W. and Heino, A. (1996). Choice of time-headway in car following and the role of time-to-collision information in braking. *Ergonomics. 39*(4), 579-592.

Modeling Driver Behavior

Hattori, Y., Asano, K., Iwama, N. & Shigematsu, T. (1994). A decelerating driver model in a car-following situation. *AVEC '94*. 414-419.

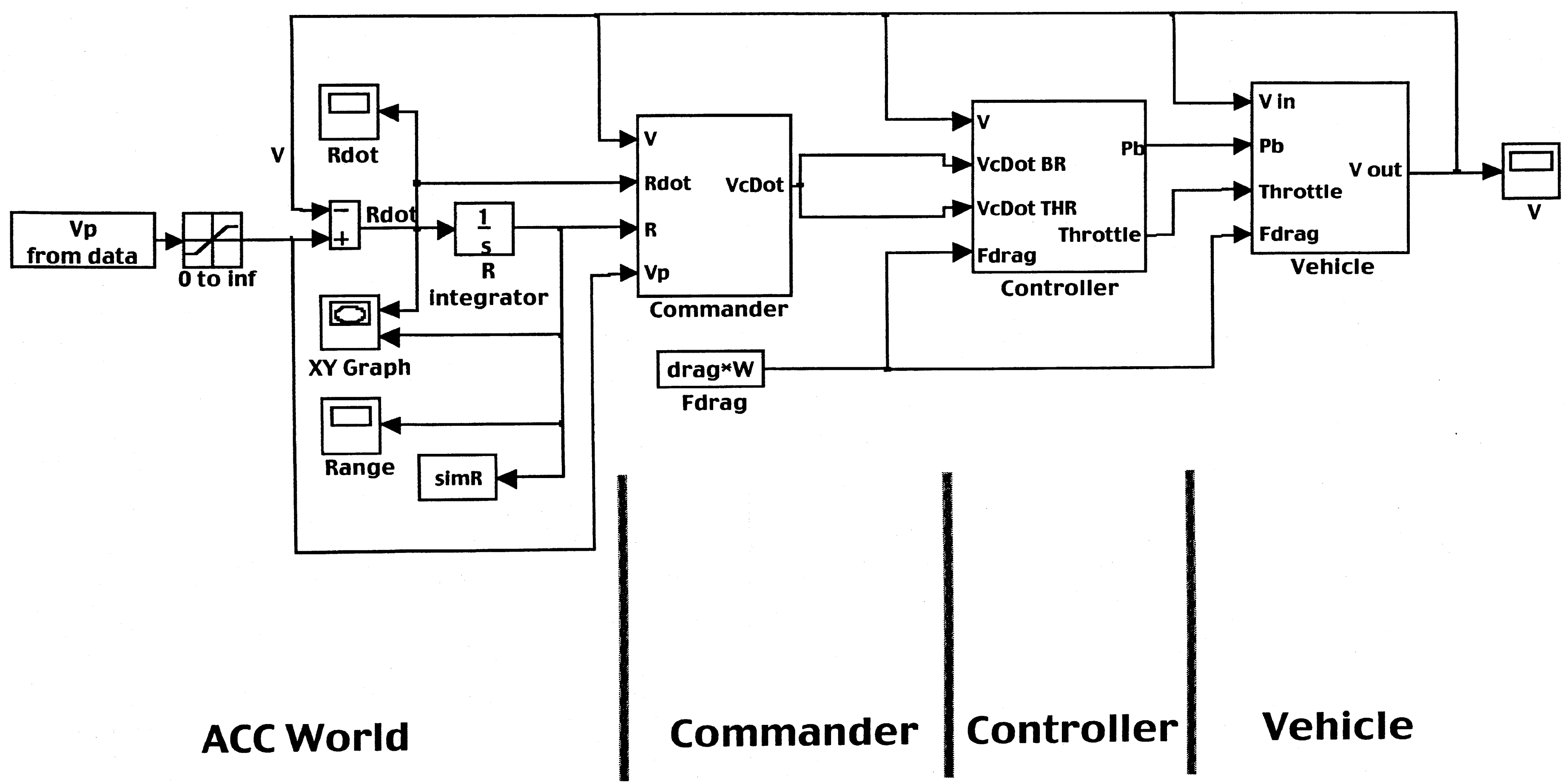
Hattori, Y., Asano, K., Iwama, N. & Shigematsu, T. (1995). Analysis of driver's decelerating strategy in a car-following situation. *Vehicle System Dynamics. 24*, 299-311.

Ludmann, J., Neunzig, D. & Weilkes, M. (1997). Traffic simulation with consideration of driver models, theory and examples. *Vehicle System Dynamics. 27*, 491-516.

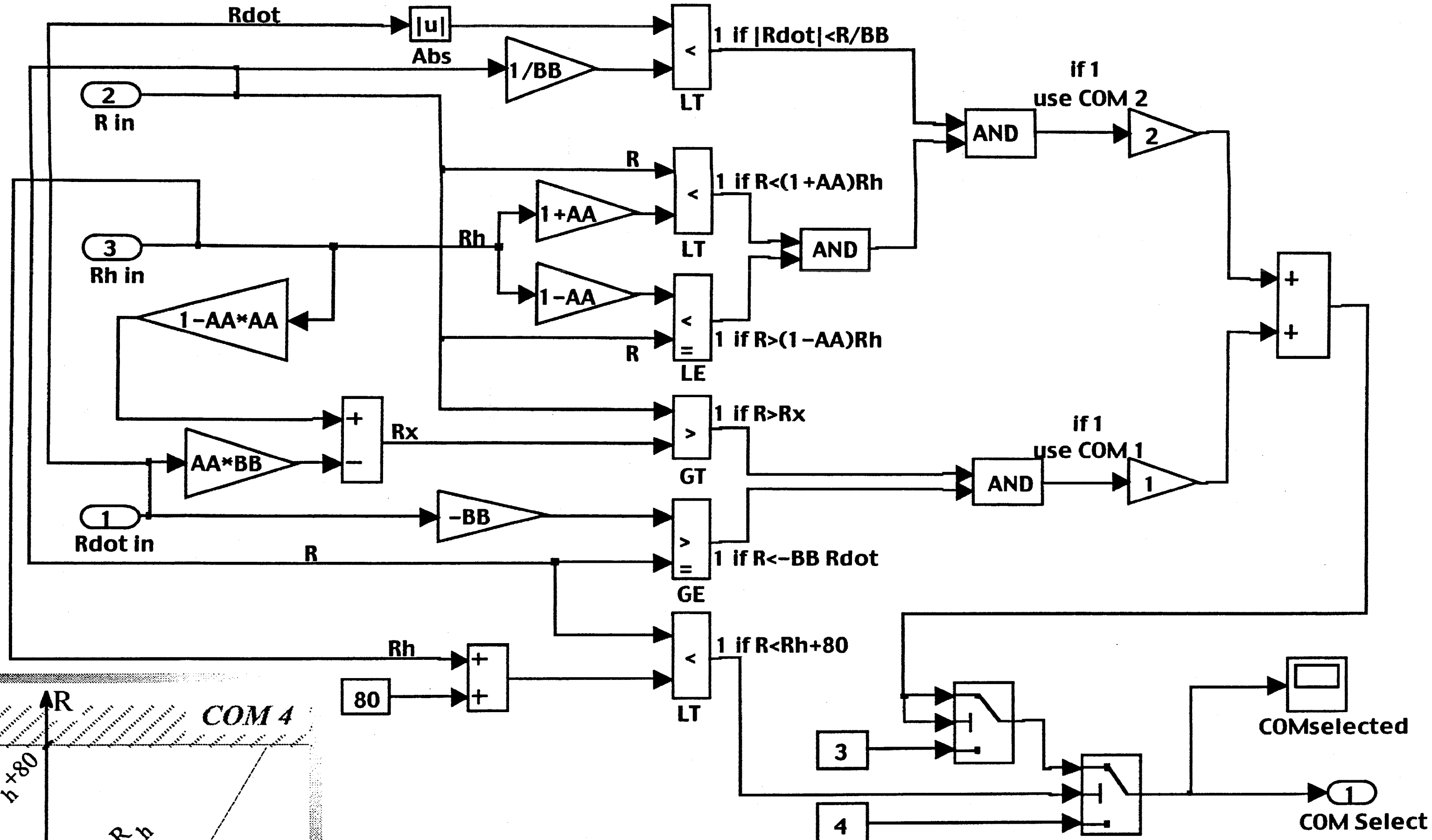
This article discusses traffic simulation models that incorporate several types of driver-based models. Models of driver following, accelerating from a stop, stopping a motor vehicle, and the use of adaptive cruise control in suburban traffic are discussed. The authors conclude that the most cost-effective means of increasing traffic flow and reducing travel time in urban areas is through the use of adaptive cruise control as well as the installation of intelligent traffic light systems.

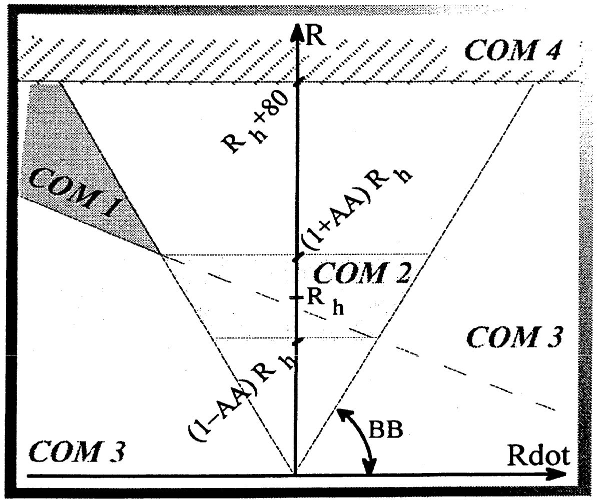
APPENDIX B

BMW Stop-and-Go Model



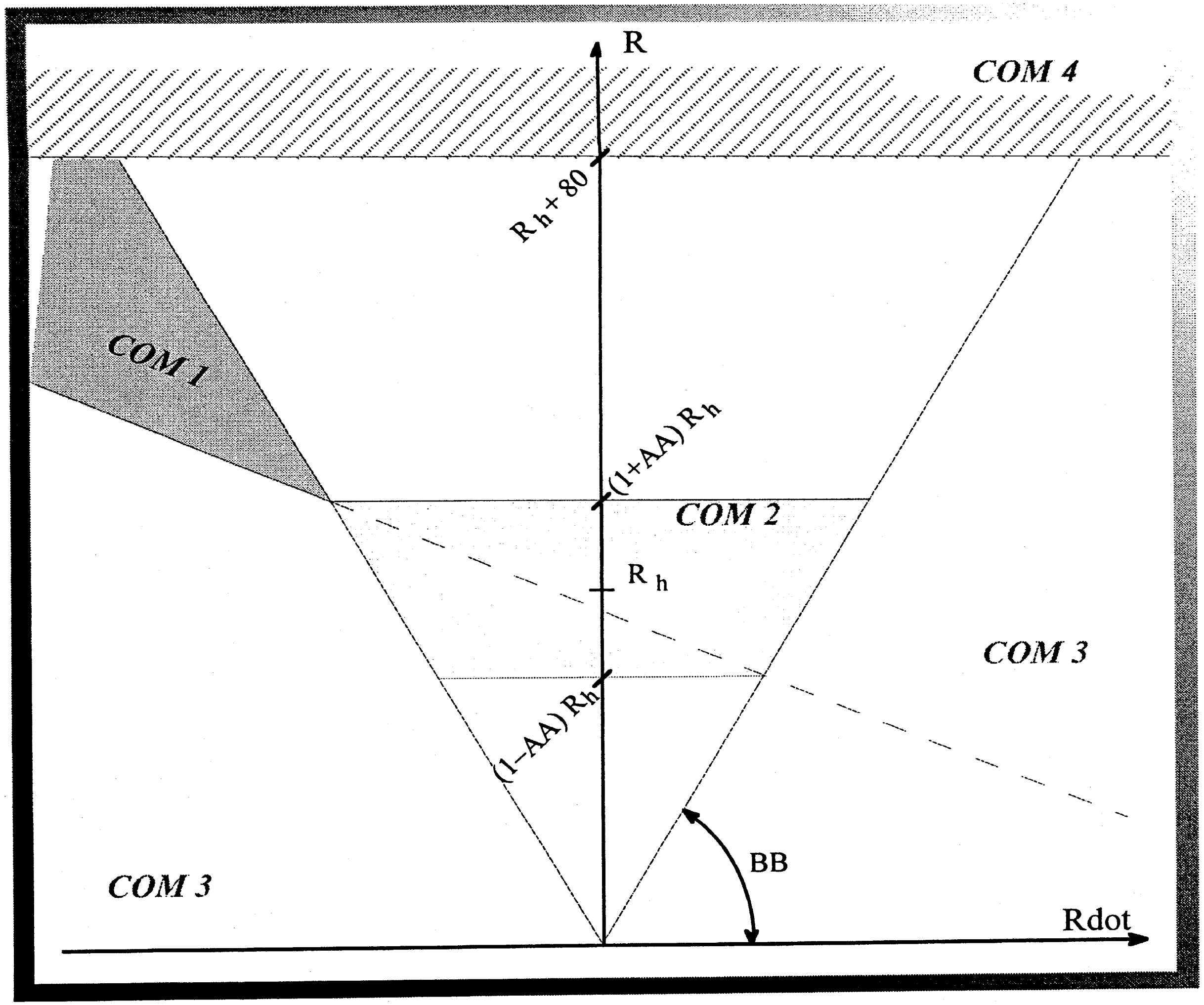
Command Selector



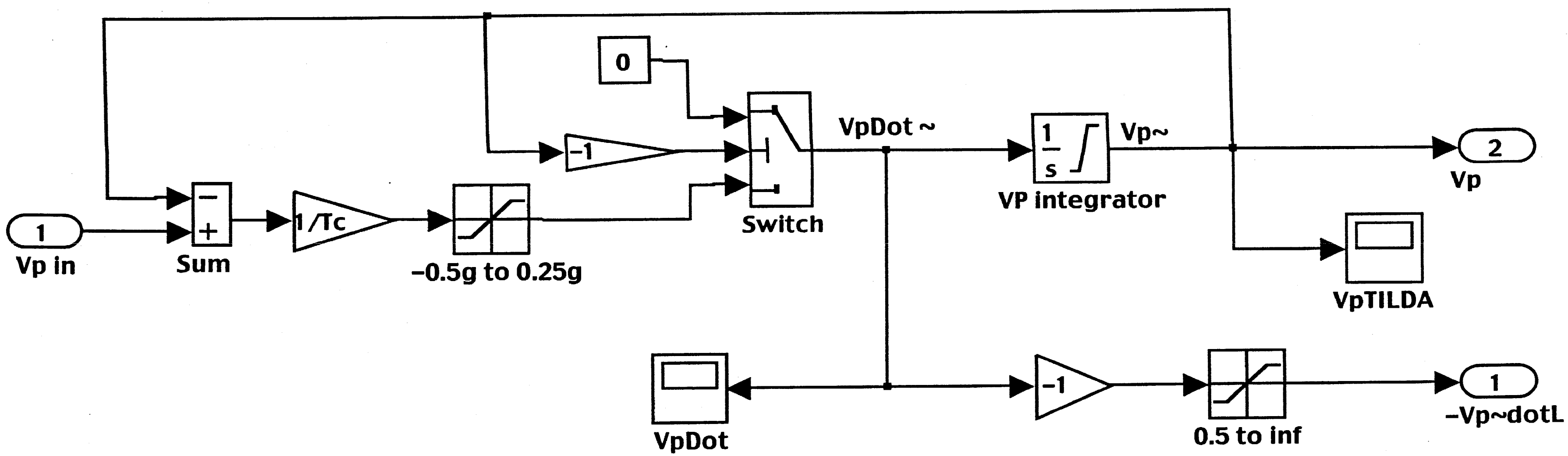


Output: Zone number to determine which command should be selected.

Command Zones

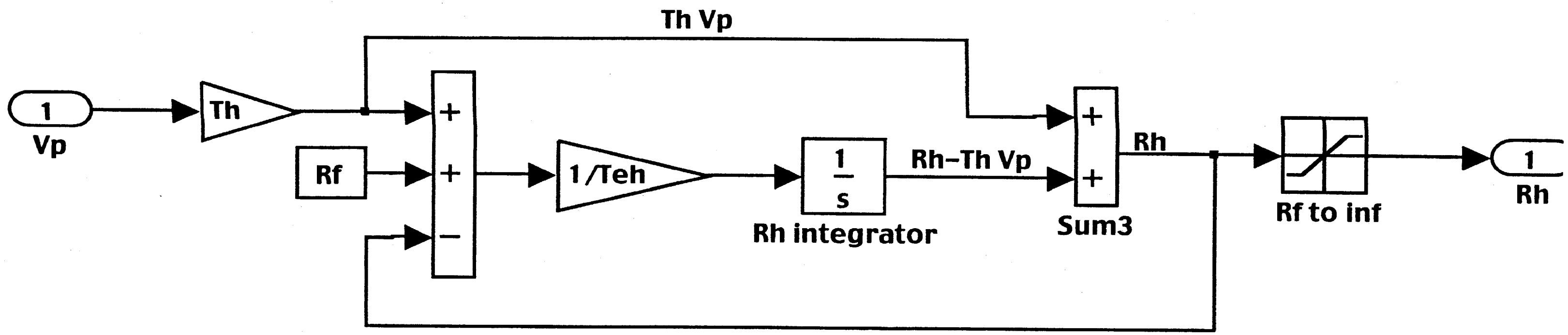


TILDA processor



$$\dot{\tilde{V}}_p = \frac{V_p - \tilde{V}_p}{T_c}$$

Rh Calculation

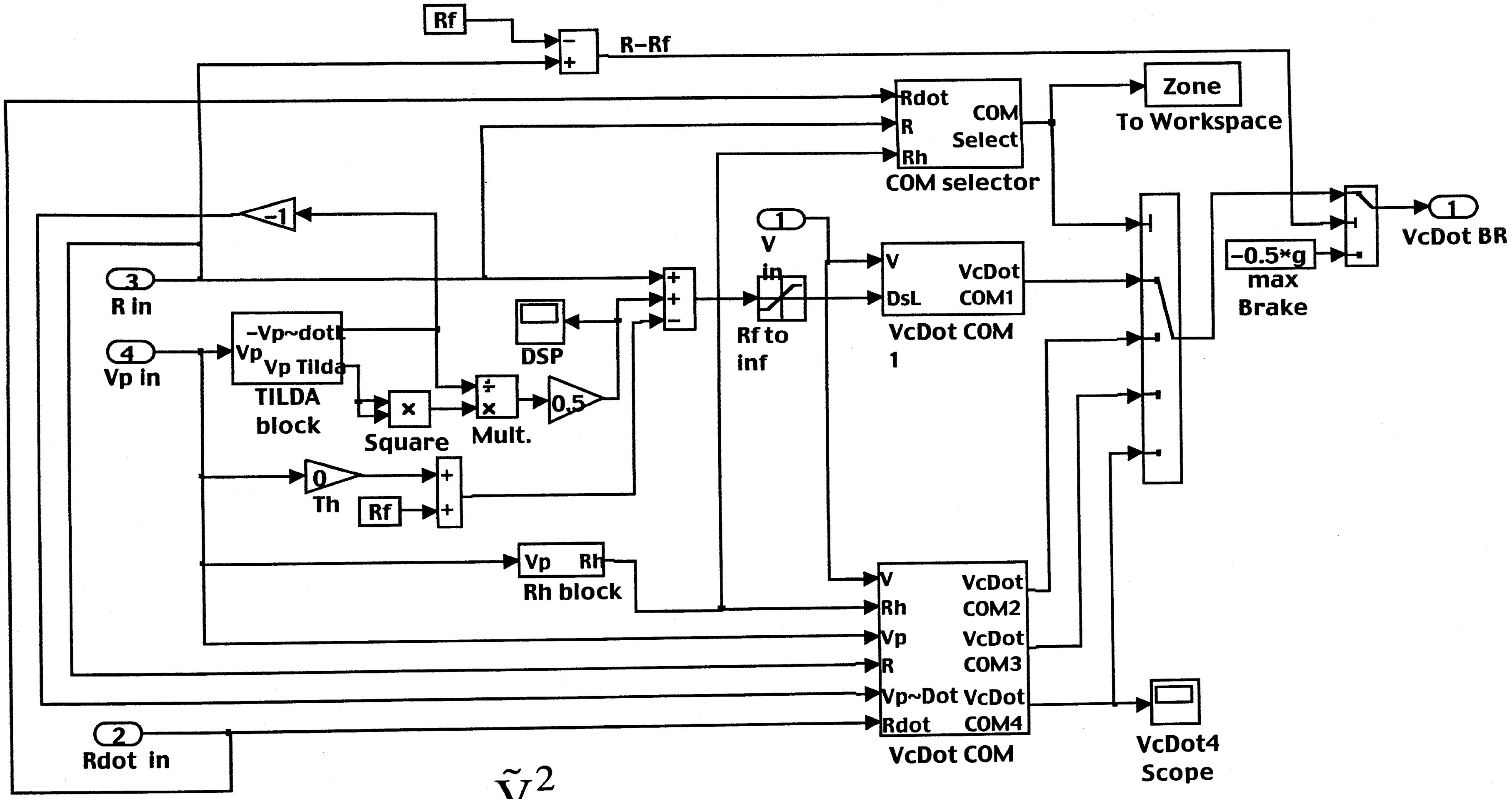


$$\dot{R}_h - T_h \cdot \dot{V}_p = \frac{-\left(R_h - R_f - T_h \cdot V_p\right)}{T_{eh}}$$

$$R_h - T_h \cdot V_p = \int \left(\dot{R}_h - T_h \cdot \dot{V}_p\right) dt$$

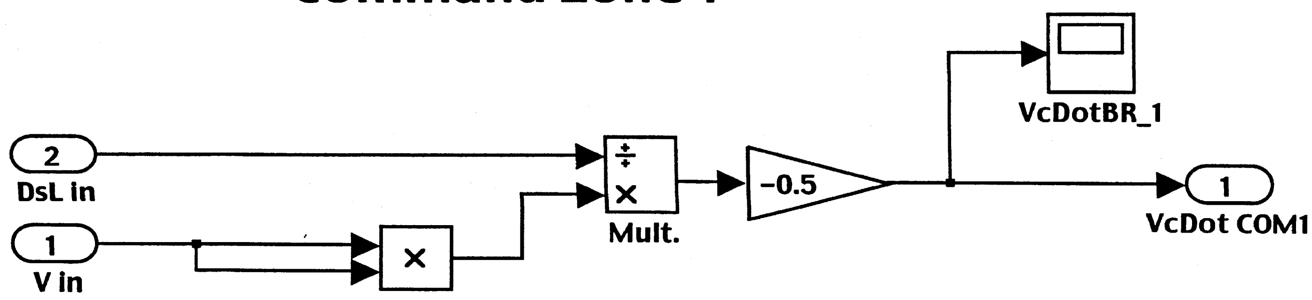
Note: We continue to work on an appropriate way to compute the desired headway range, Th

Commander



$$D_s = R + \frac{\tilde{V}_p^2}{2 \cdot \dot{\tilde{V}}_p} - R_f \qquad \dot{V}_c = f(Zone)$$

Command Zone 1

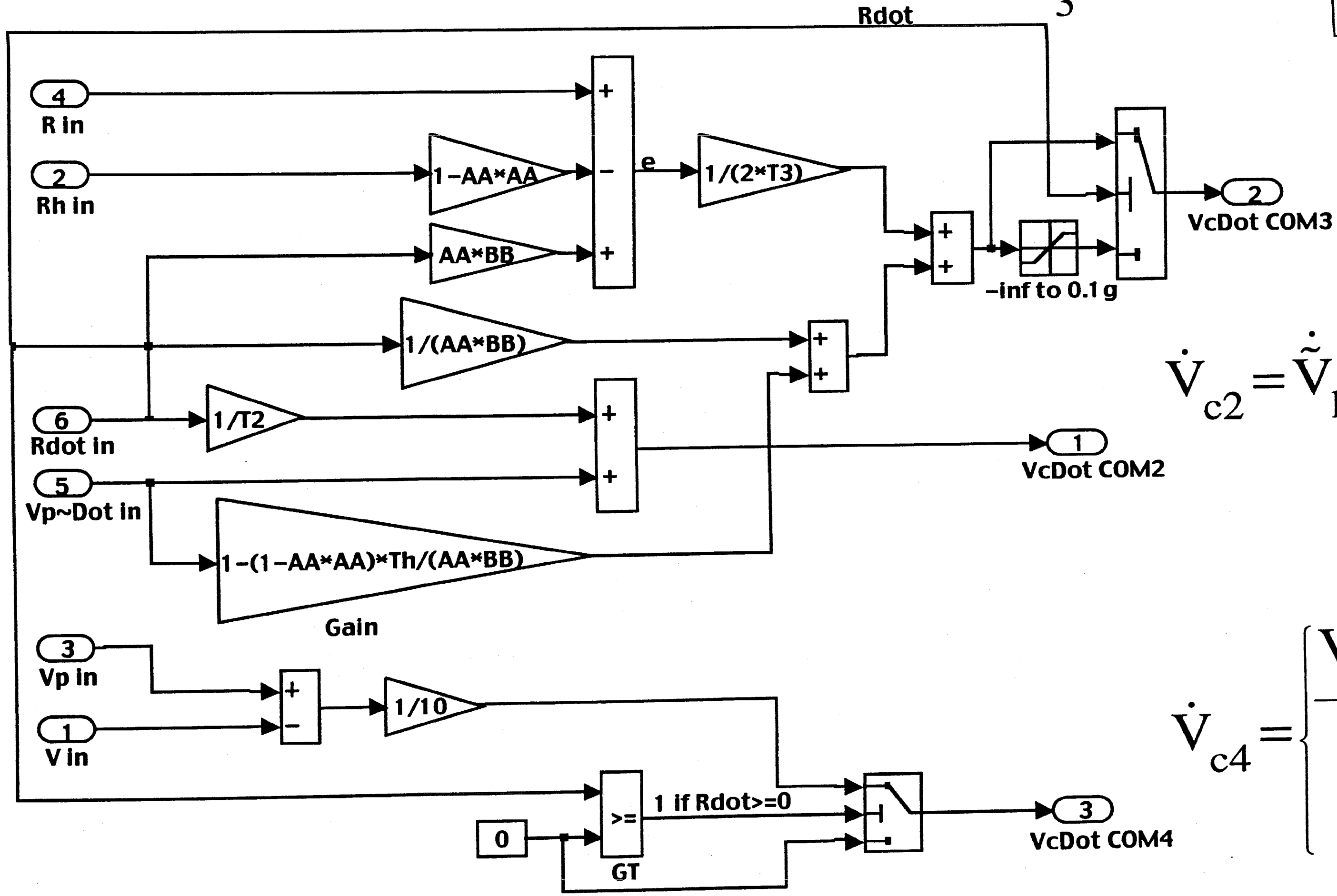


$$\dot{V}_{c1} = \frac{V^2}{-2D_s}$$

Command Zones 2, 3, and 4

$$e = R - \left(1 - A^2\right)\cdot R_h + \dot{R}\cdot A\cdot B$$

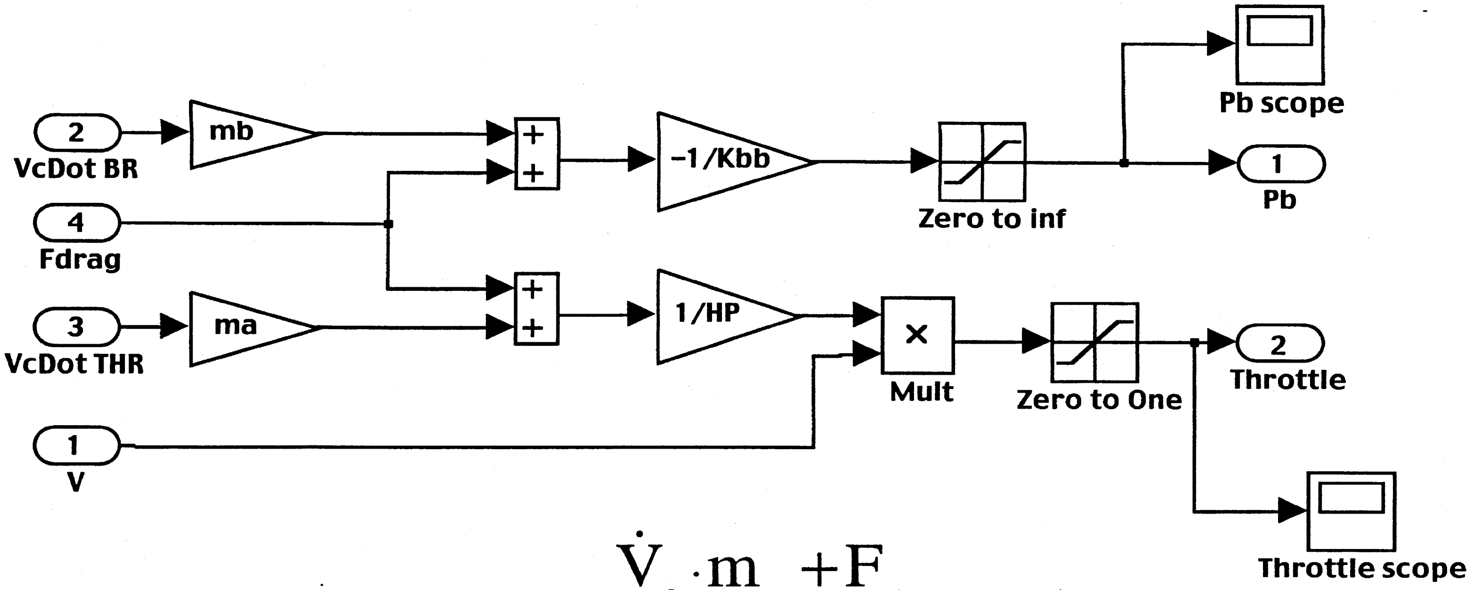
$$\dot{V}_{c3} = \frac{e}{2\cdot T_3} + \frac{\dot{R}}{A\cdot B} + \dot{\tilde{V}}_p\left[1 - \frac{\left(1 - A^2\right)\cdot T_h}{A\cdot B}\right]$$



$$\dot{V}_{c2} = \dot{\tilde{V}}_p + \frac{\dot{R}}{T_2}$$

$$\dot{V}_{c4} = \begin{cases} \dfrac{V_p - V}{10} & \dot{R} > 0 \\ 0 & \dot{R} \le 0 \end{cases}$$

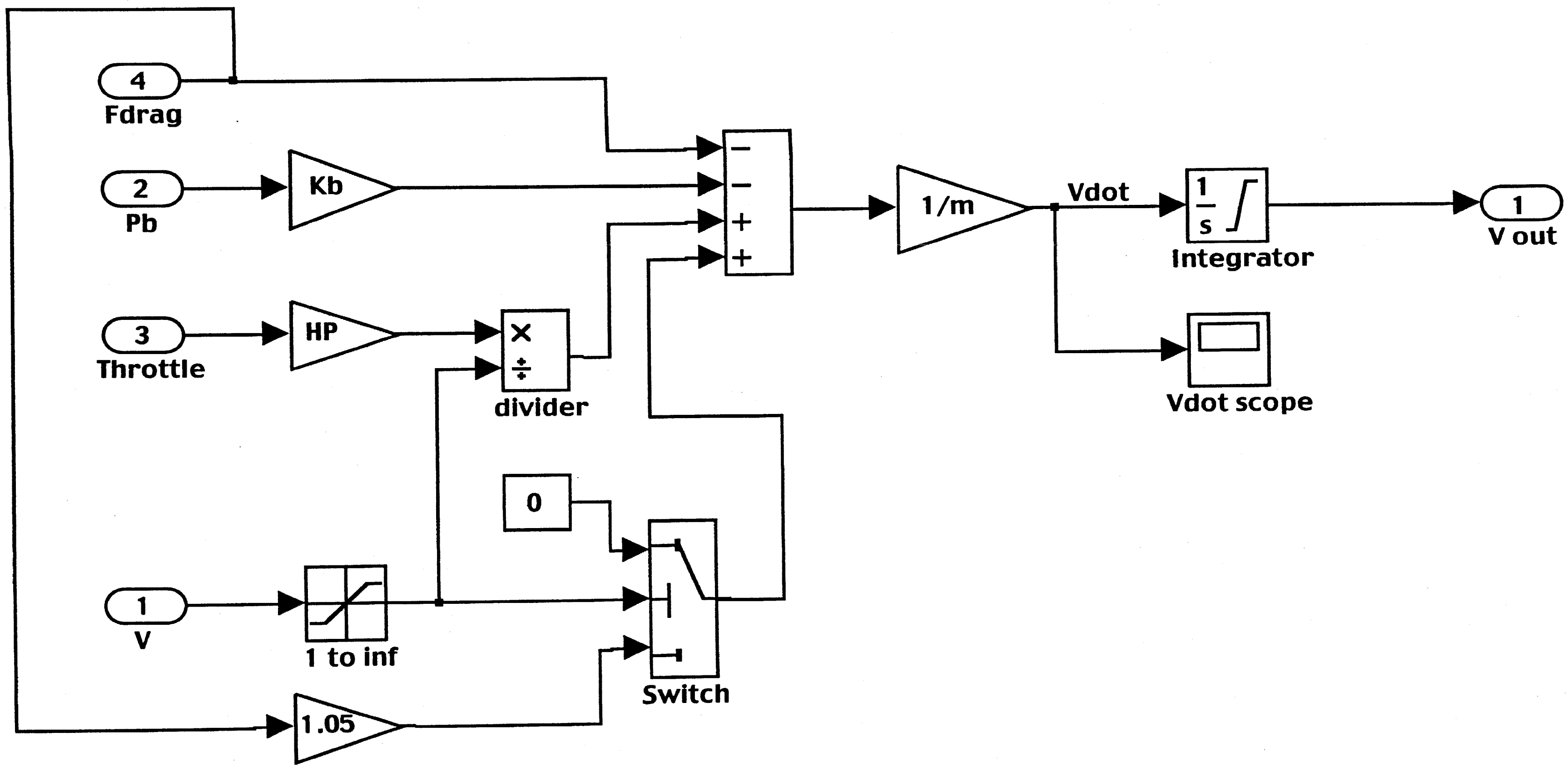
Controller



$$P_b = \frac{\dot{V}_c \cdot m_b + F_{drag}}{-K_{bb}}$$

$$\delta = \frac{\dot{V}_c \cdot m_a + F_{drag}}{HP} \cdot V$$

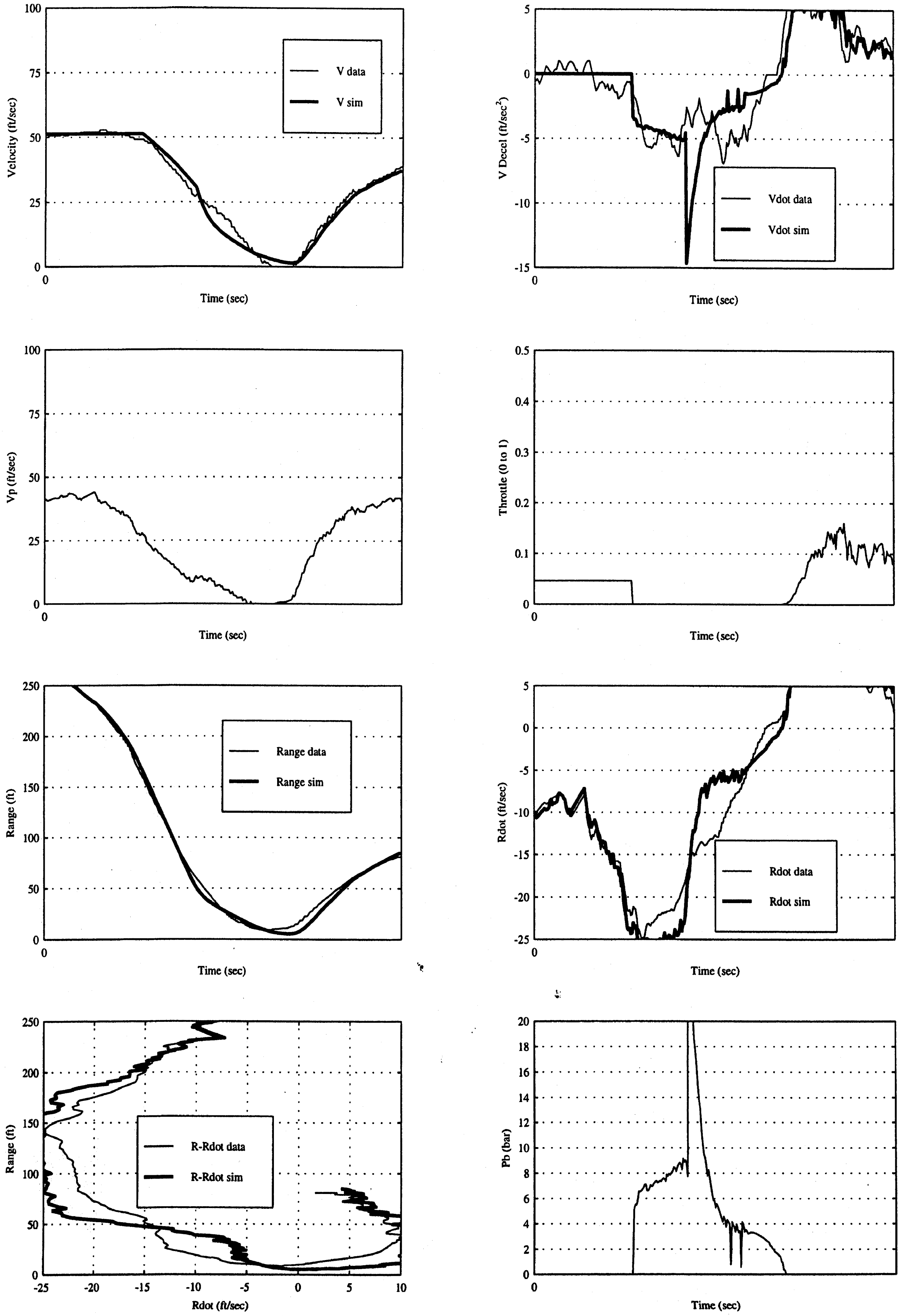
Vehicle



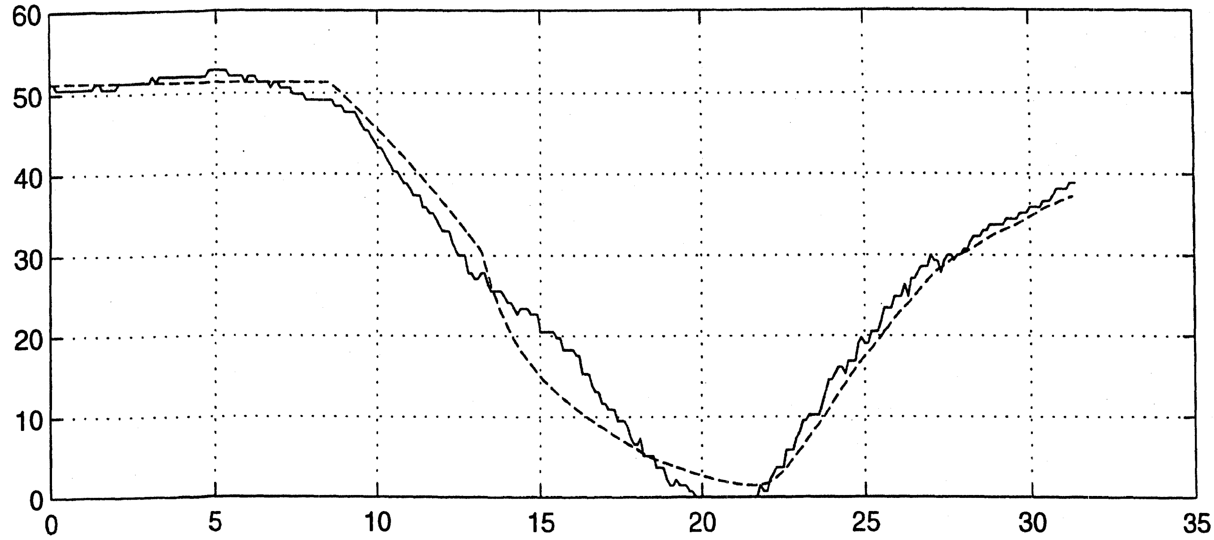
$$m\dot{V} = \frac{\delta \cdot HP}{V} - F_b - F_{drag}$$

APPENDIX C

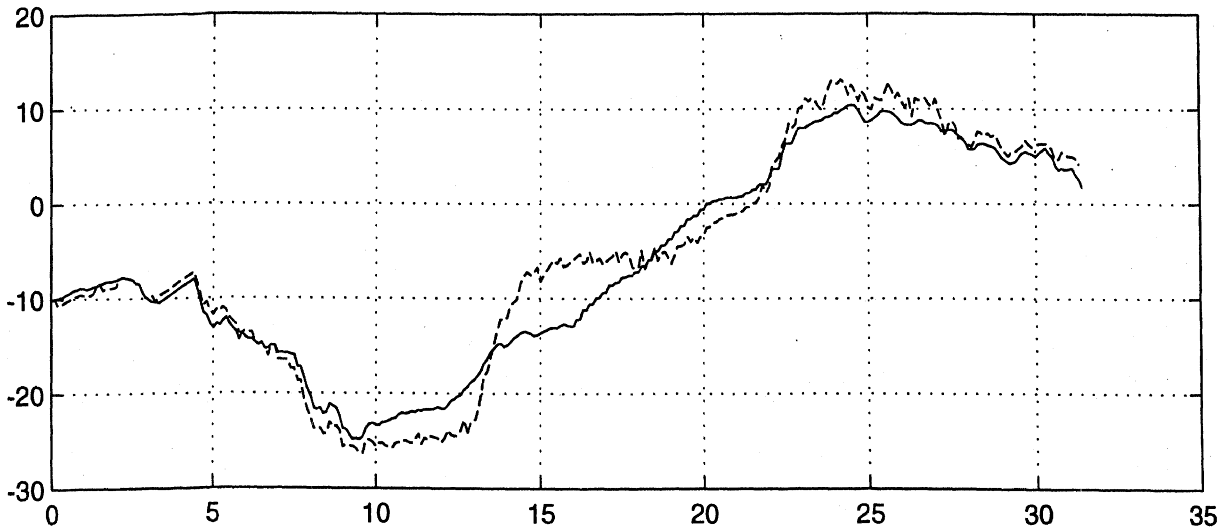
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.3, Tc = 2.8, T2 = 2.8, T3 = 2.3
Driver: z133$_1$03.txt



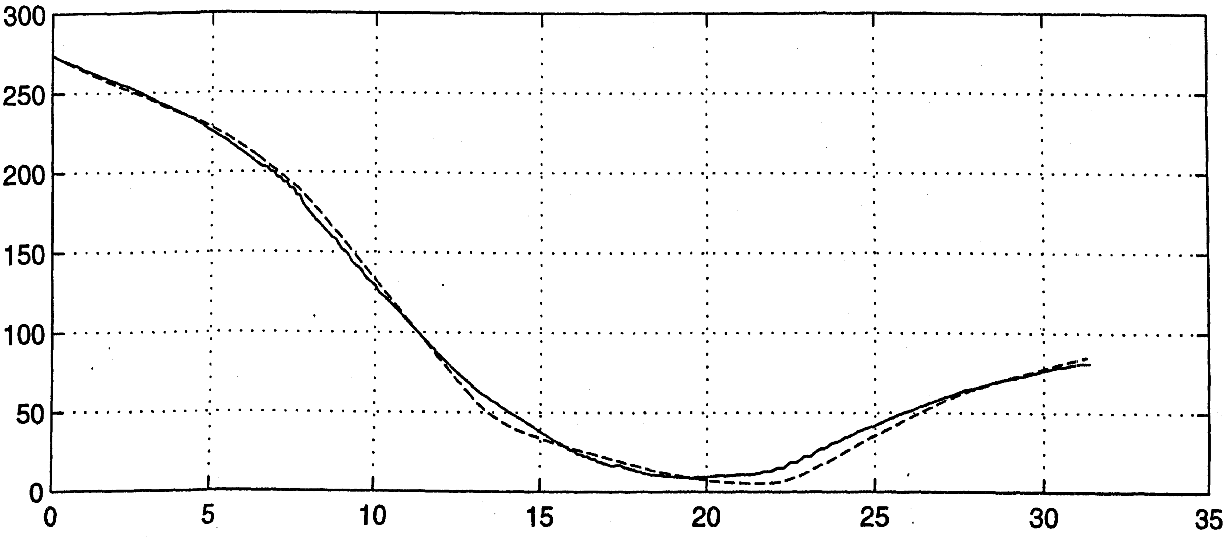
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.3, Tc = 2.8, T2 = 2.8, T3 = 2.3, rms = 4.74, meanRerr = 3.73
Driver: z133_1 03.txt



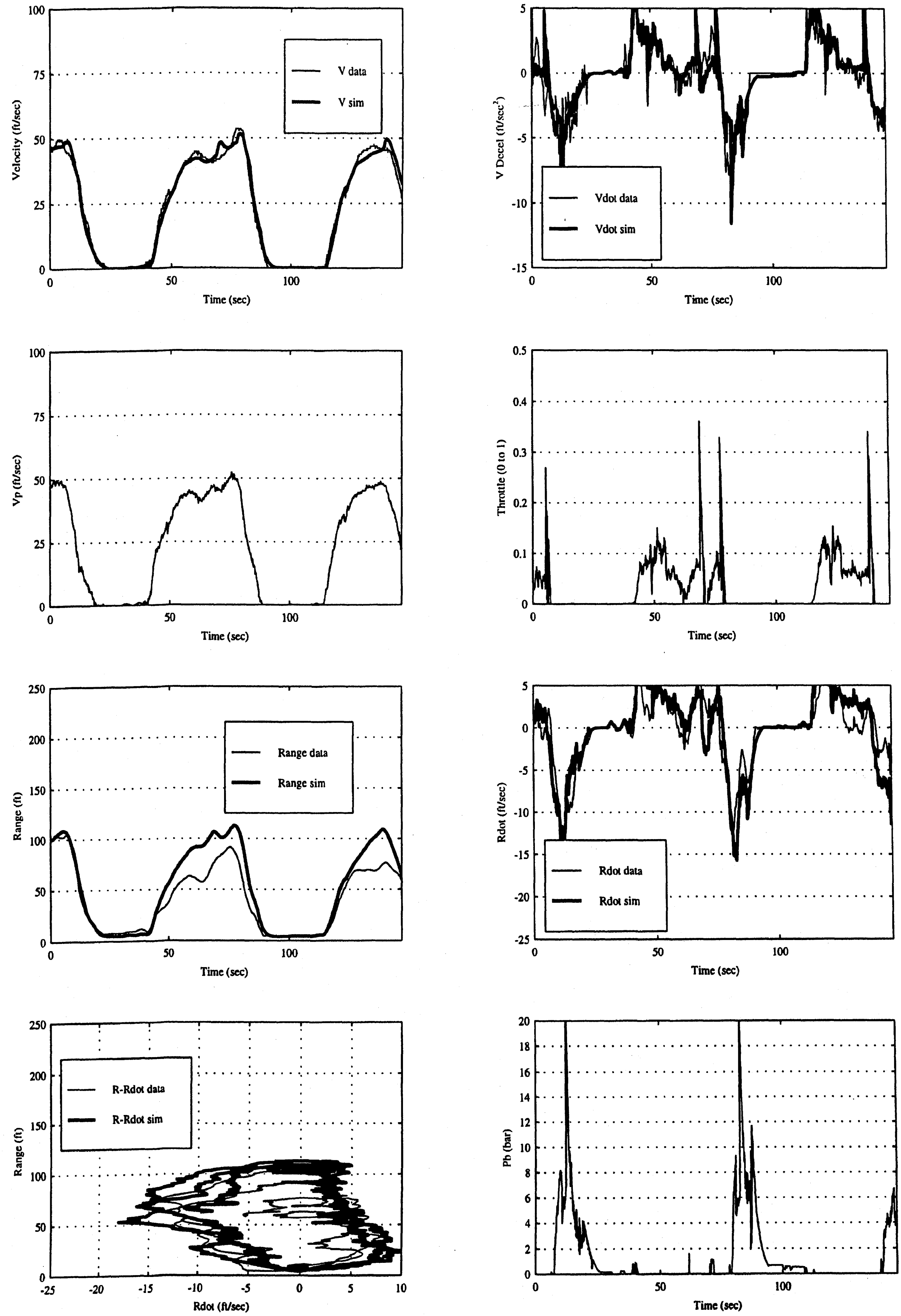
Rdot



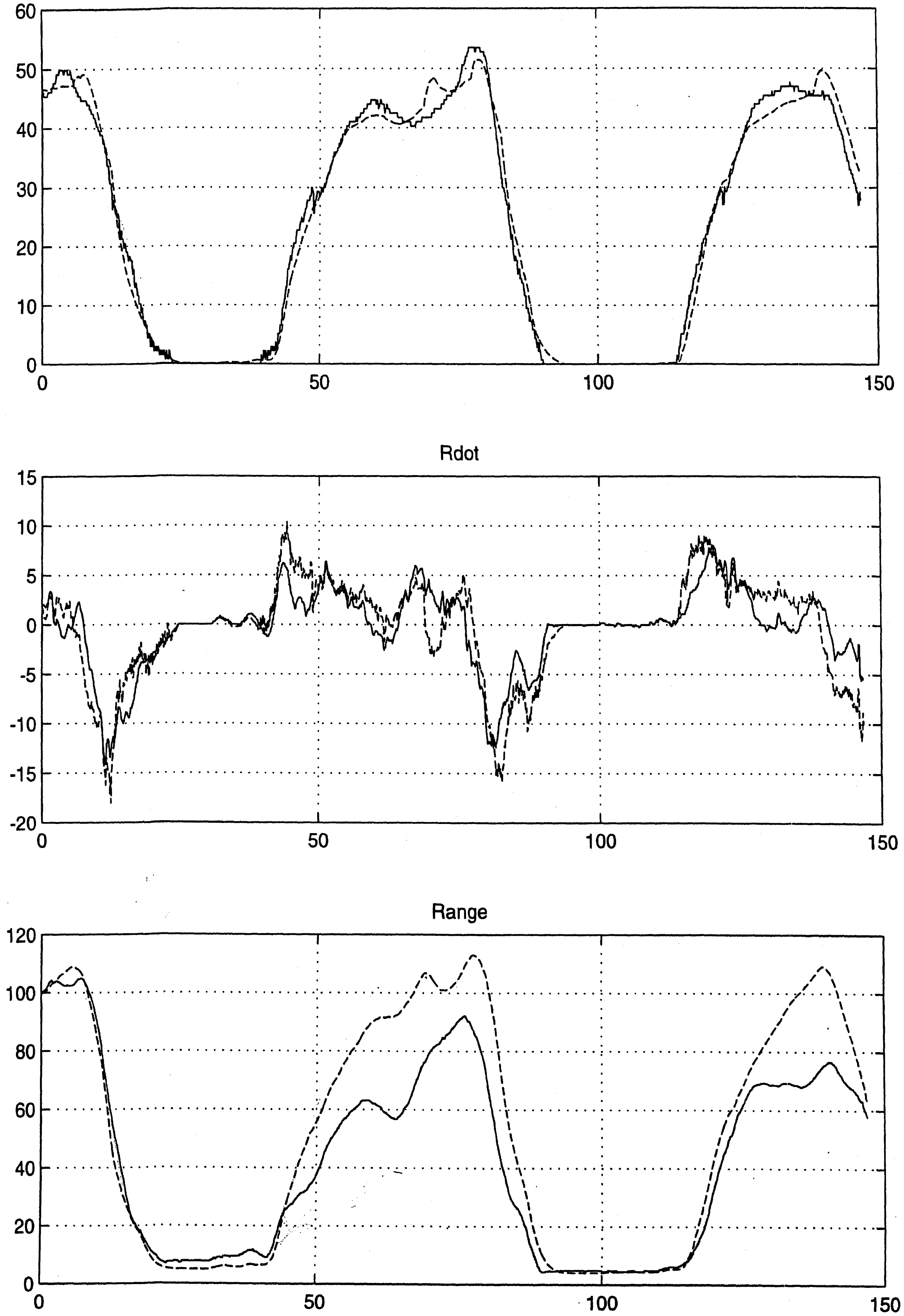
Range



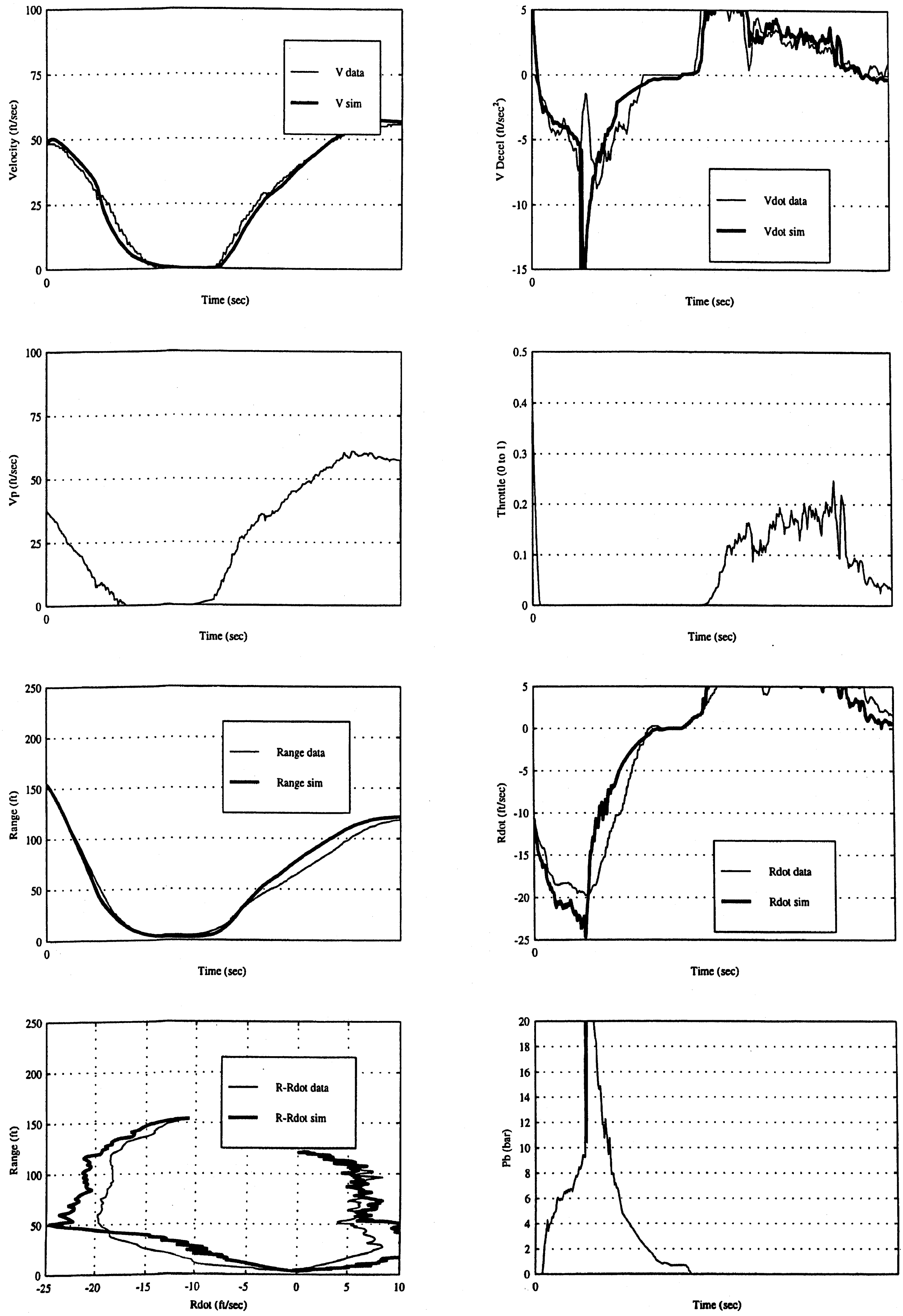
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.8, Tc = 2.8, T2 = 2.8, T3 = 1.8
Driver: z133$_1$04.txt

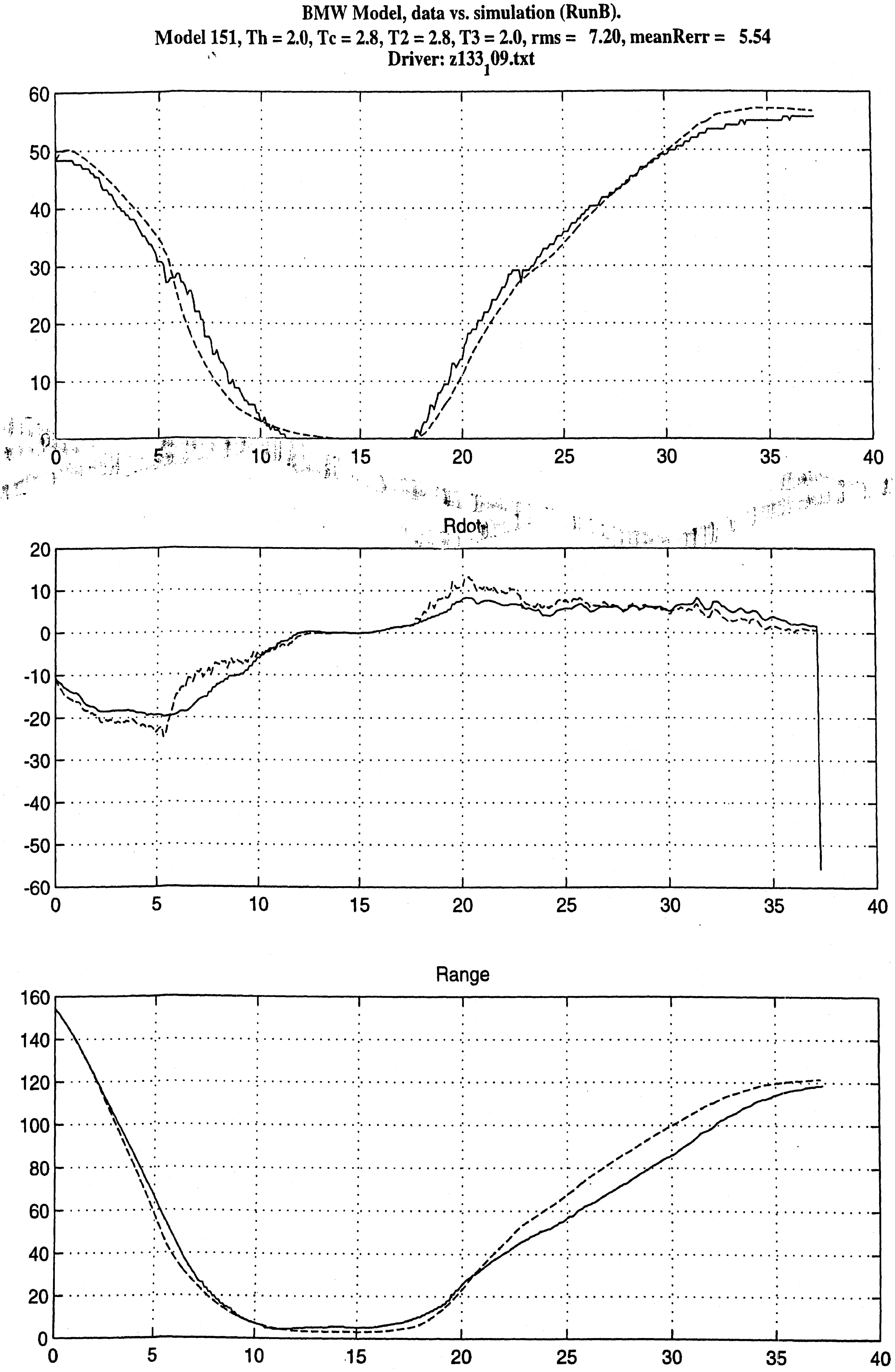


BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.8, Tc = 2.8, T2 = 2.8, T3 = 1.8, rms = 16.32, meanRerr = 11.63
Driver: $z133_1 04$.txt

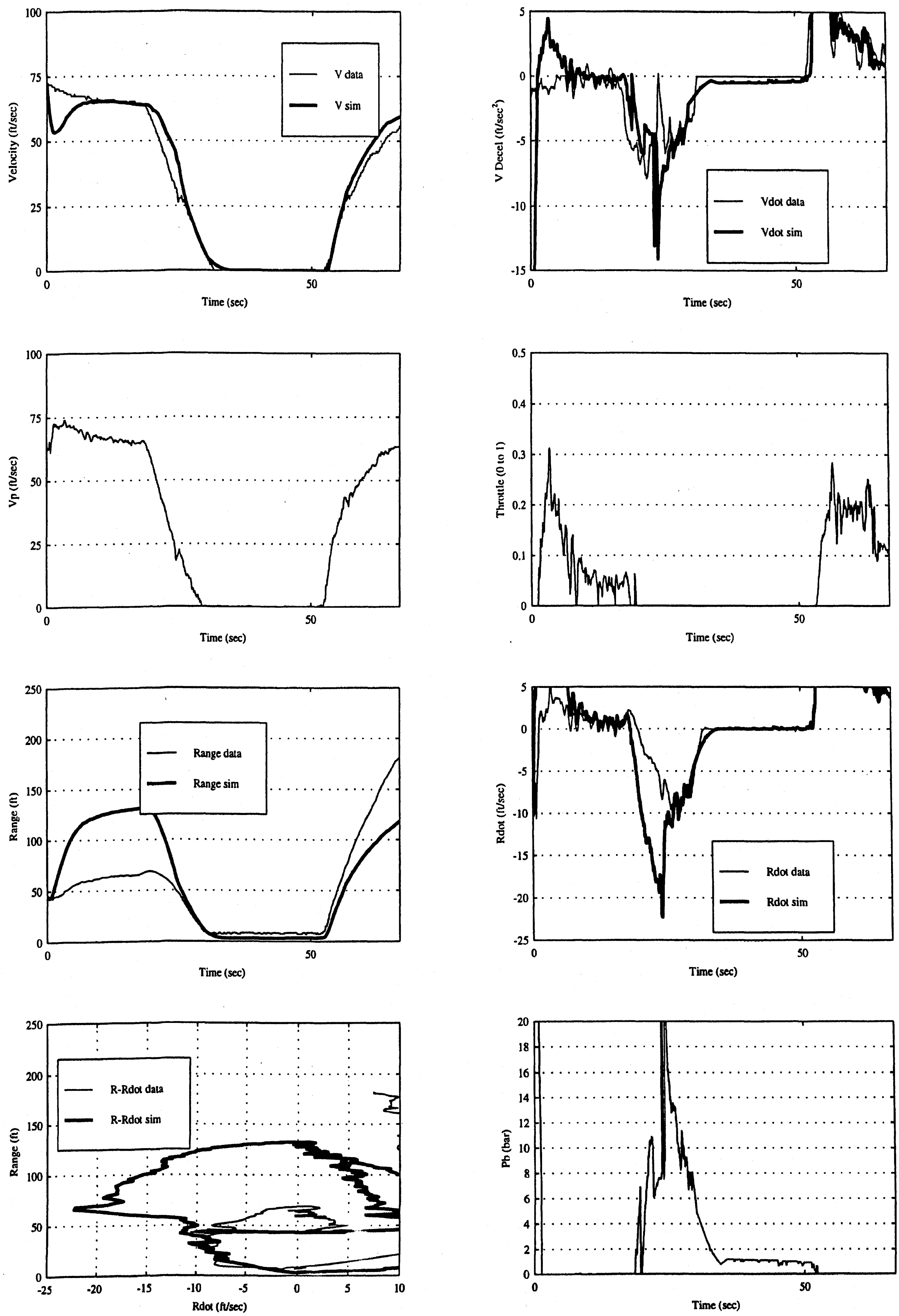


BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0
Driver: z133$_1$09.txt

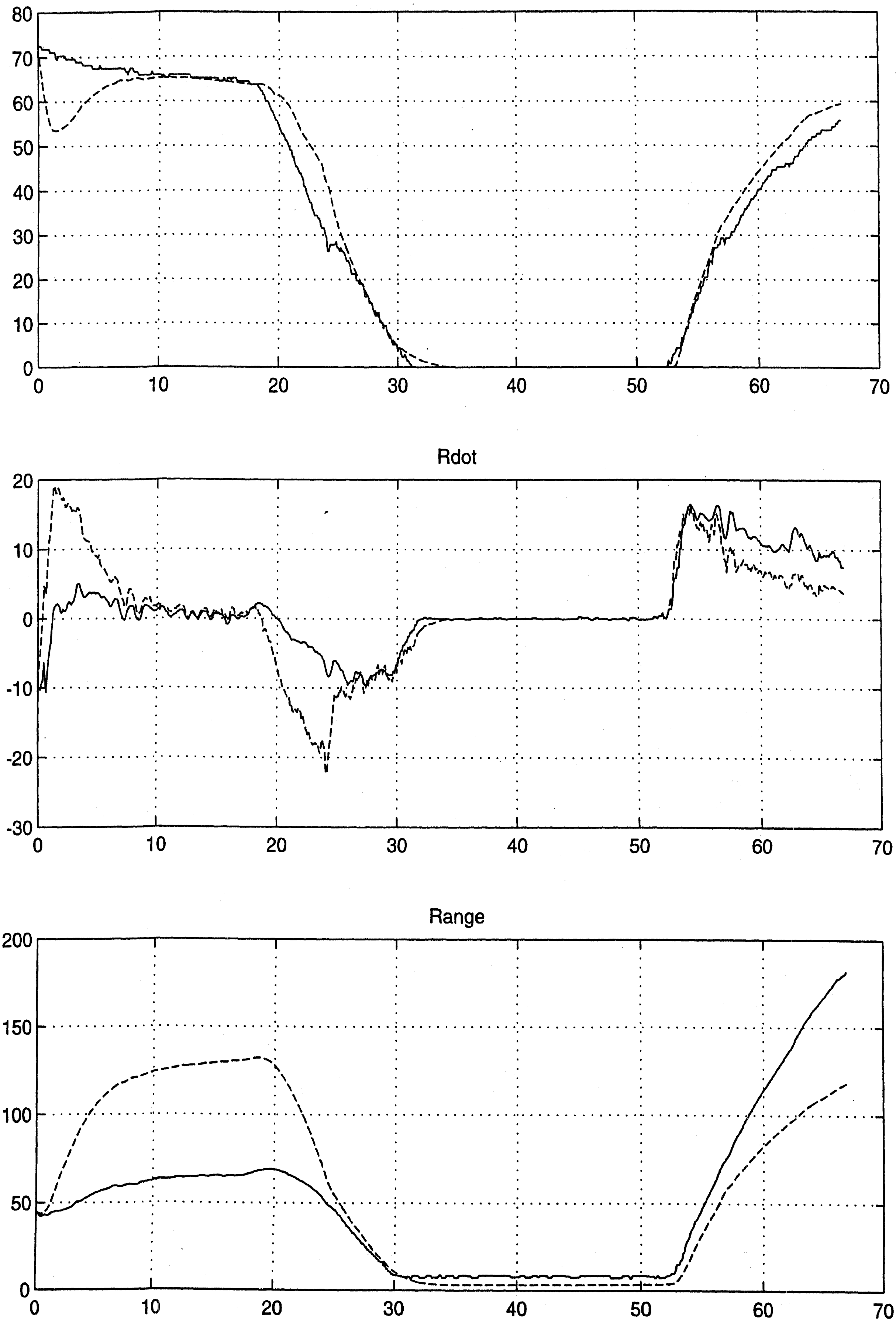



BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0, rms = 7.20, meanRerr = 5.54
Driver: z133_1 09.txt
60
50
40
30
20
10
0
5
10
15
20
25
30
35
40
Rdot
20
10
0
-10
-20
-30
-40
-50
-60
Range
160
140
120
100
80
60
40
20

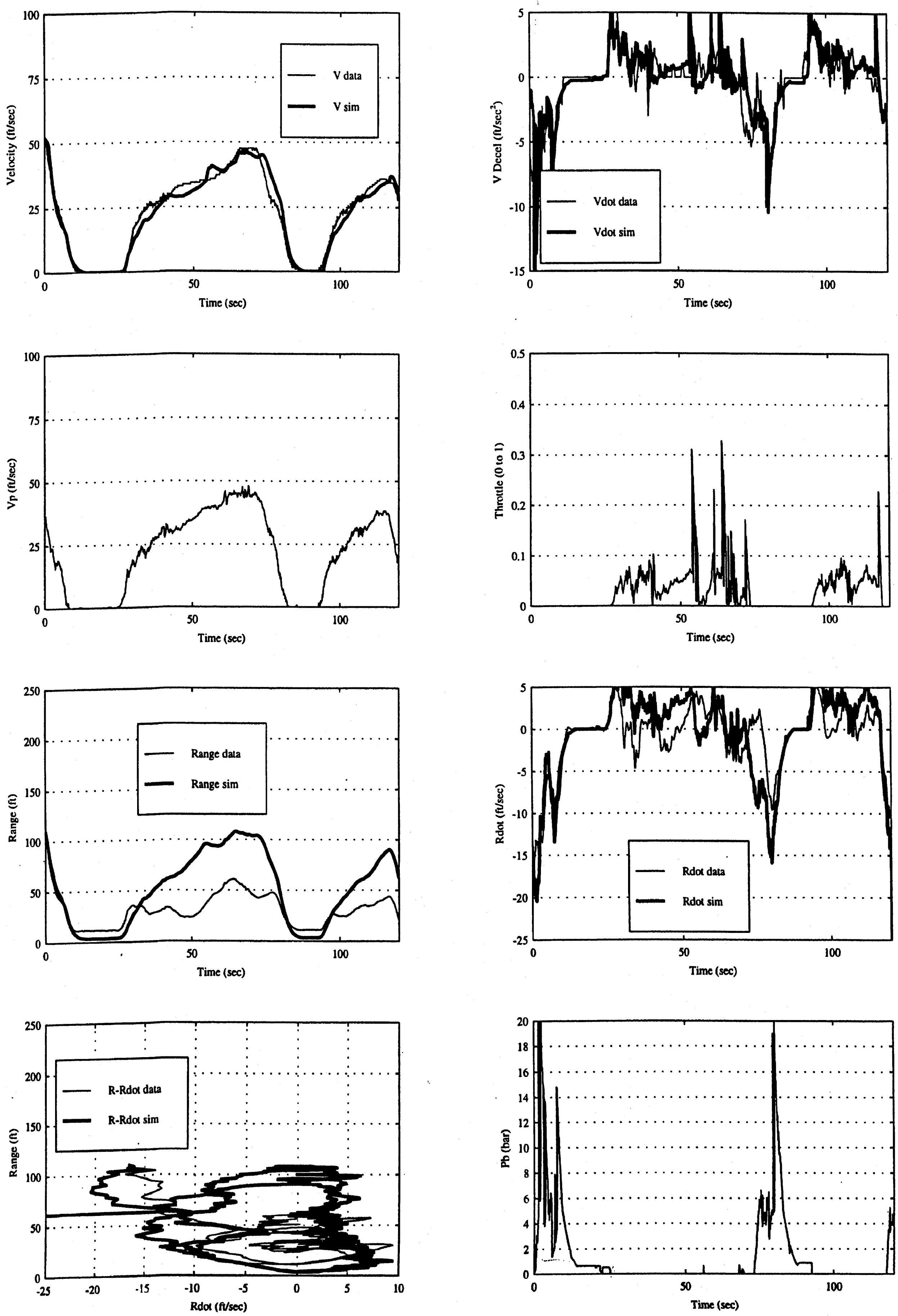
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.8, Tc = 2.8, T2 = 2.8, T3 = 1.8
Driver: z133$_1$10.txt



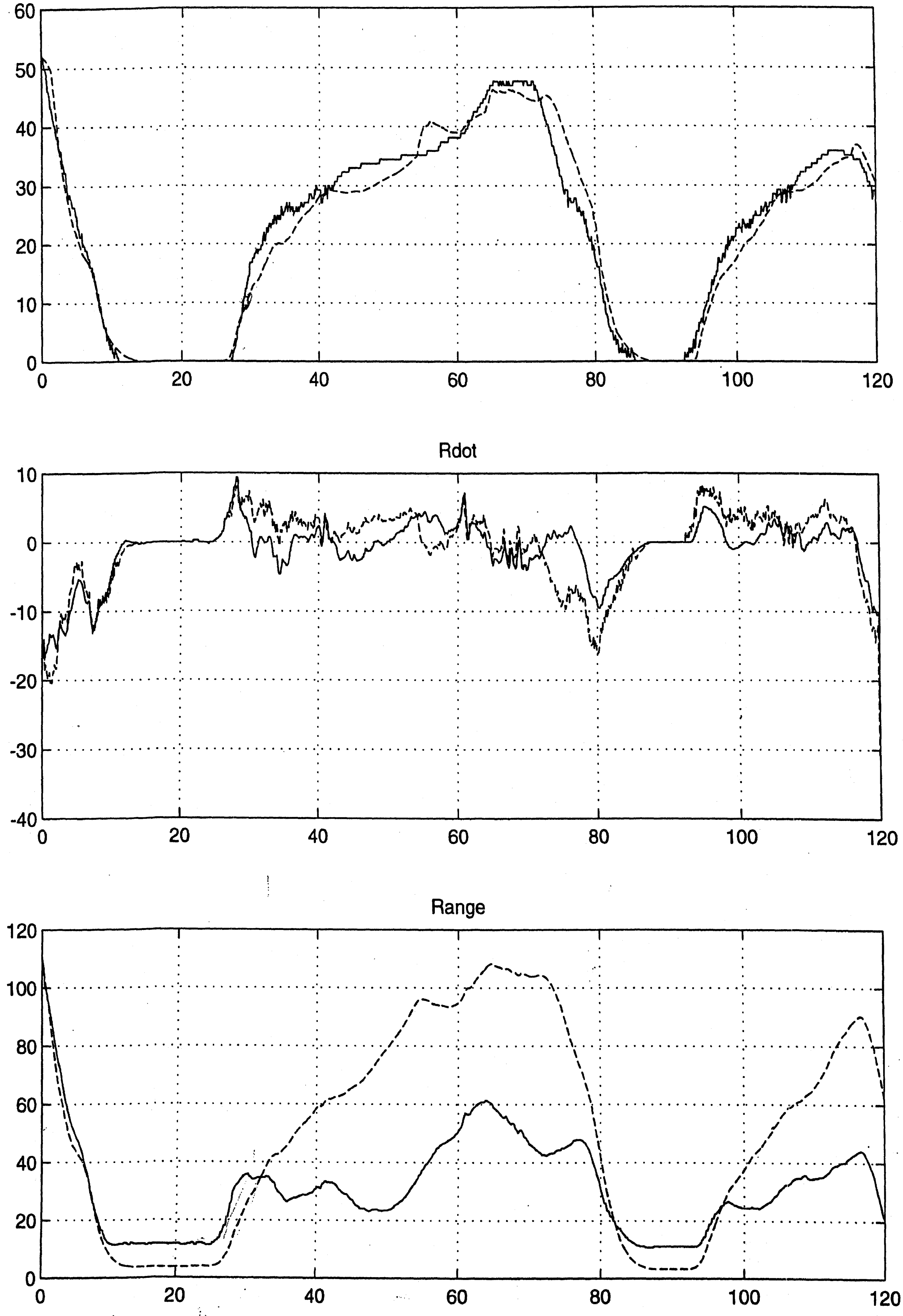
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.8, Tc = 2.8, T2 = 2.8, T3 = 1.8, rms = 36.53, meanRerr = 26.72
Driver: z133$_1$10.txt



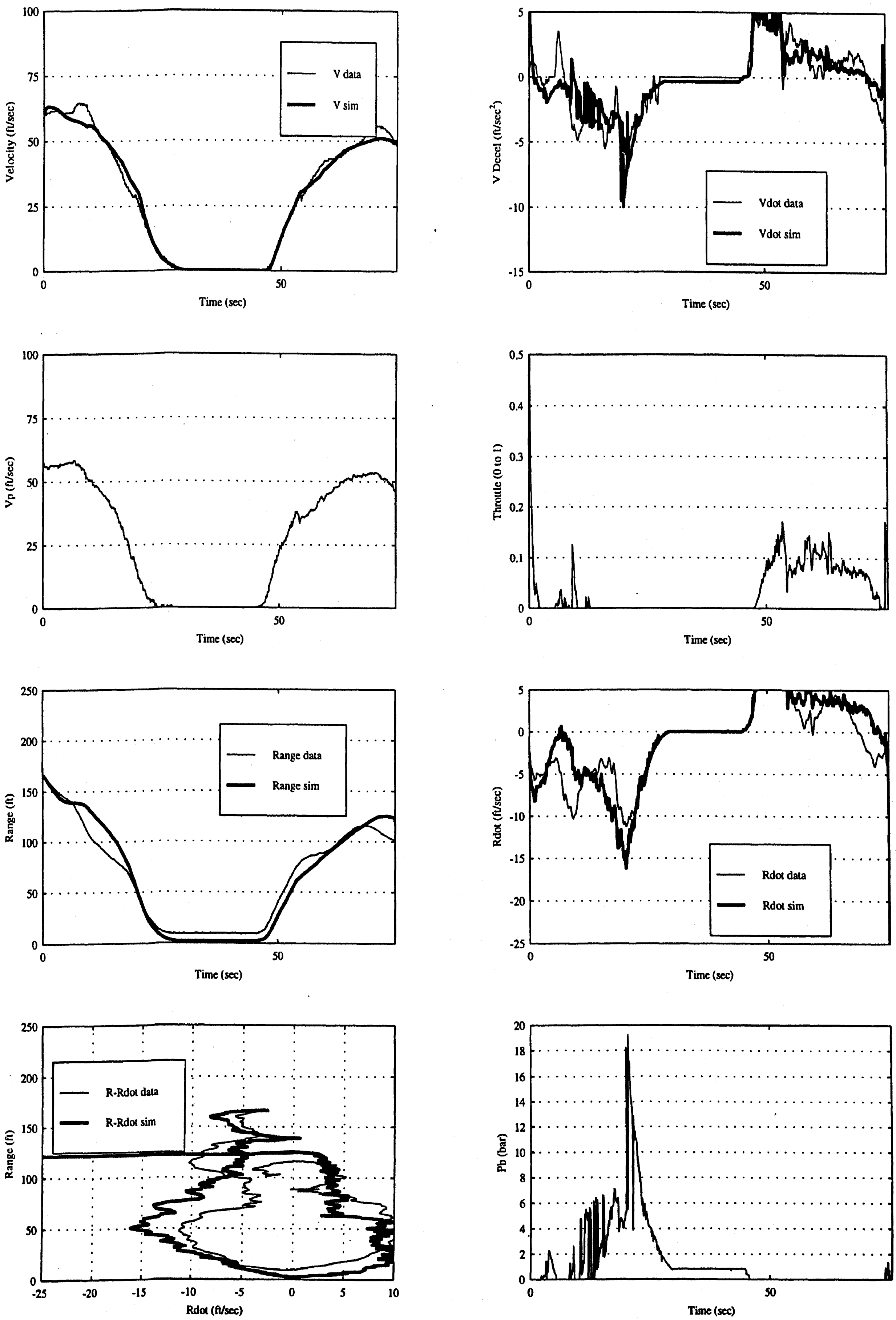
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9
Driver: z133$_1$15.txt



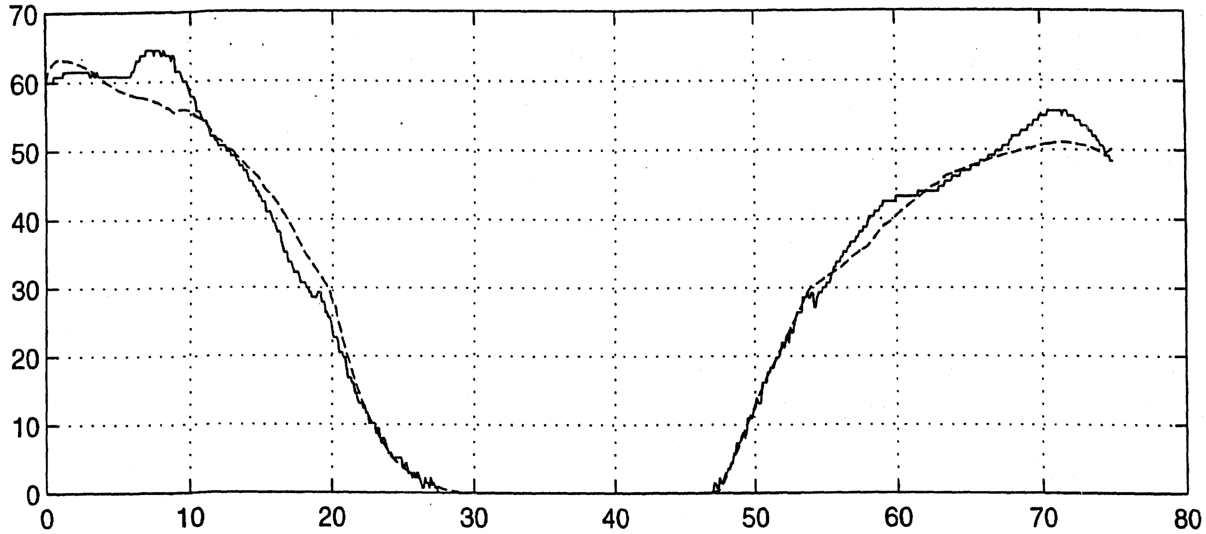
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9, rms = 31.36, meanRerr = 24.47
Driver: z133_1 15.txt

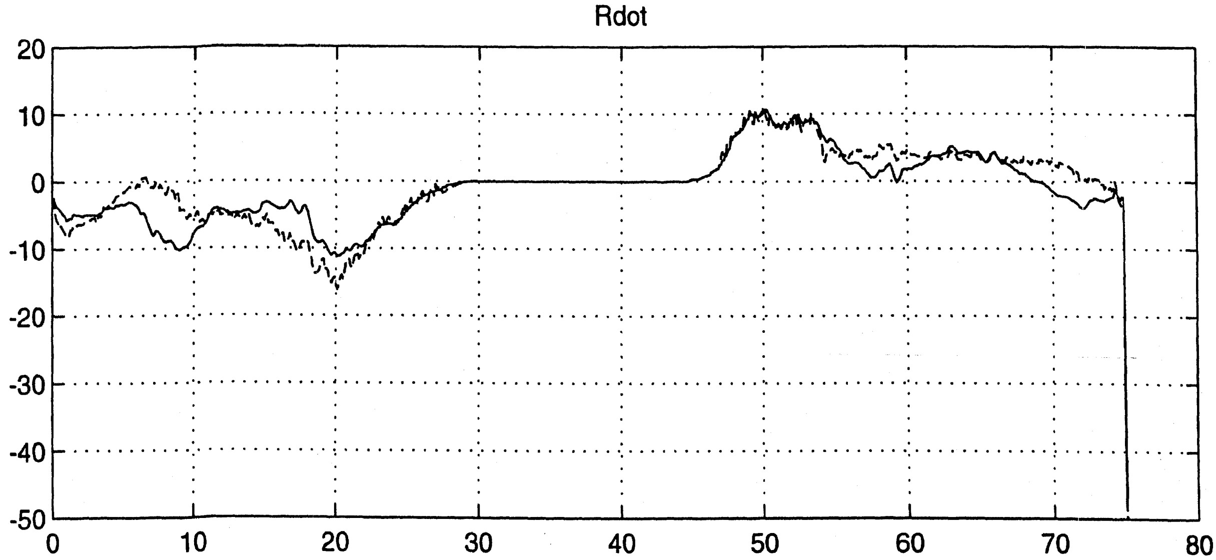


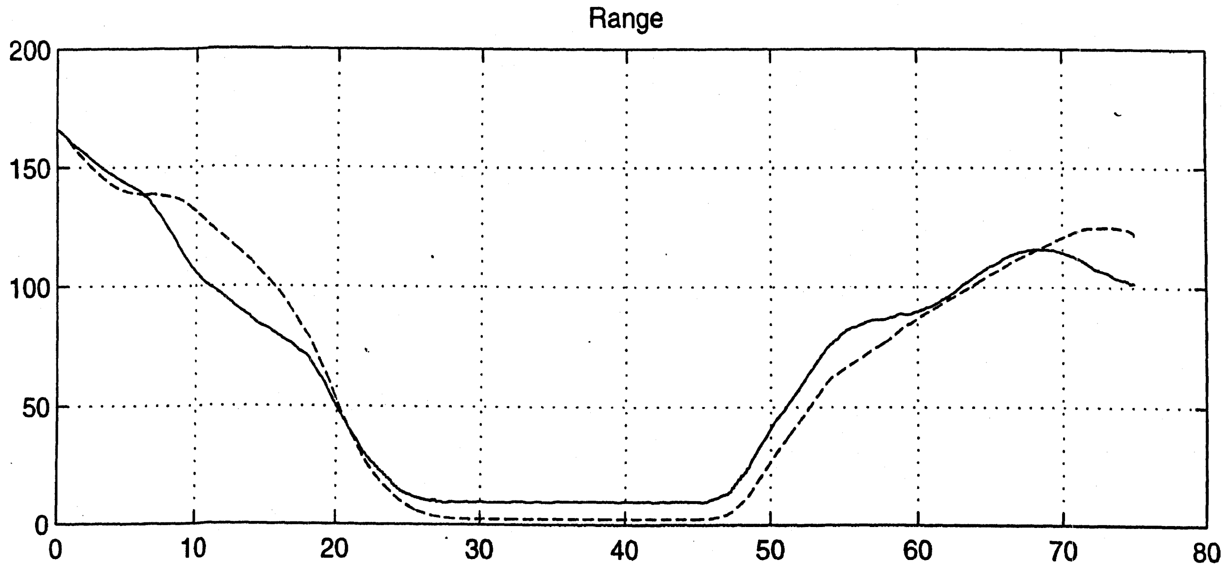
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.1, Tc = 2.8, T2 = 2.8, T3 = 2.1
Driver: z133$_1$23.txt



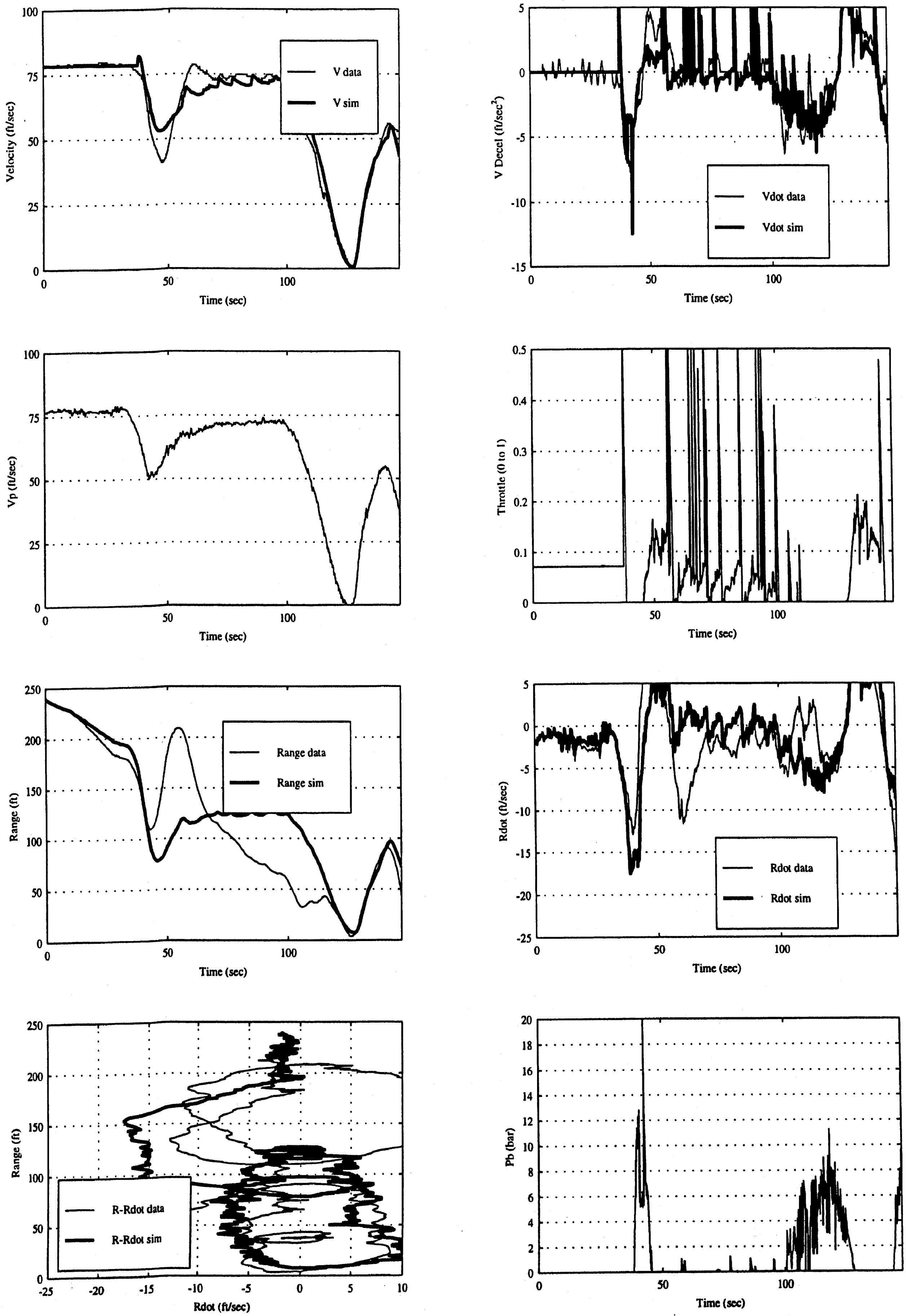
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.1, Tc = 2.8, T2 = 2.8, T3 = 2.1, rms = 11.35, meanRerr = 9.06
Driver: z133_1 23.txt



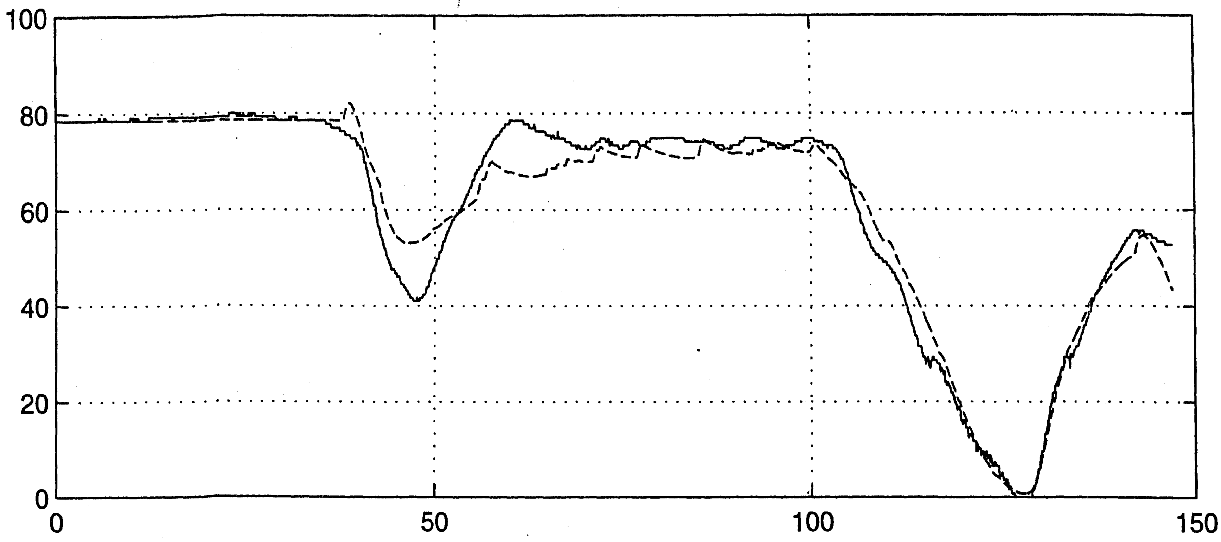




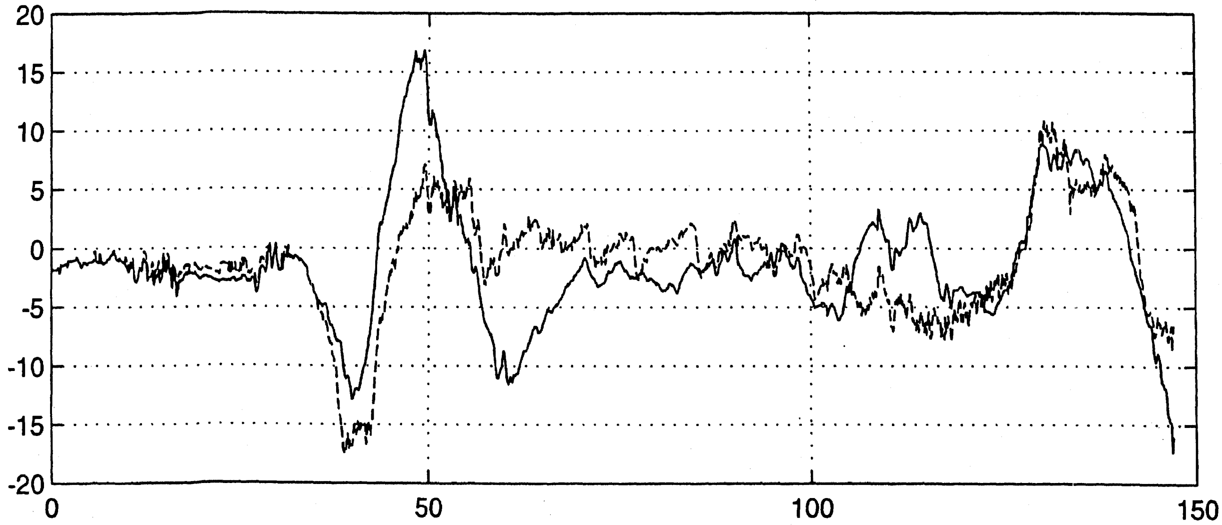
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.4, Tc = 2.8, T2 = 2.8, T3 = 1.4
Driver: z133_1 26.txt



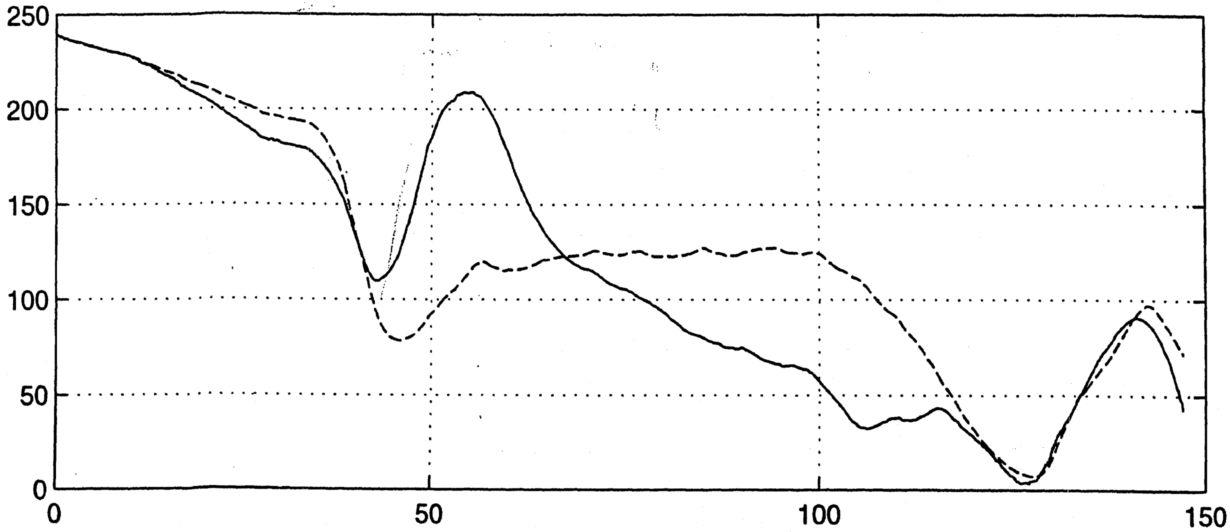
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.4, Tc = 2.8, T2 = 2.8, T3 = 1.4, rms = 39.67, meanRerr = 27.42
Driver: z133_1 26.txt



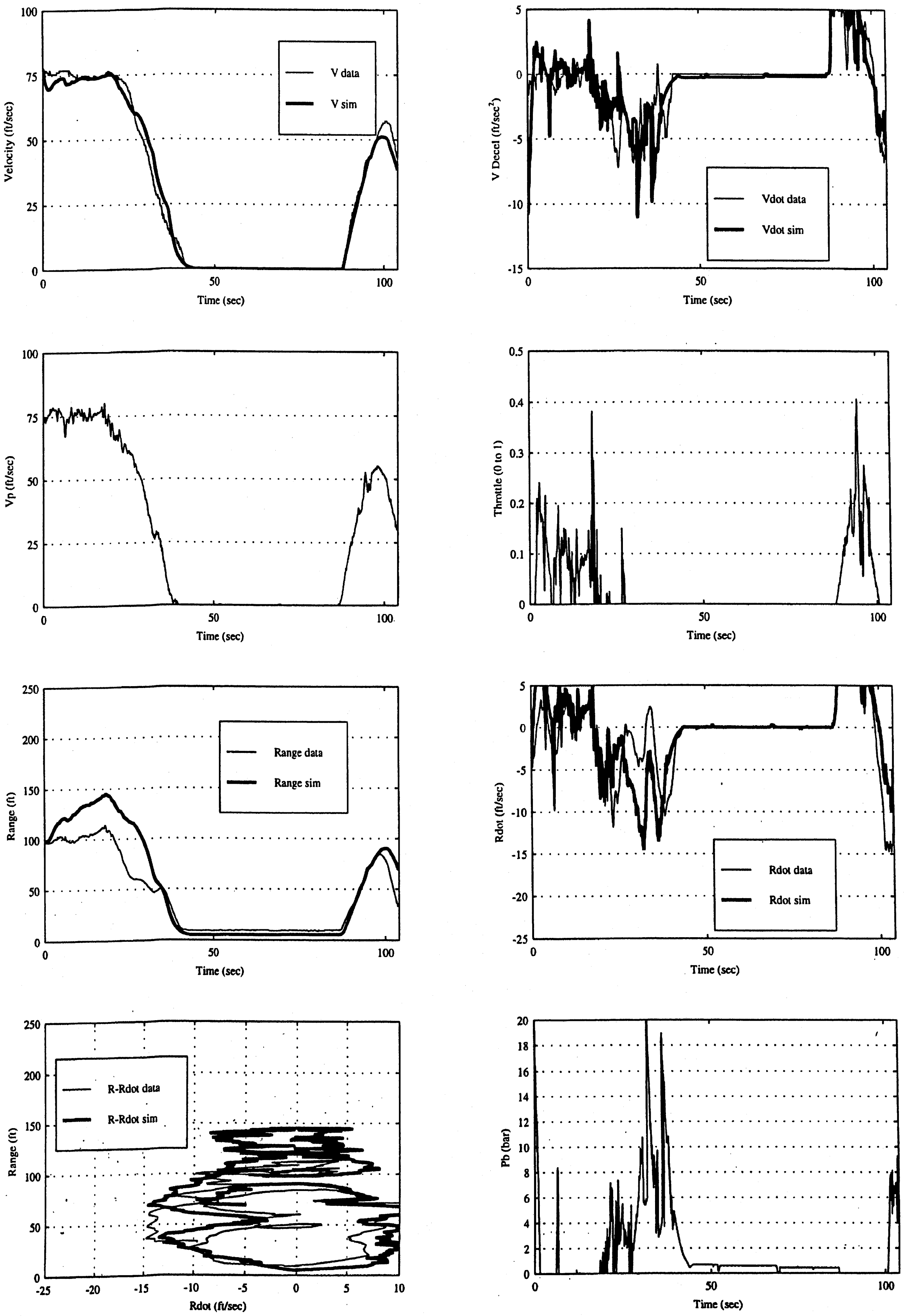
Rdot



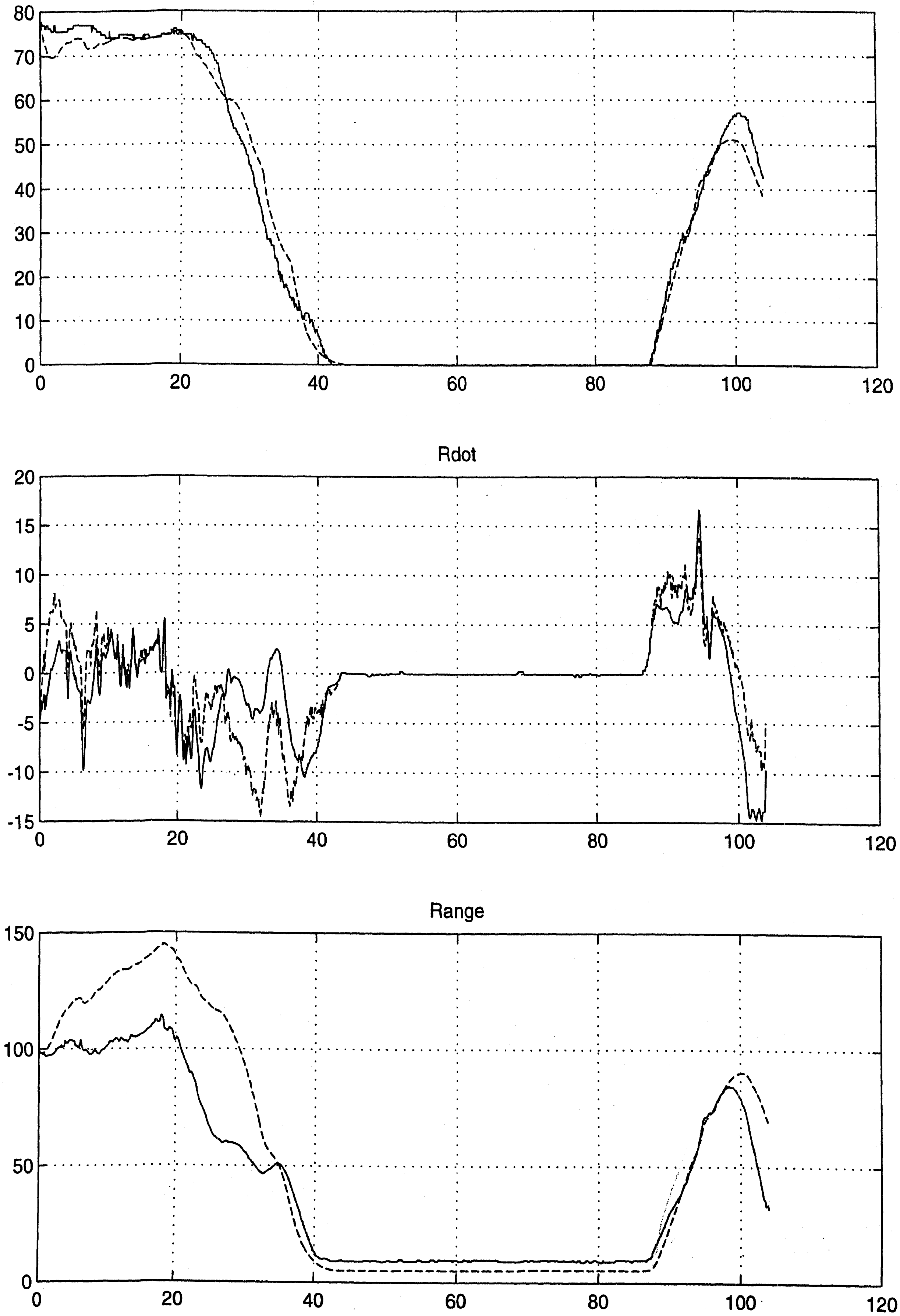
Range



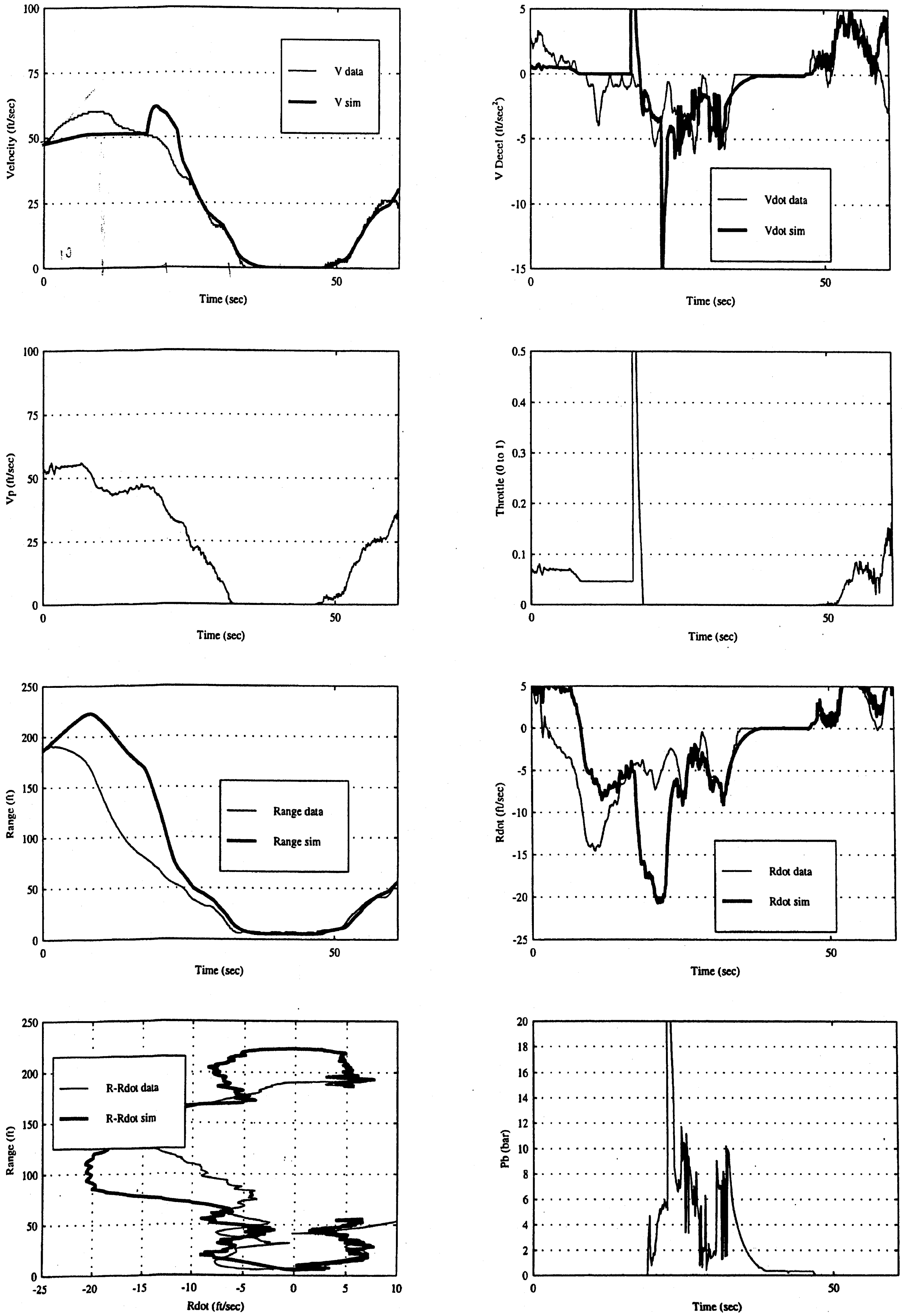
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6
Driver: z133$_1$32.txt



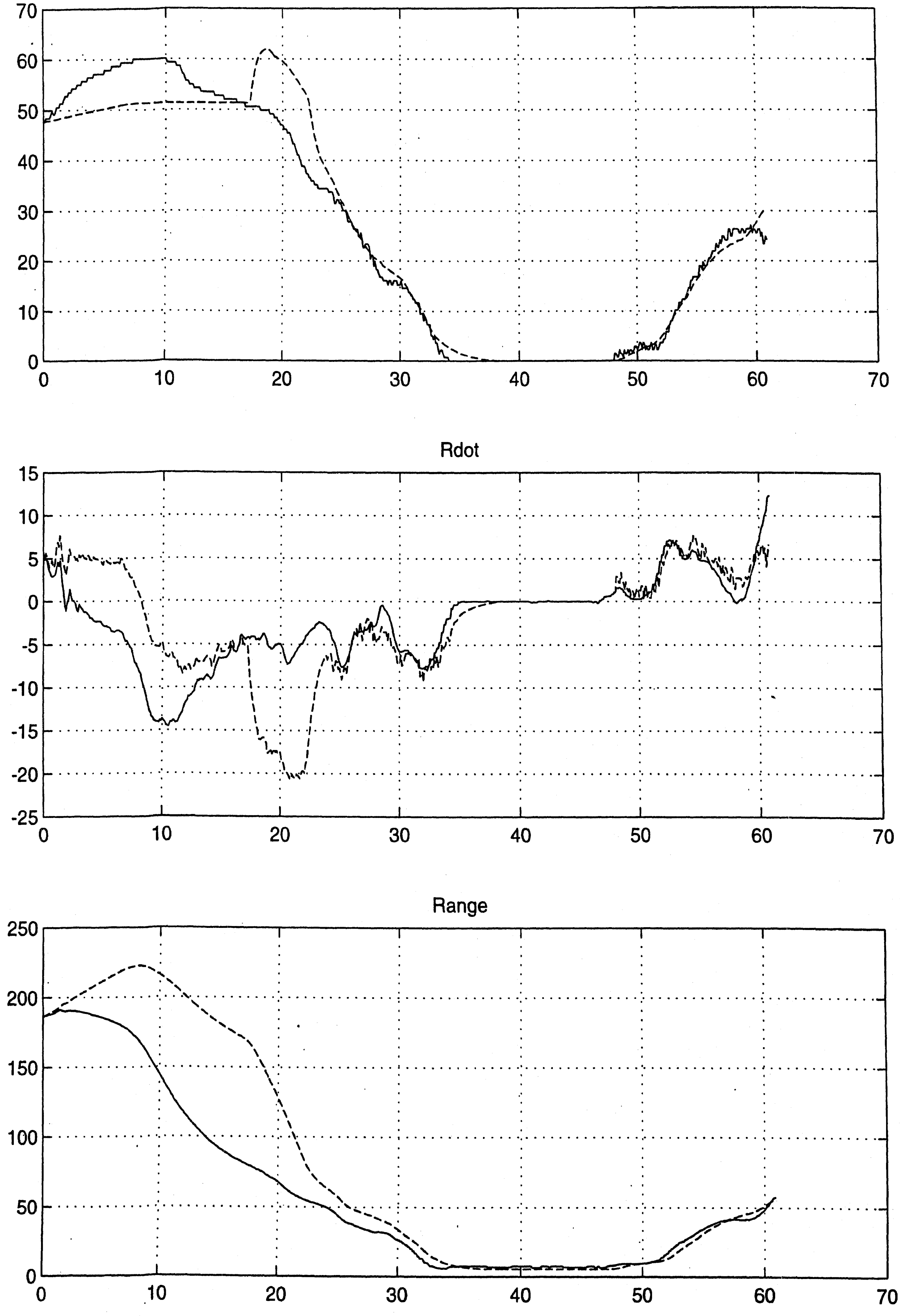
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6, rms = 19.81, meanRerr = 13.23
Driver: $z133_1 32$.txt



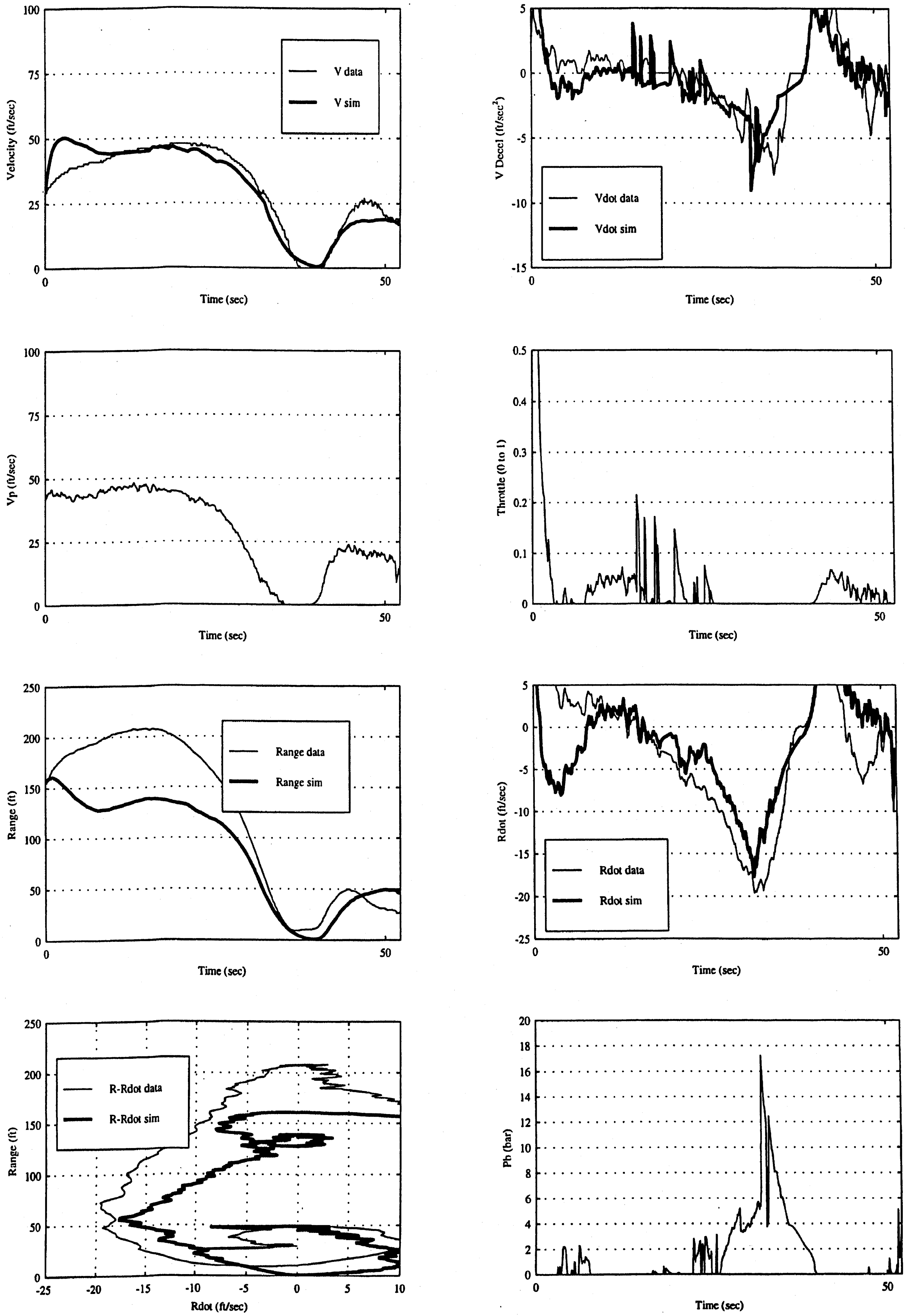
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6
Driver: $z133_141$.txt



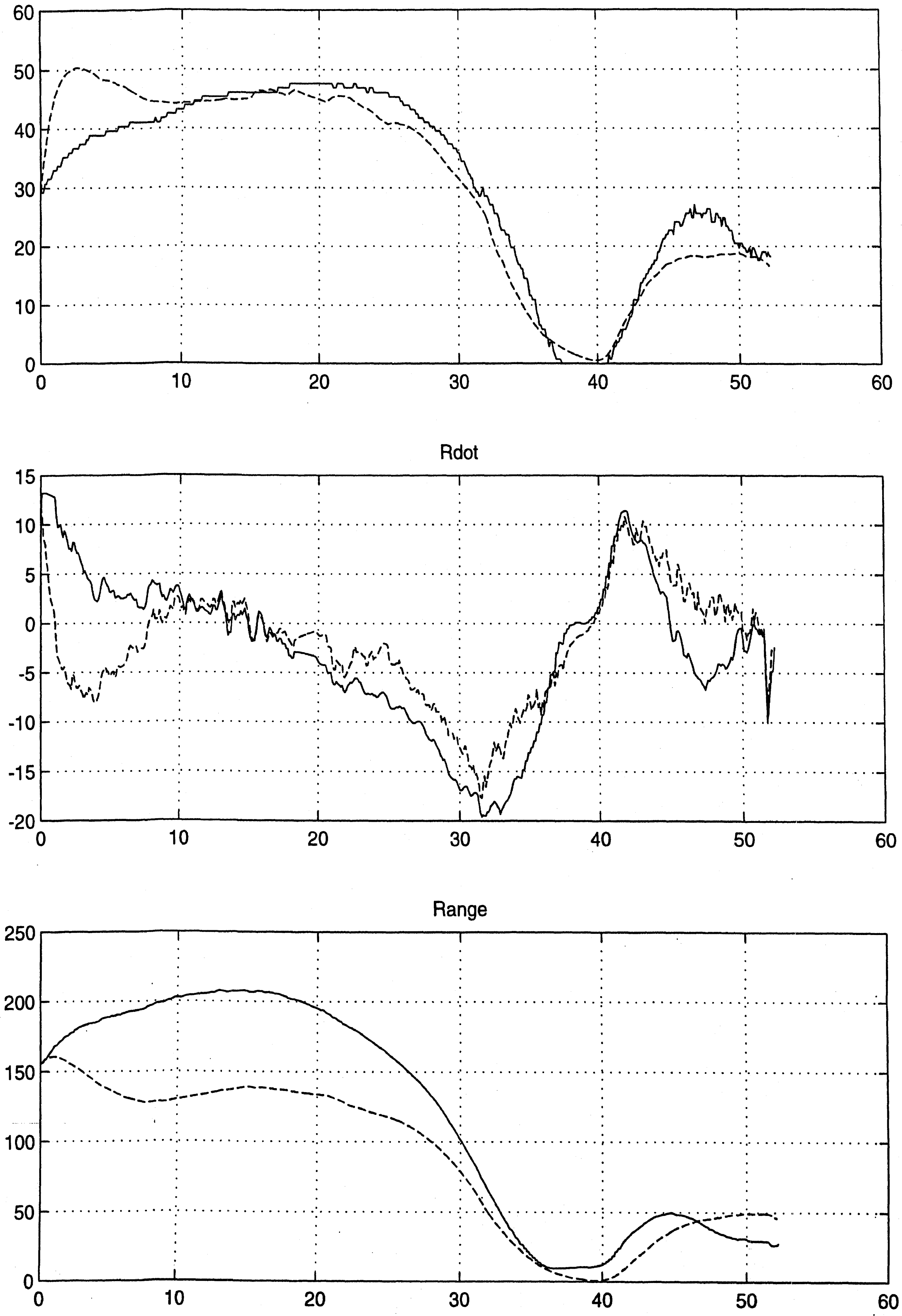
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6, rms = 38.26, meanRerr = 22.98
Driver: z133_1 41.txt



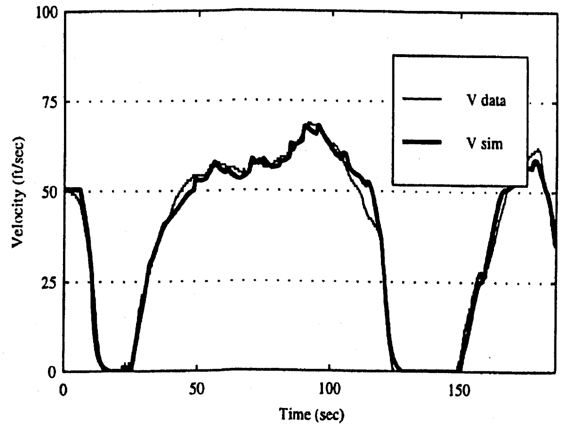
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.5, Tc = 2.8, T2 = 2.8, T3 = 2.5
Driver: z133$_1$44.txt

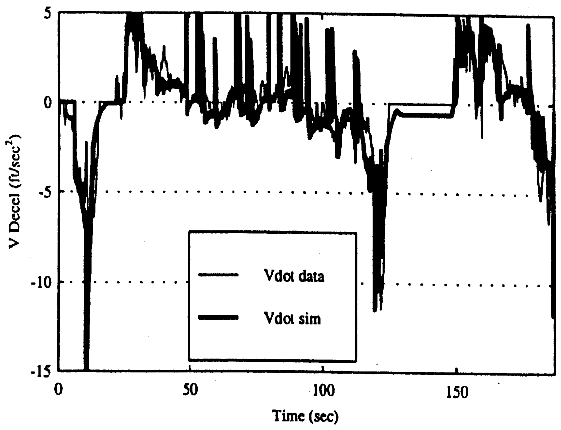


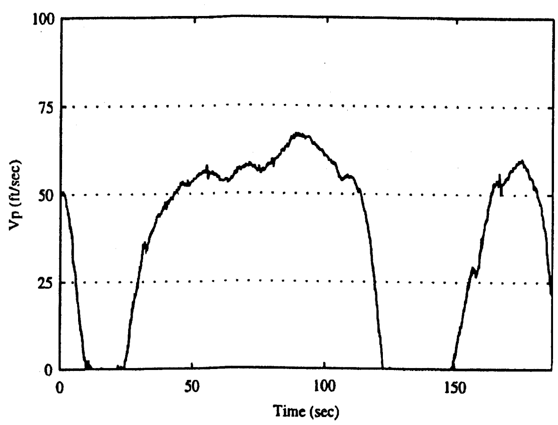
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.5, Tc = 2.8, T2 = 2.8, T3 = 2.5, rms = 43.52, meanRerr = 35.39
Driver: z133_1 44.txt

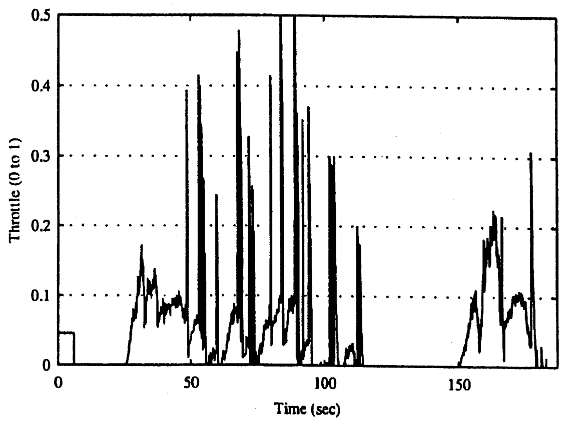


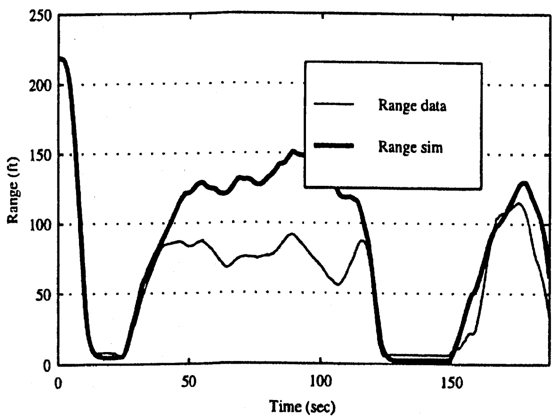
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9
Driver: z133_1 55.txt

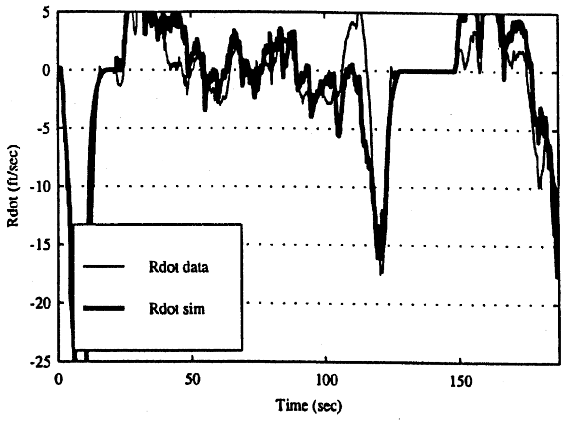


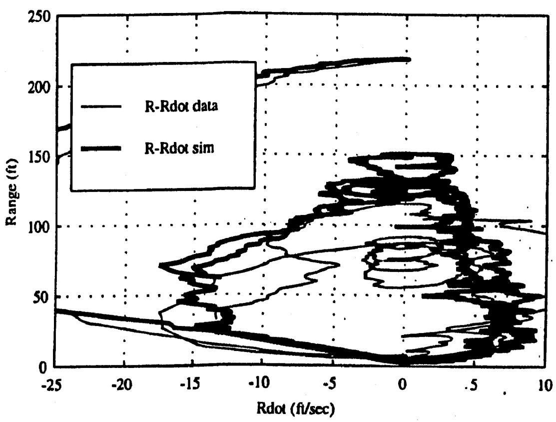


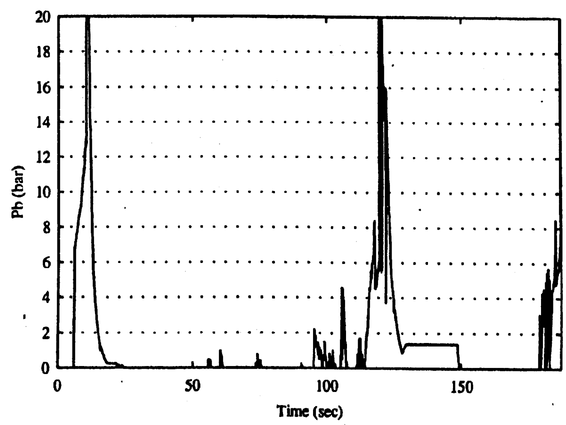




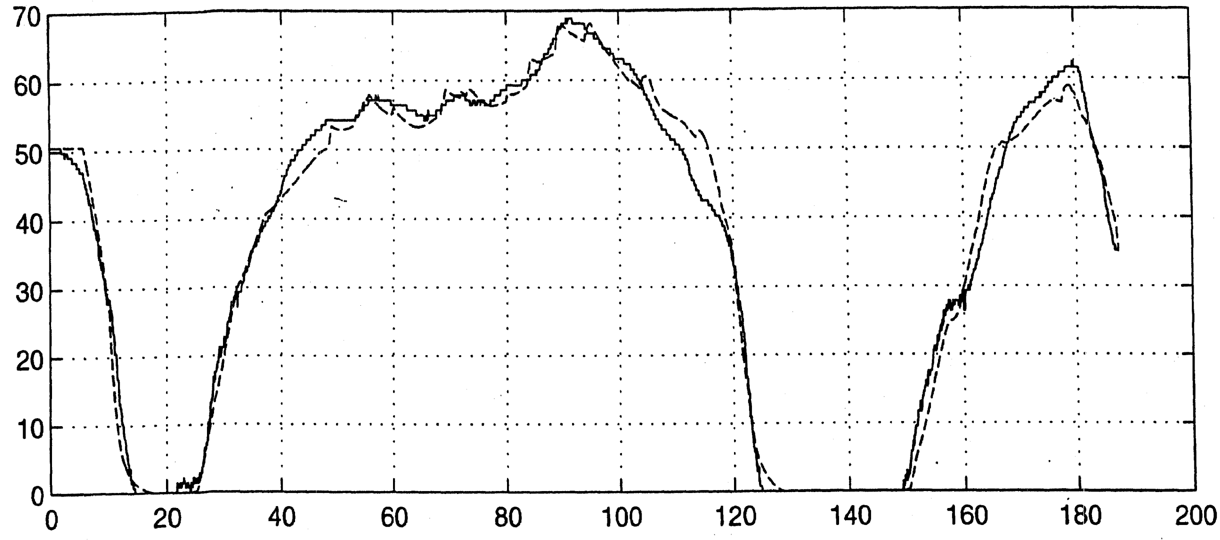




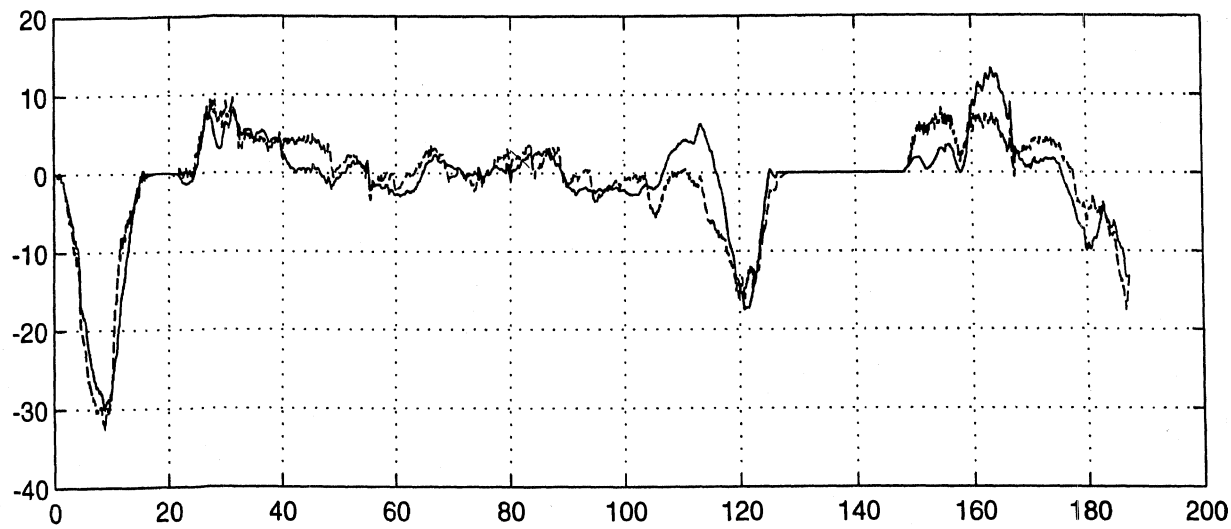




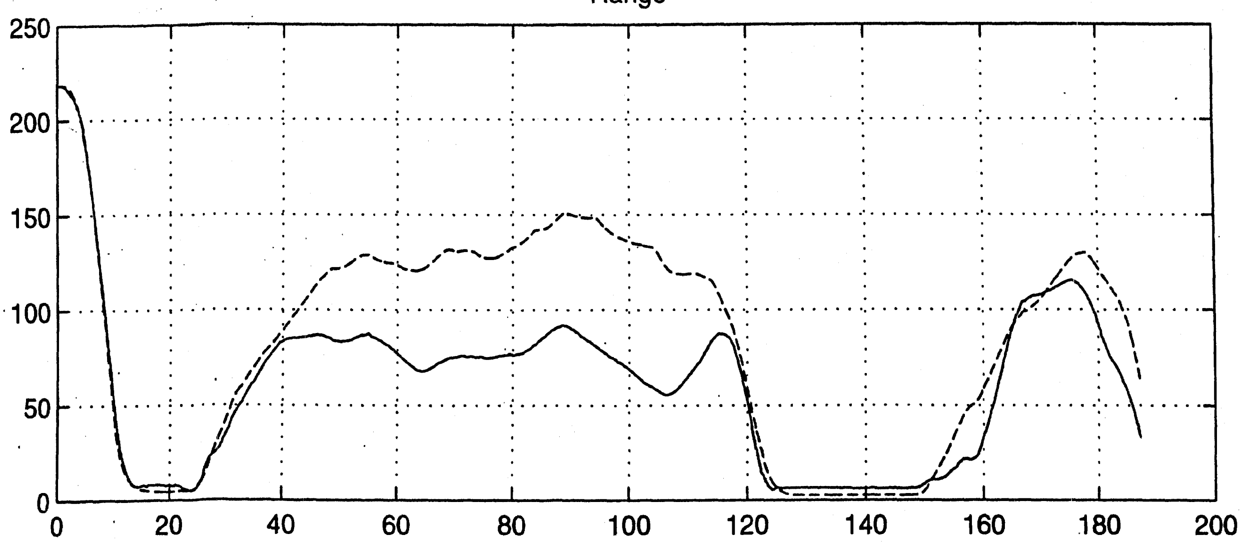
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9, rms = 34.85, meanRerr = 25.34
Driver: z133_1 55.txt



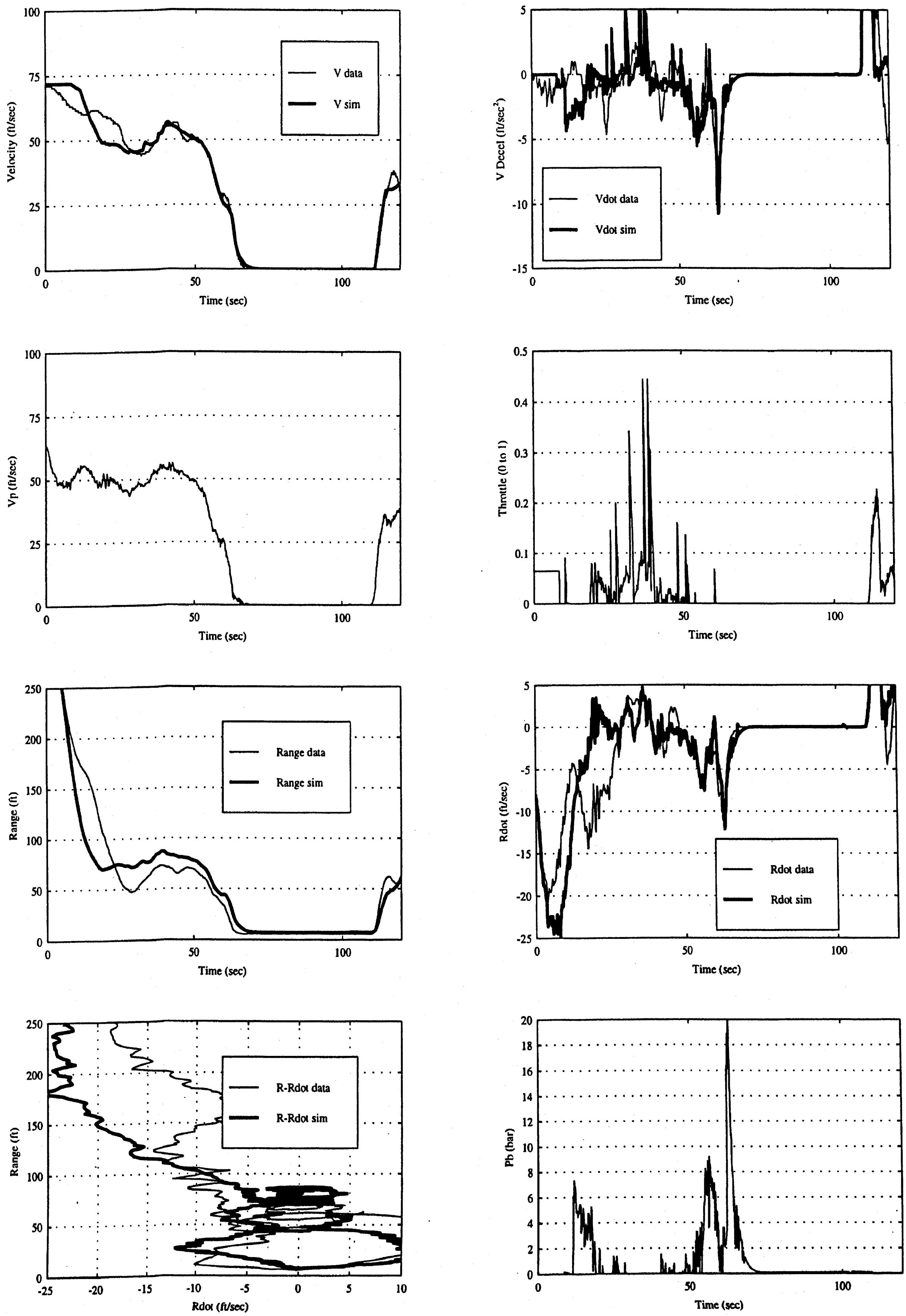
Rdot



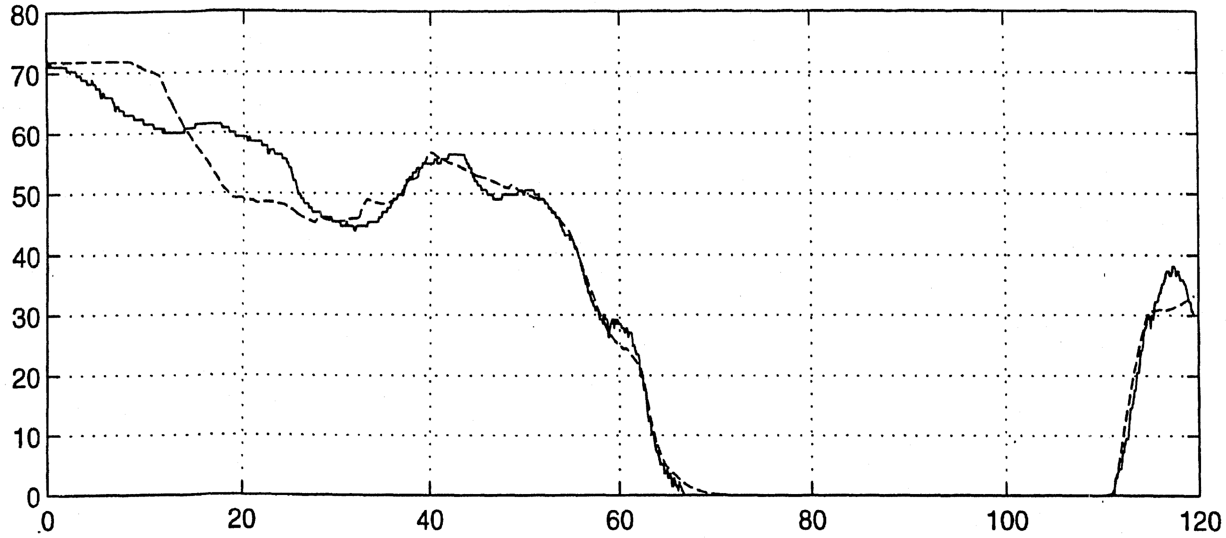
Range

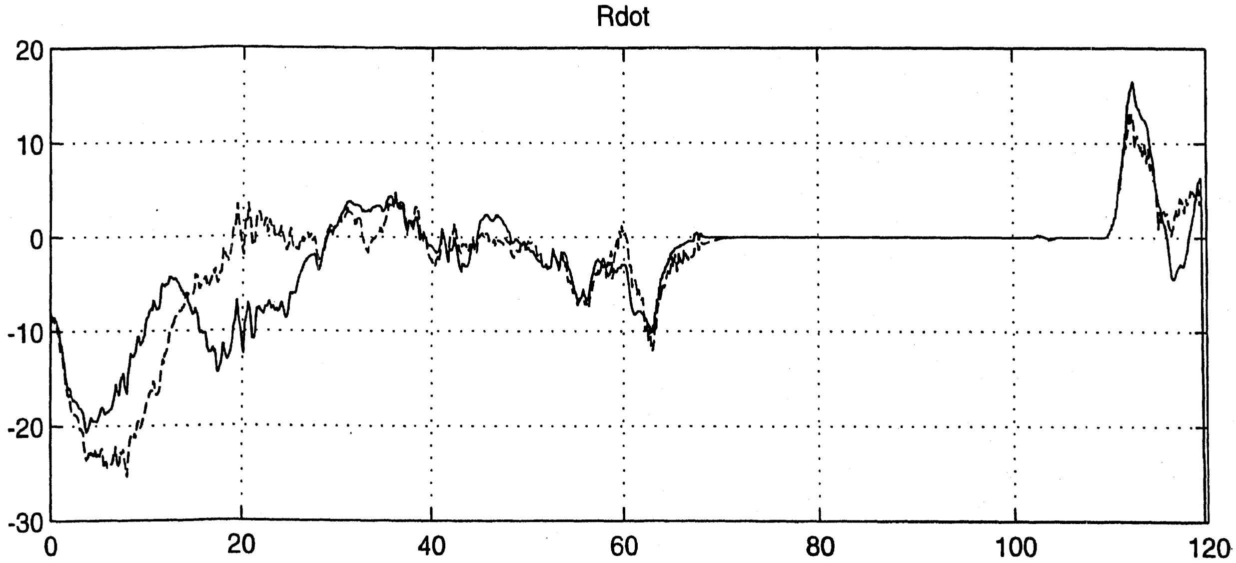


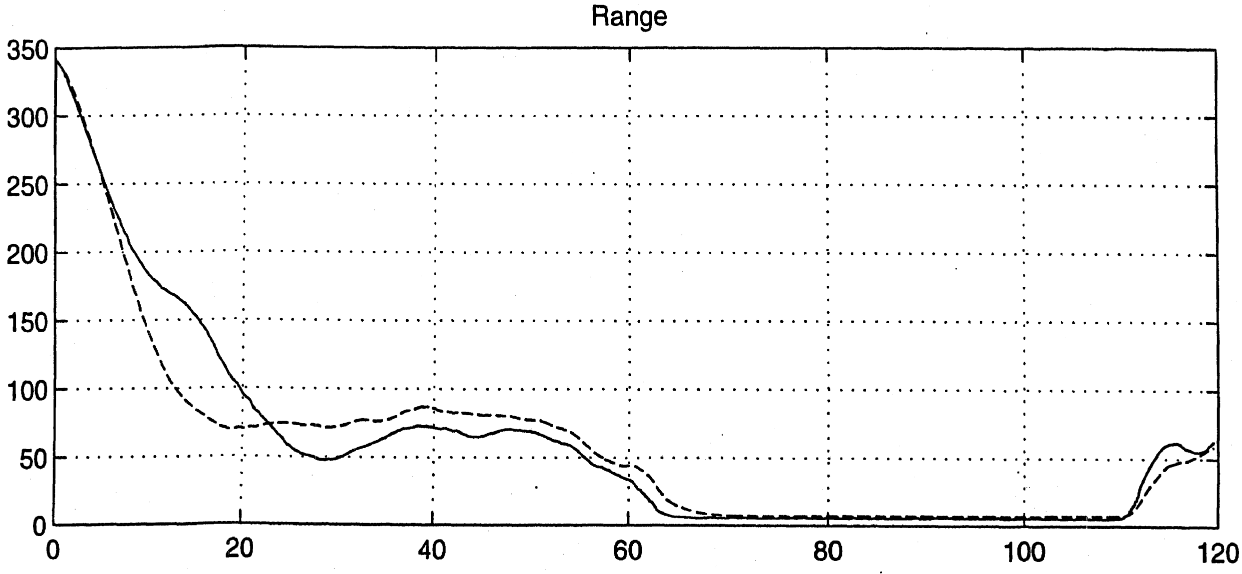
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.2, Tc = 2.8, T2 = 2.8, T3 = 1.2
Driver: $z133_1 70$.txt



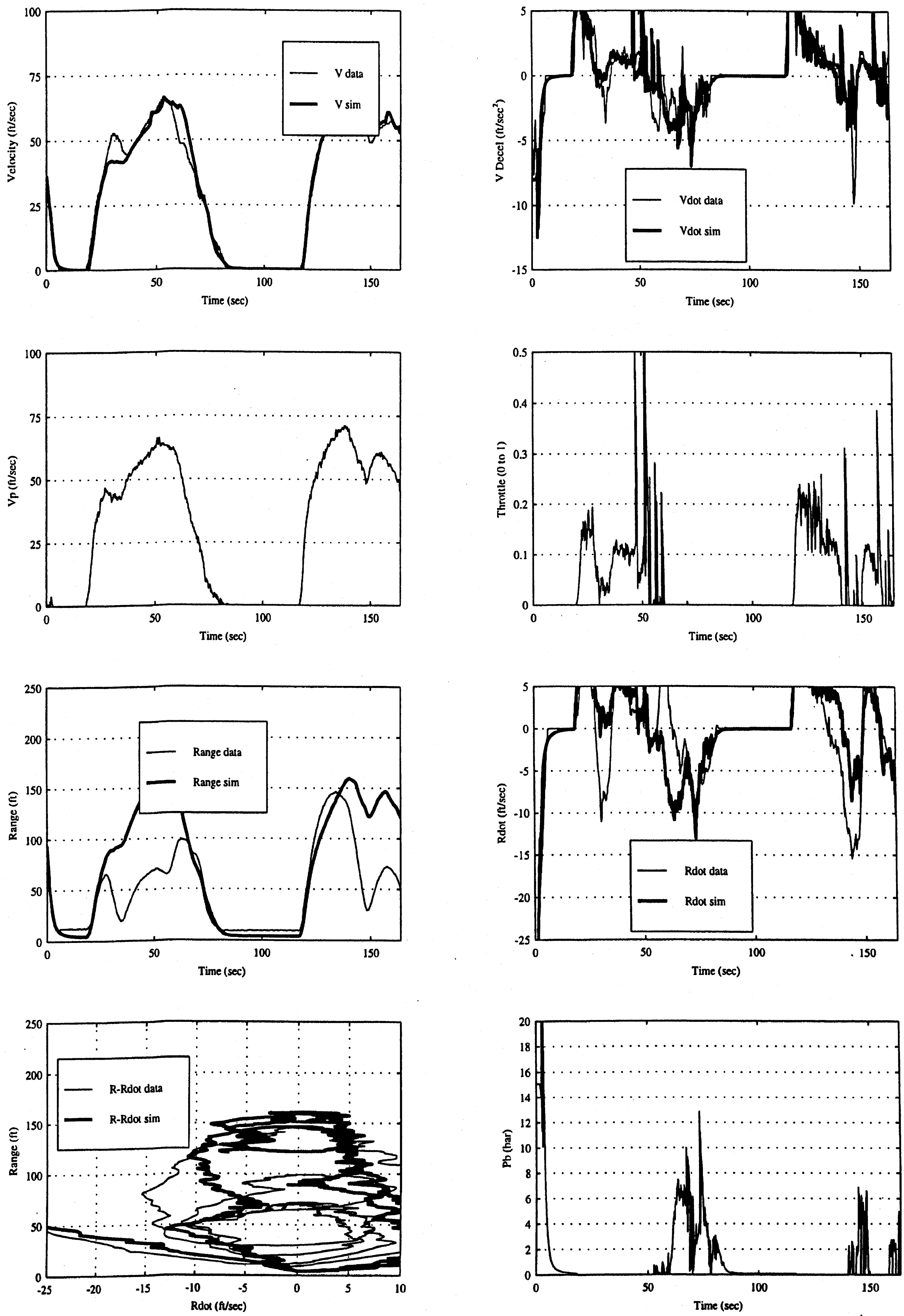
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.2, Tc = 2.8, T2 = 2.8, T3 = 1.2, rms = 19.55, meanRerr = 12.11
Driver: z133_1 70.txt



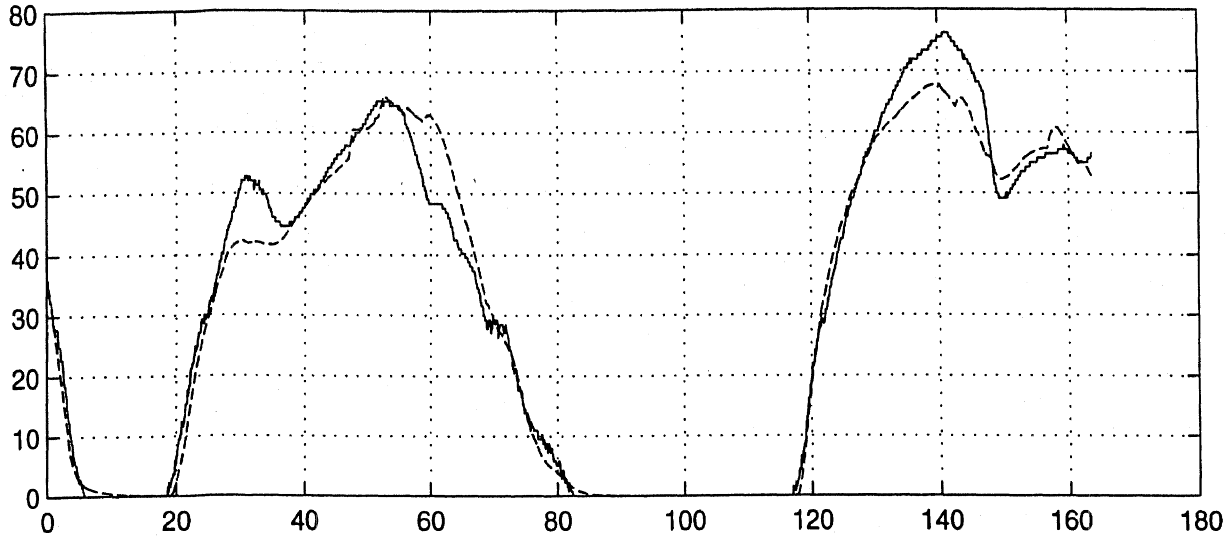




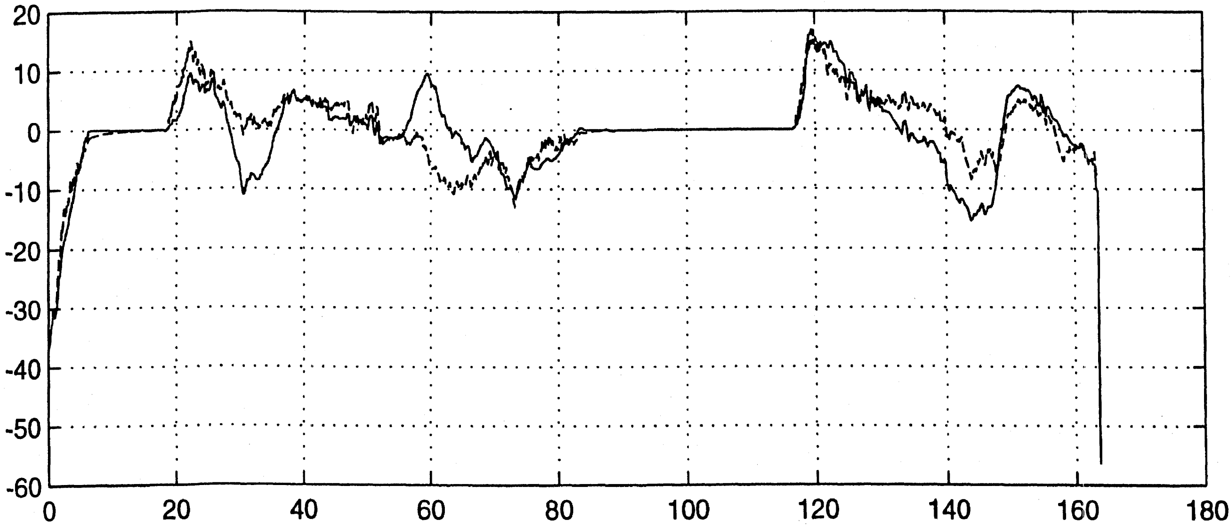
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.1, Tc = 2.8, T2 = 2.8, T3 = 2.1
Driver: $z133_1 75$.txt



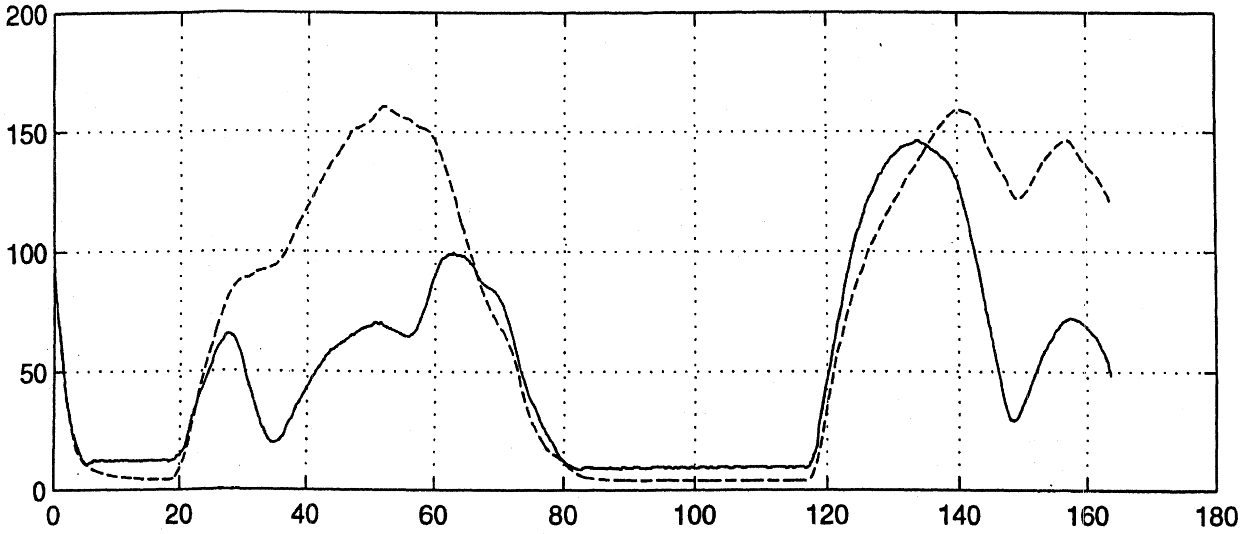
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.1, Tc = 2.8, T2 = 2.8, T3 = 2.1, rms = 45.12, meanRerr = 30.65
Driver: z133$_1$75.txt



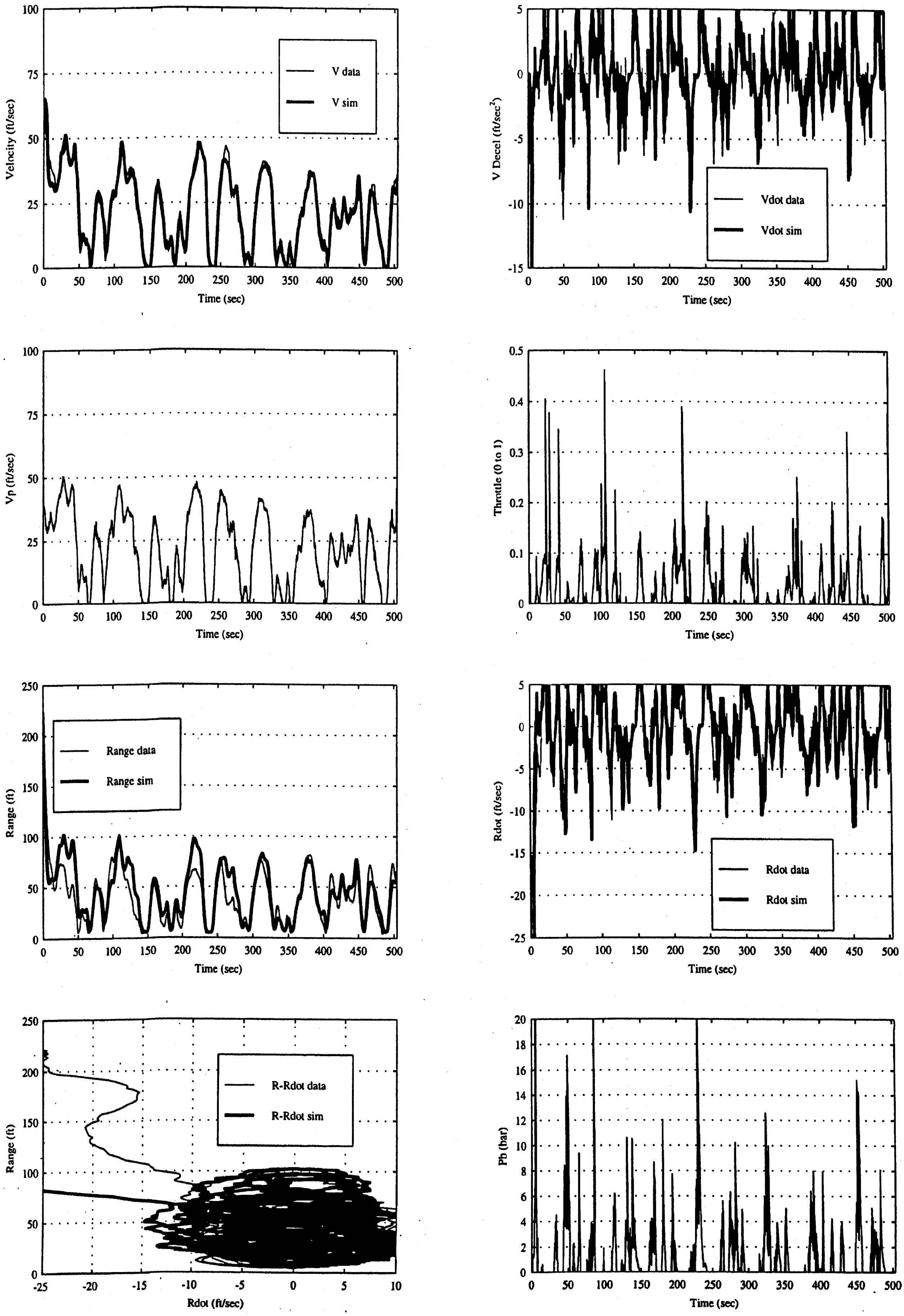
Rdot



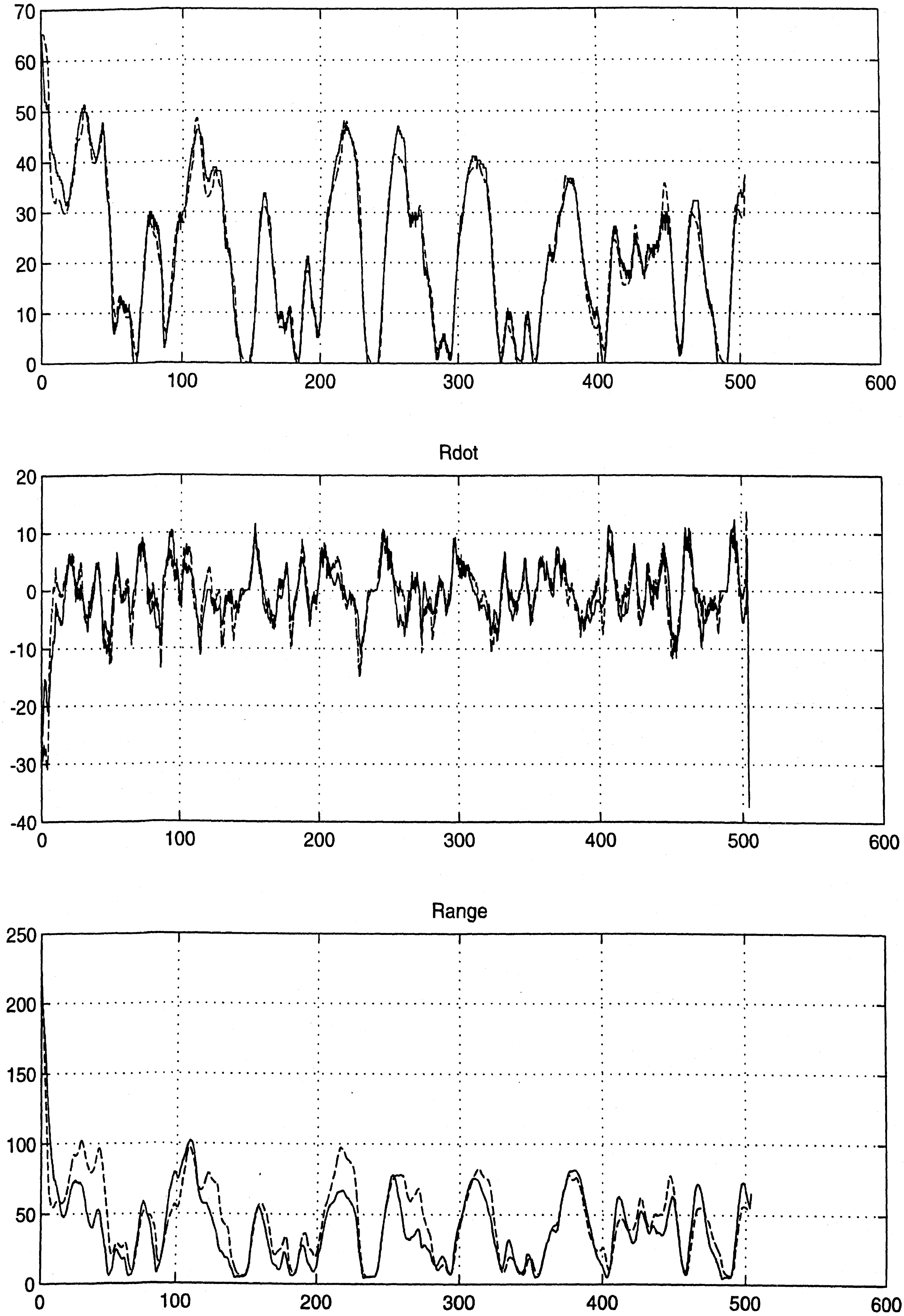
Range



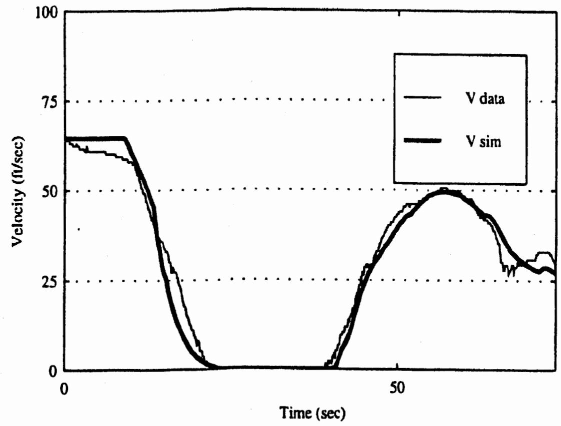
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6
Driver: z133$_4$0.txt

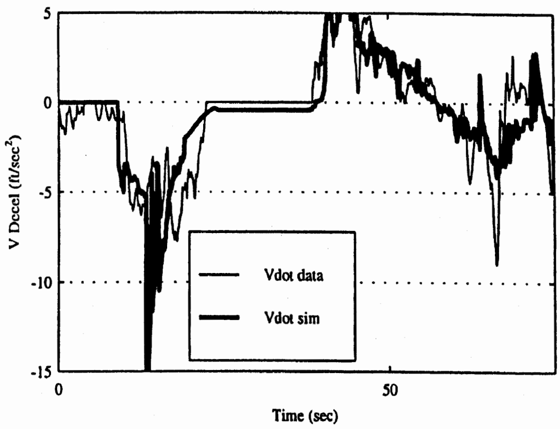


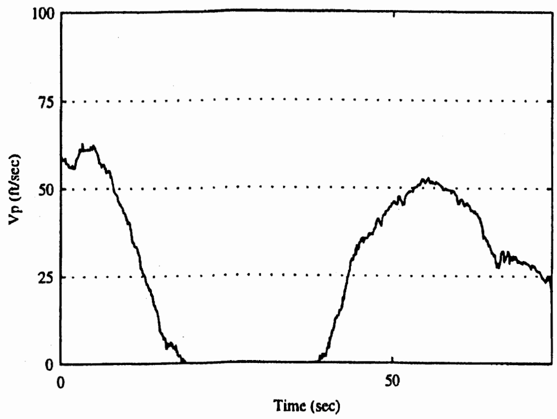
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6, rms = 15.34, meanRerr = 11.36
Driver: z133_4 0.txt

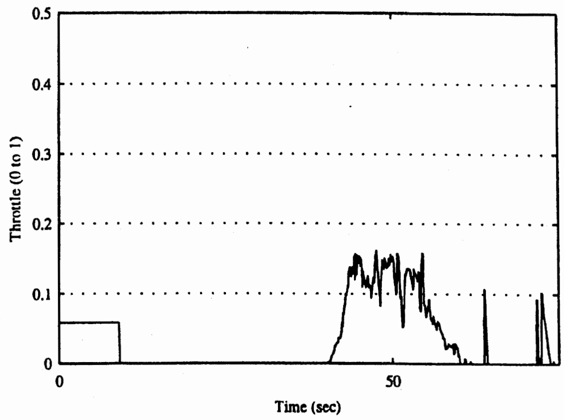


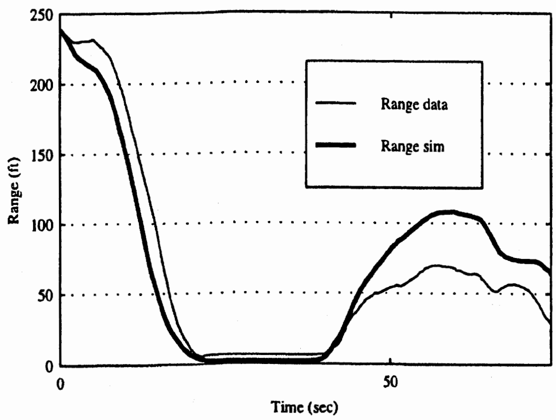
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0
Driver: $z133_9$.txt

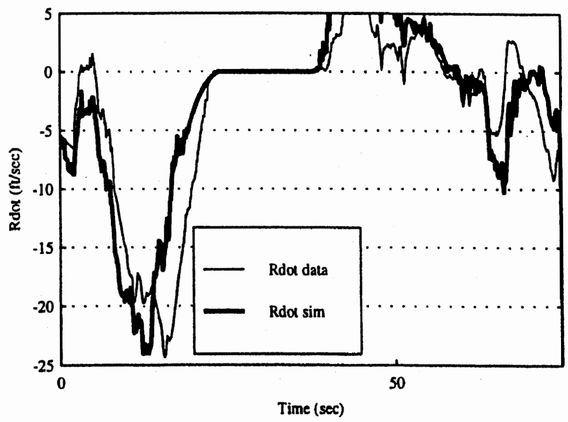


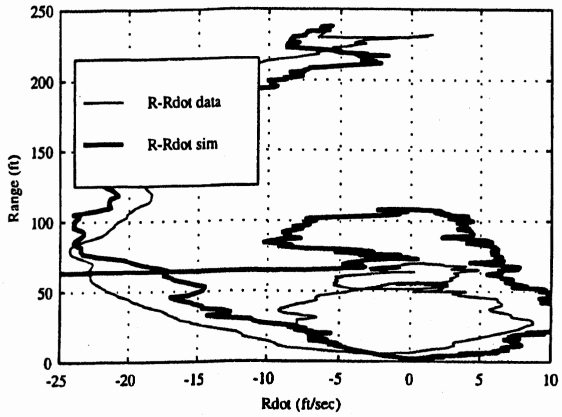


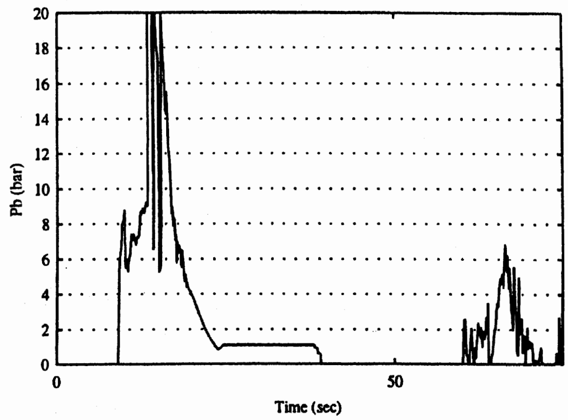




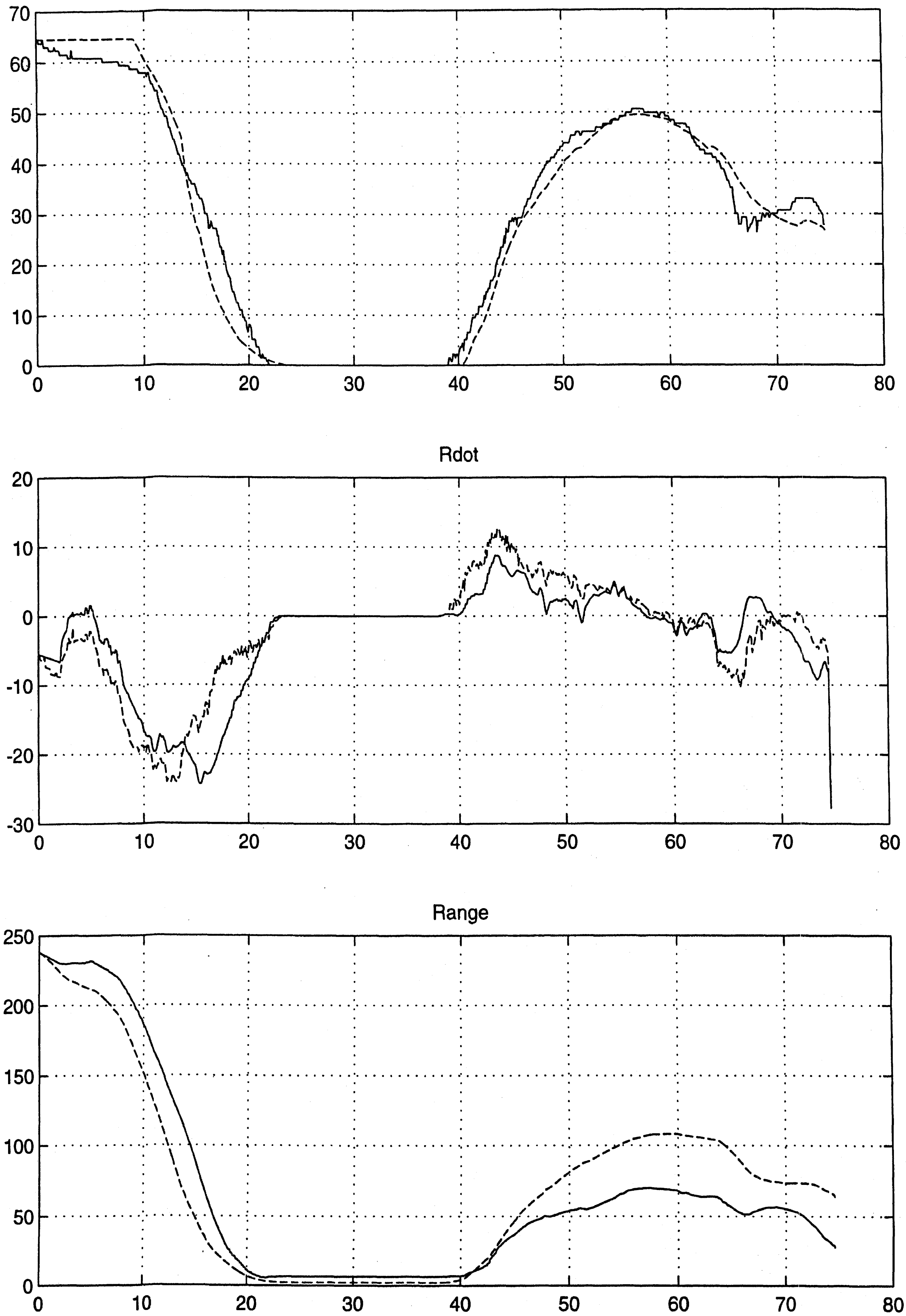




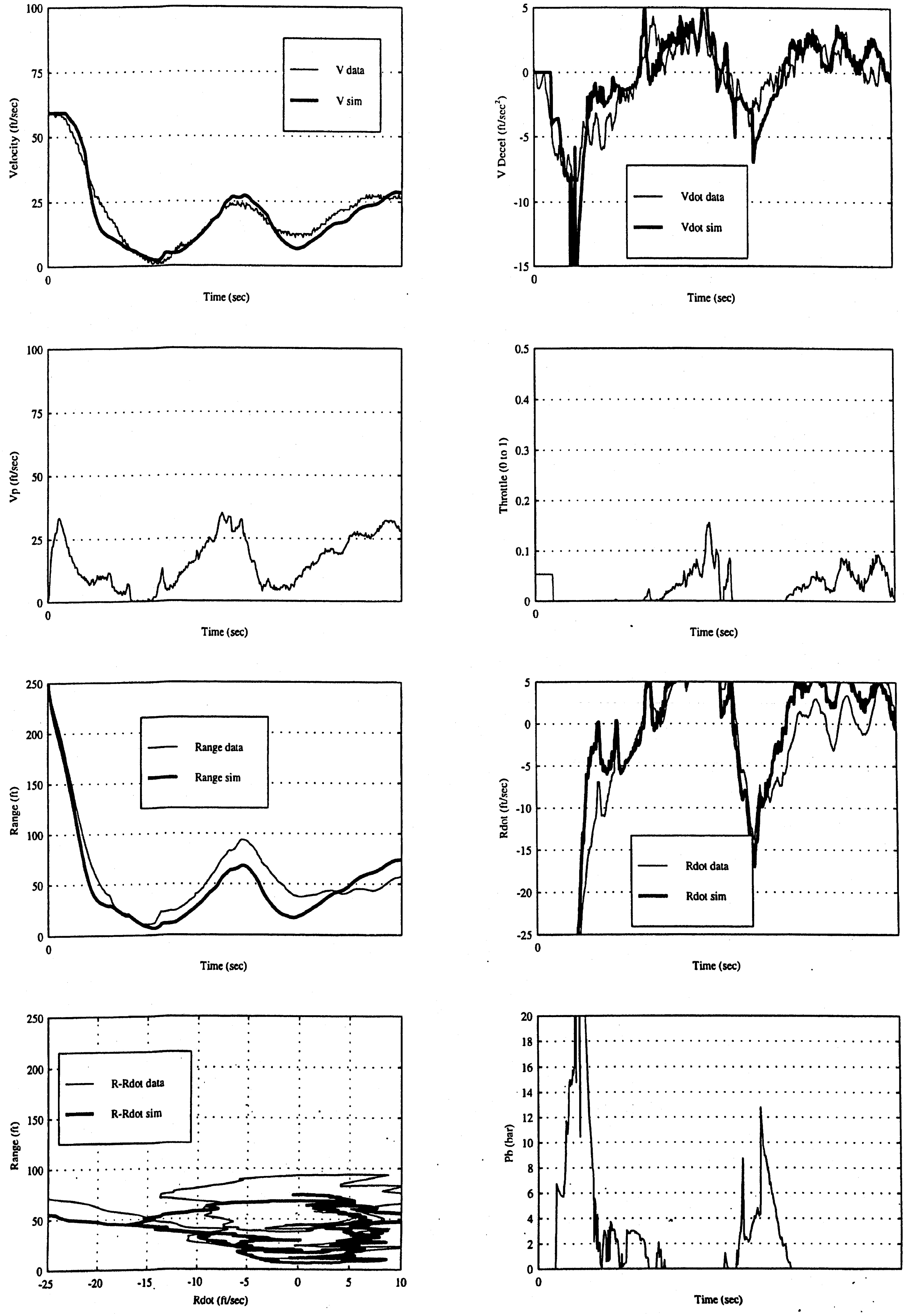




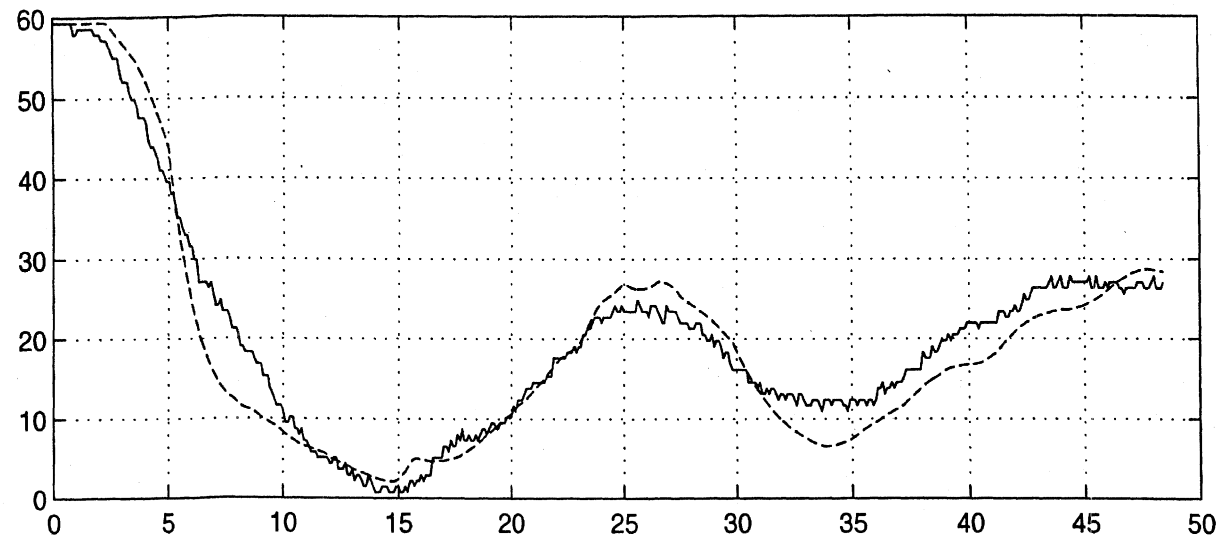
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0, rms = 24.63, meanRerr = 19.57
Driver: $z133_9$.txt



BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.6, Tc = 2.8, T2 = 2.8, T3 = 2.6
Driver: z143_01.txt

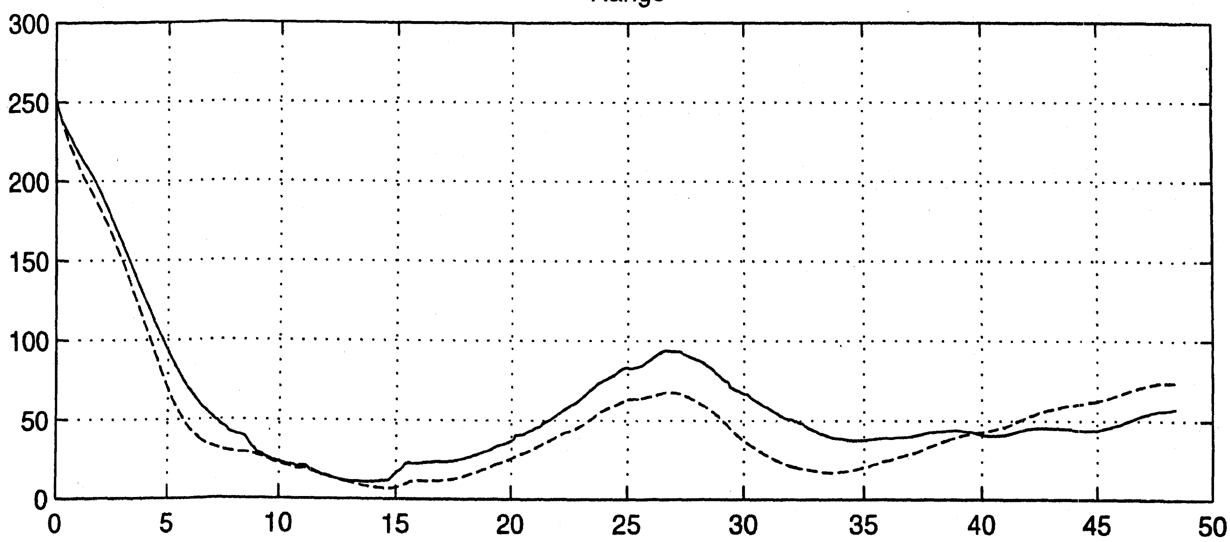


BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.6, Tc = 2.8, T2 = 2.8, T3 = 2.6, rms = 16.51, meanRerr = 14.10
Driver: z143_1 01.txt

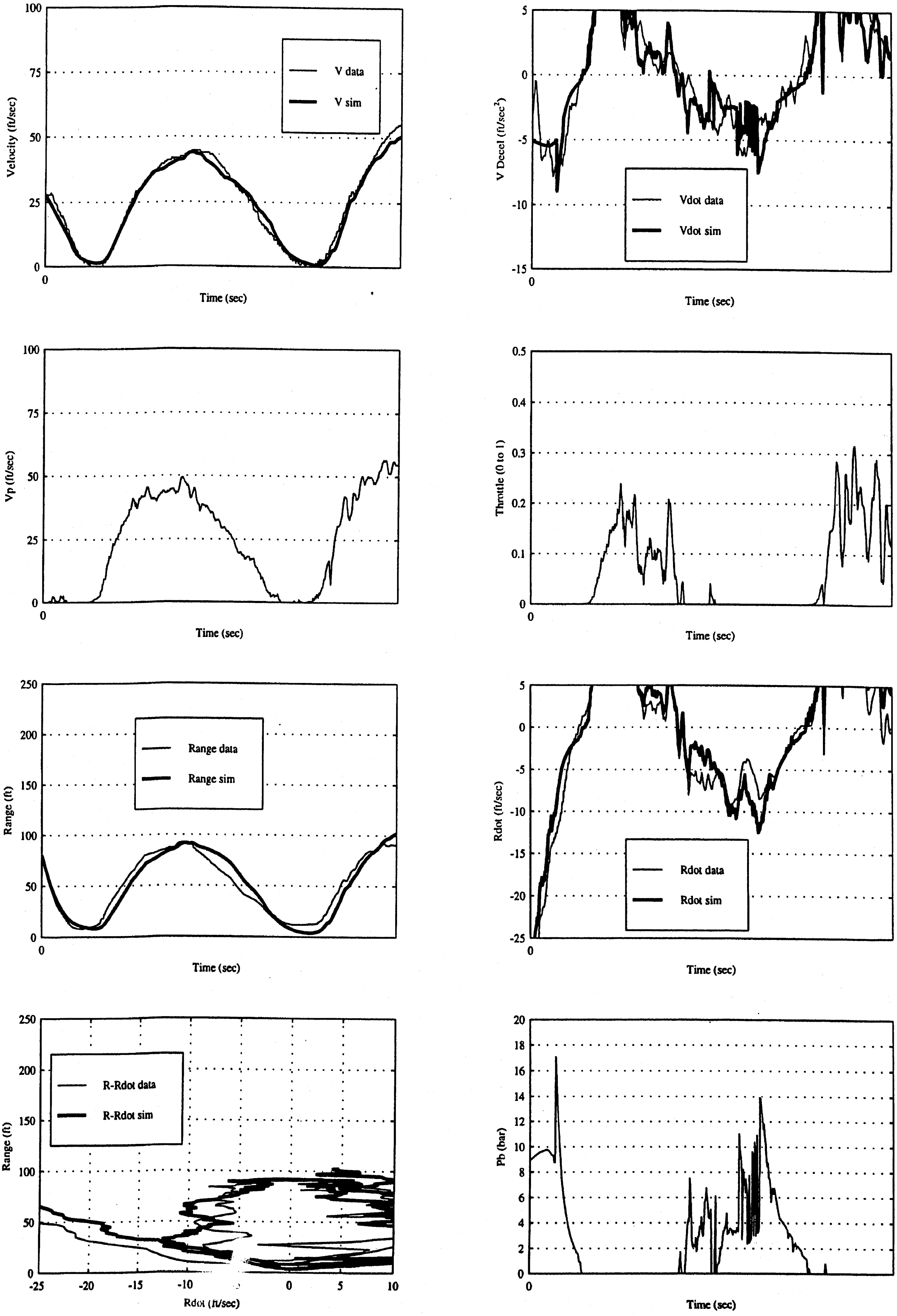


Rdot

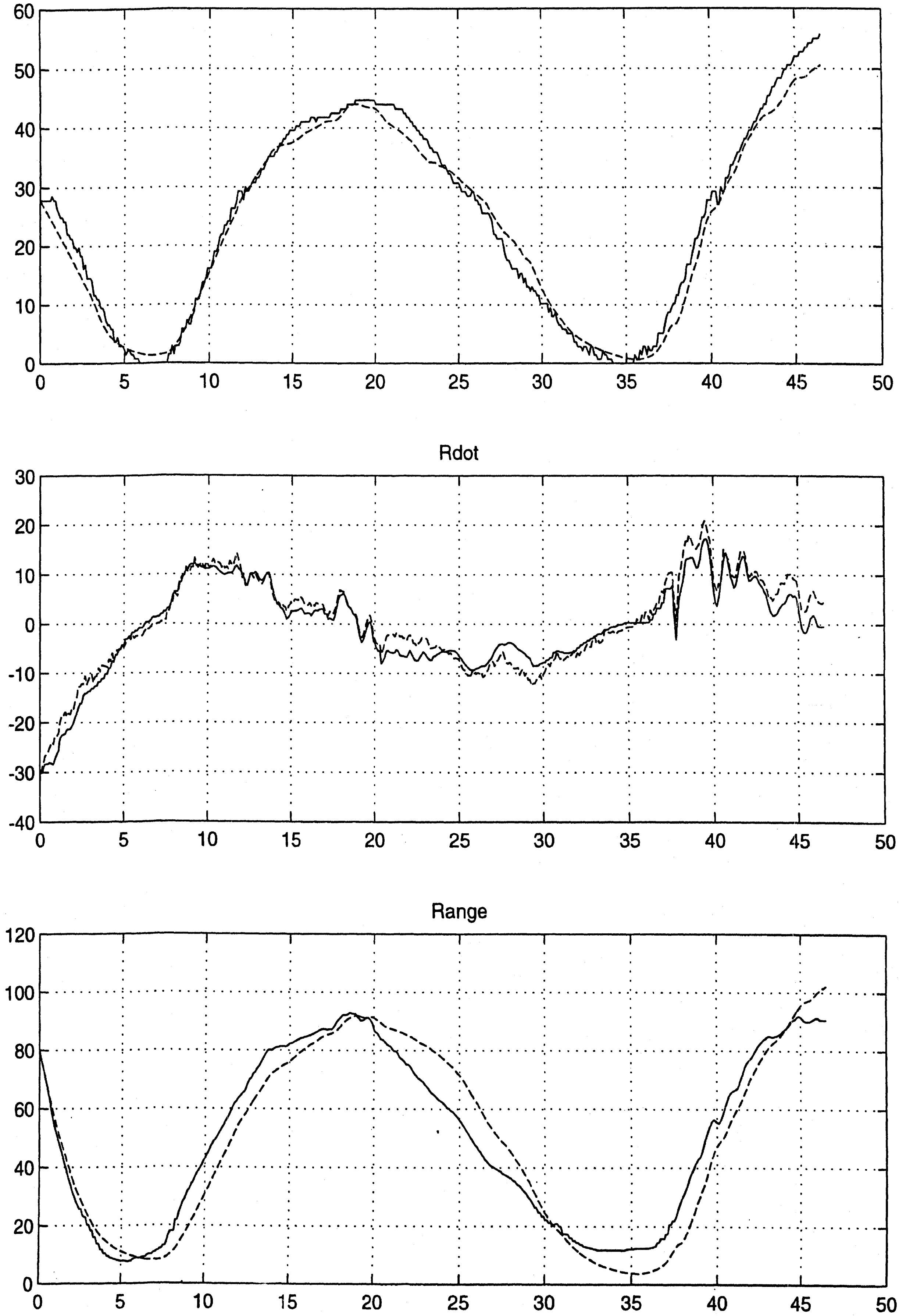
Range



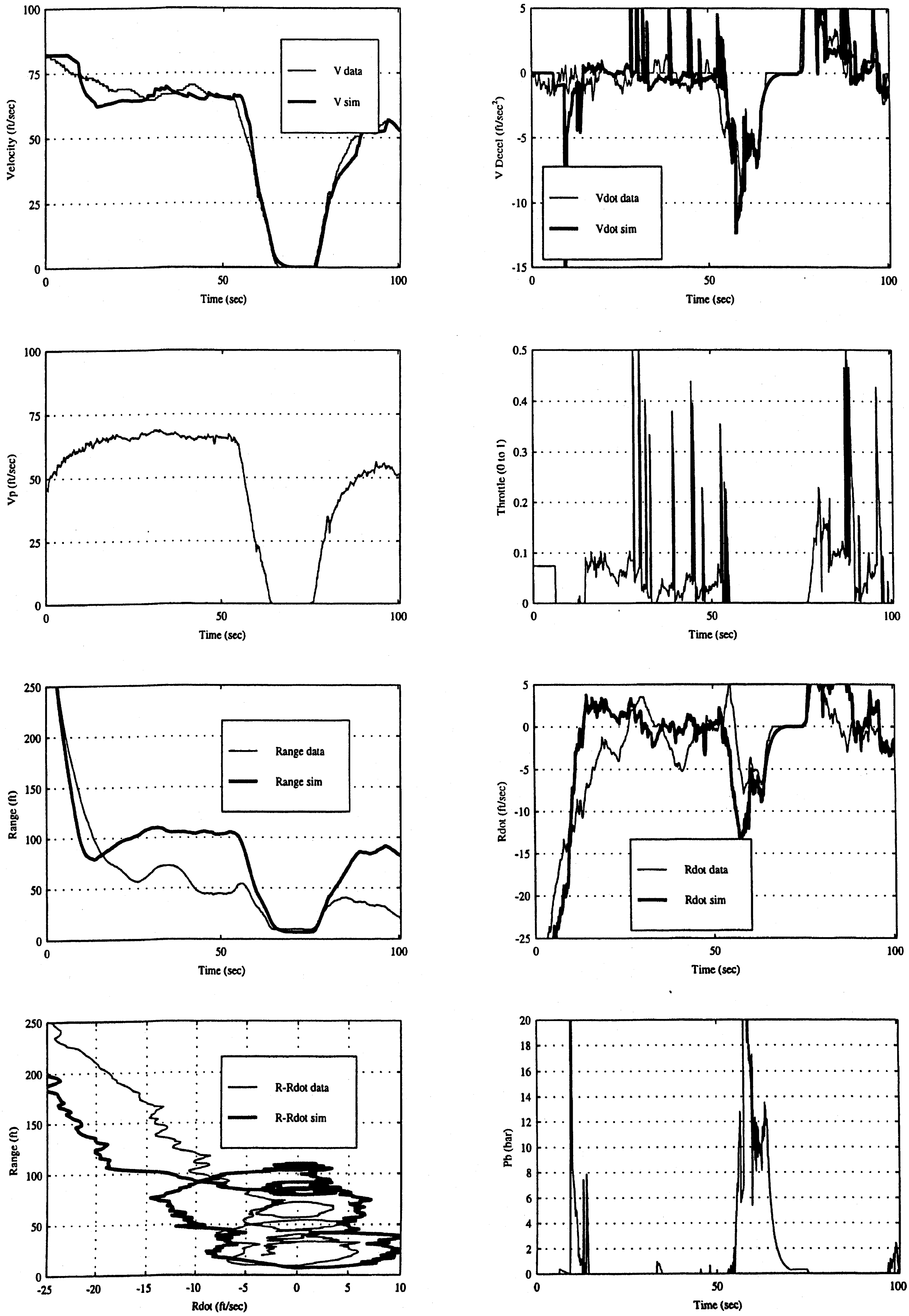
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0
Driver: z143_1 11.txt



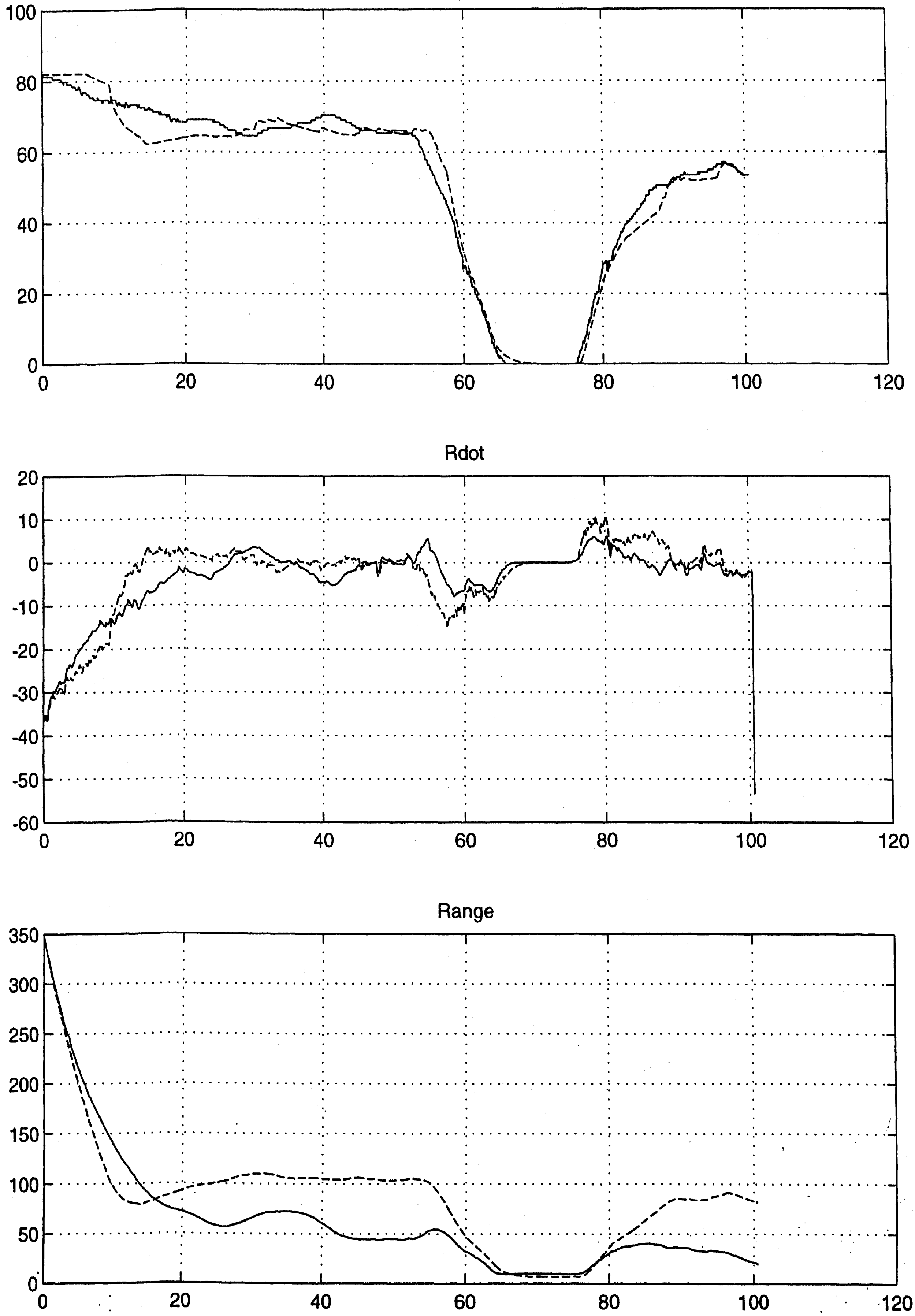
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0, rms = 8.35, meanRerr = 6.95
Driver: $z143_1 11$.txt



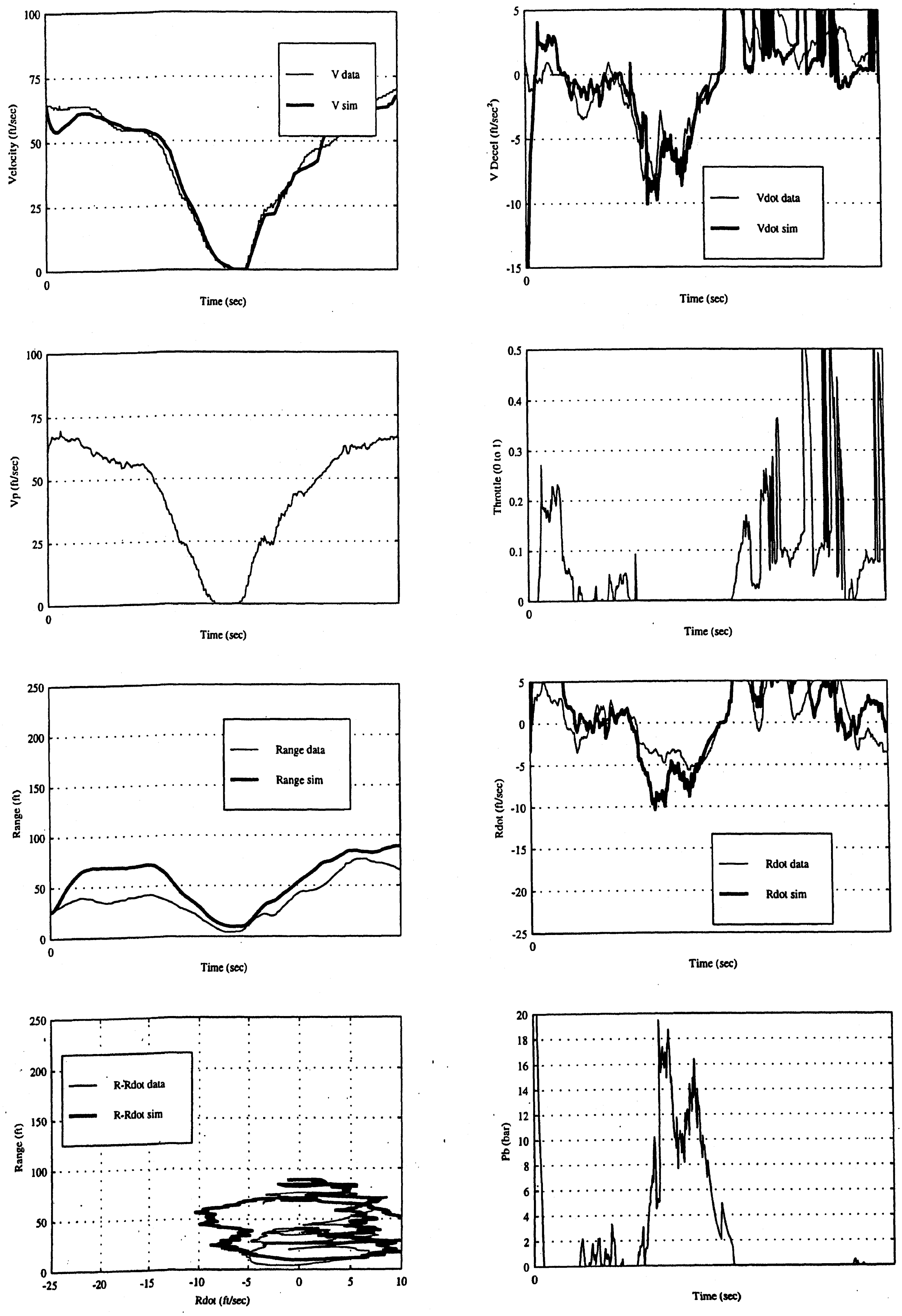
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3
Driver: z143$_1$26.txt



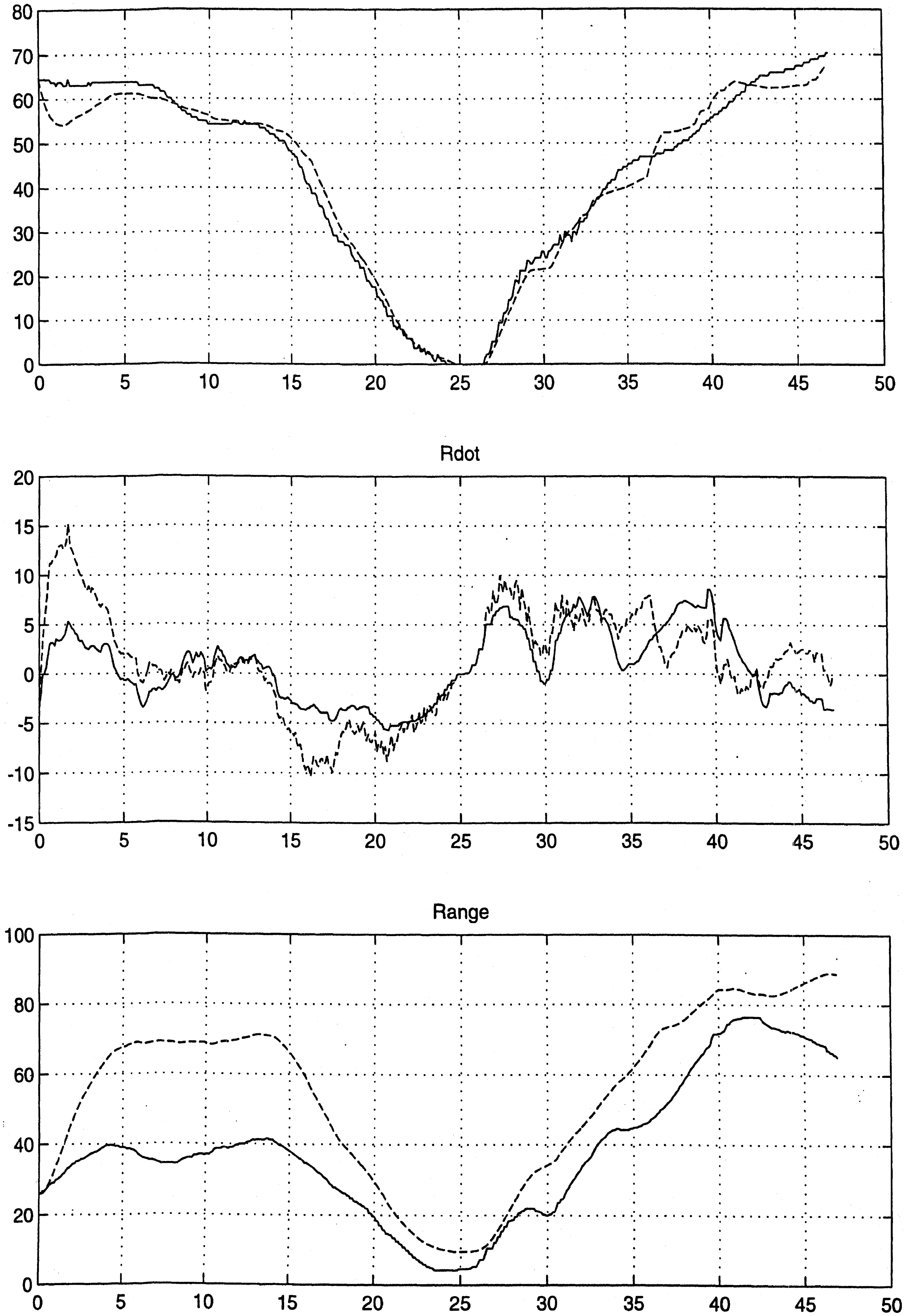
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3, rms = 37.18, meanRerr = 30.56
Driver: z143_1 26.txt



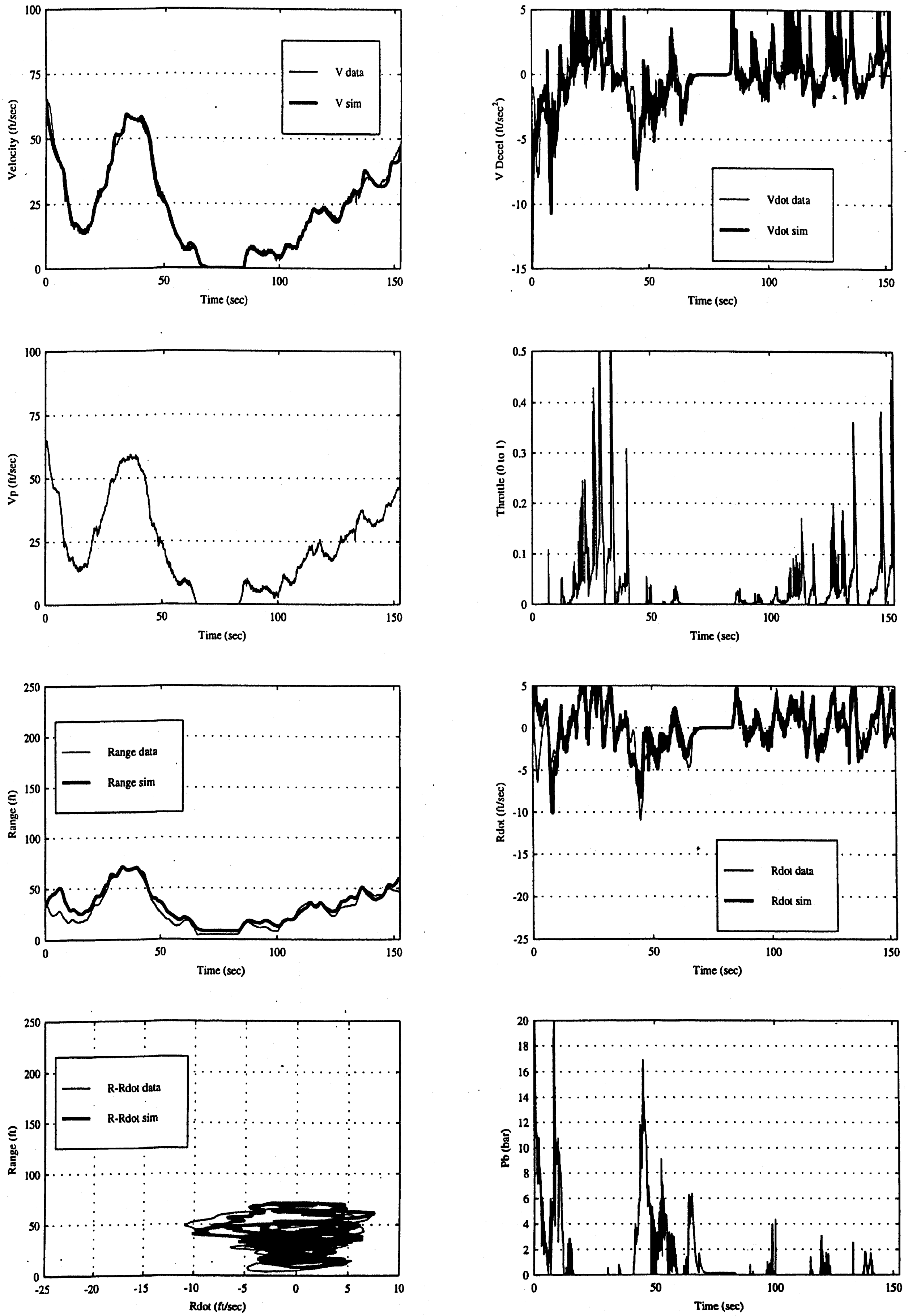
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.0, Tc = 2.8, T2 = 2.8, T3 = 1.0
Driver: z143$_1$55.txt



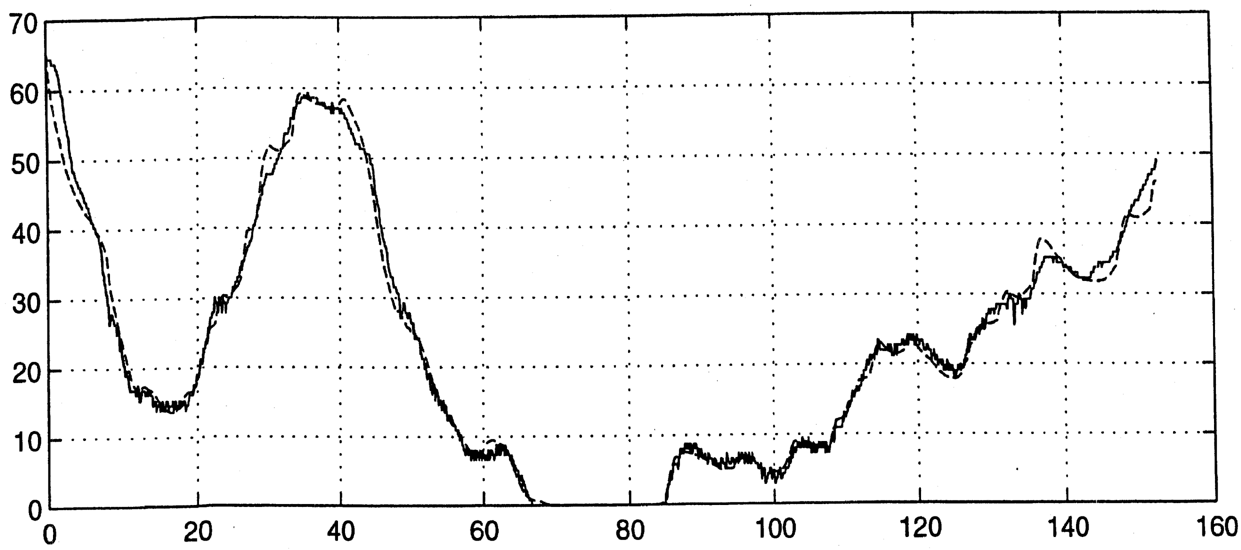
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.0, Tc = 2.8, T2 = 2.8, T3 = 1.0, rms = 19.21, meanRerr = 16.35
Driver: z143$_1$55.txt

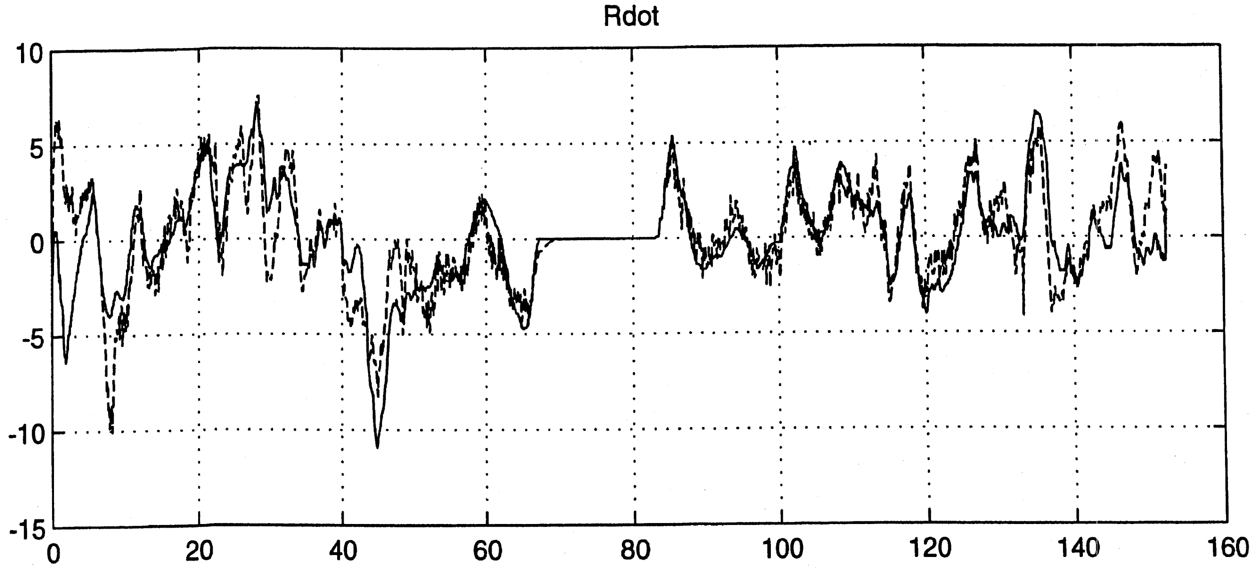


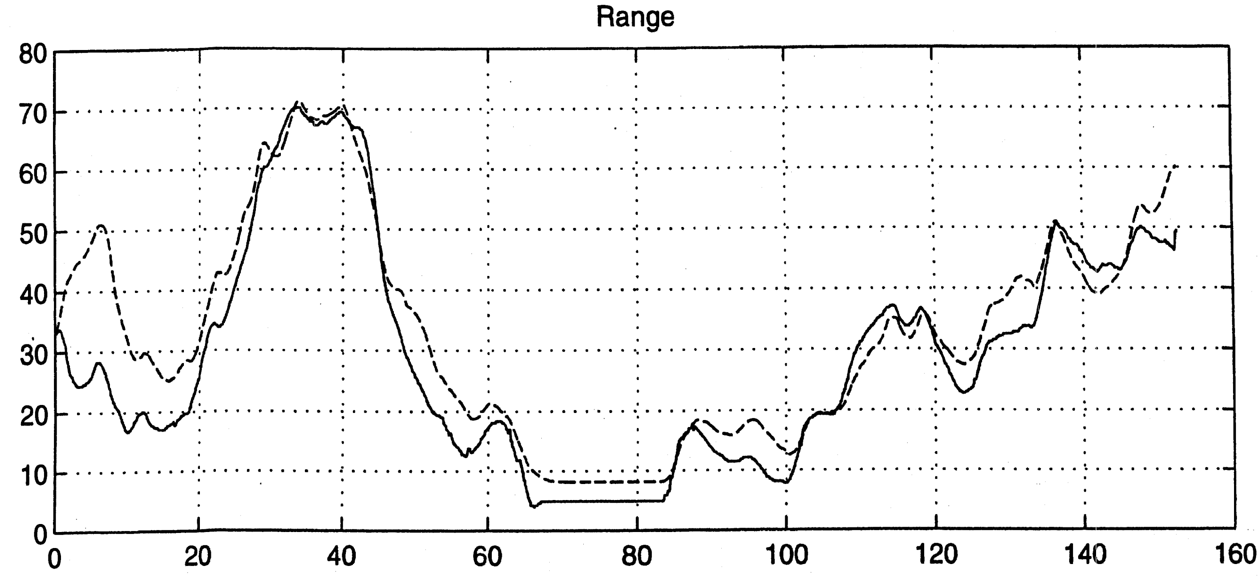
BMW Model, data vs. simulation (RunB).
Model 151, Th = 0.9, Tc = 2.8, T2 = 2.8, T3 = 0.9
Driver: z143$_2$1.txt



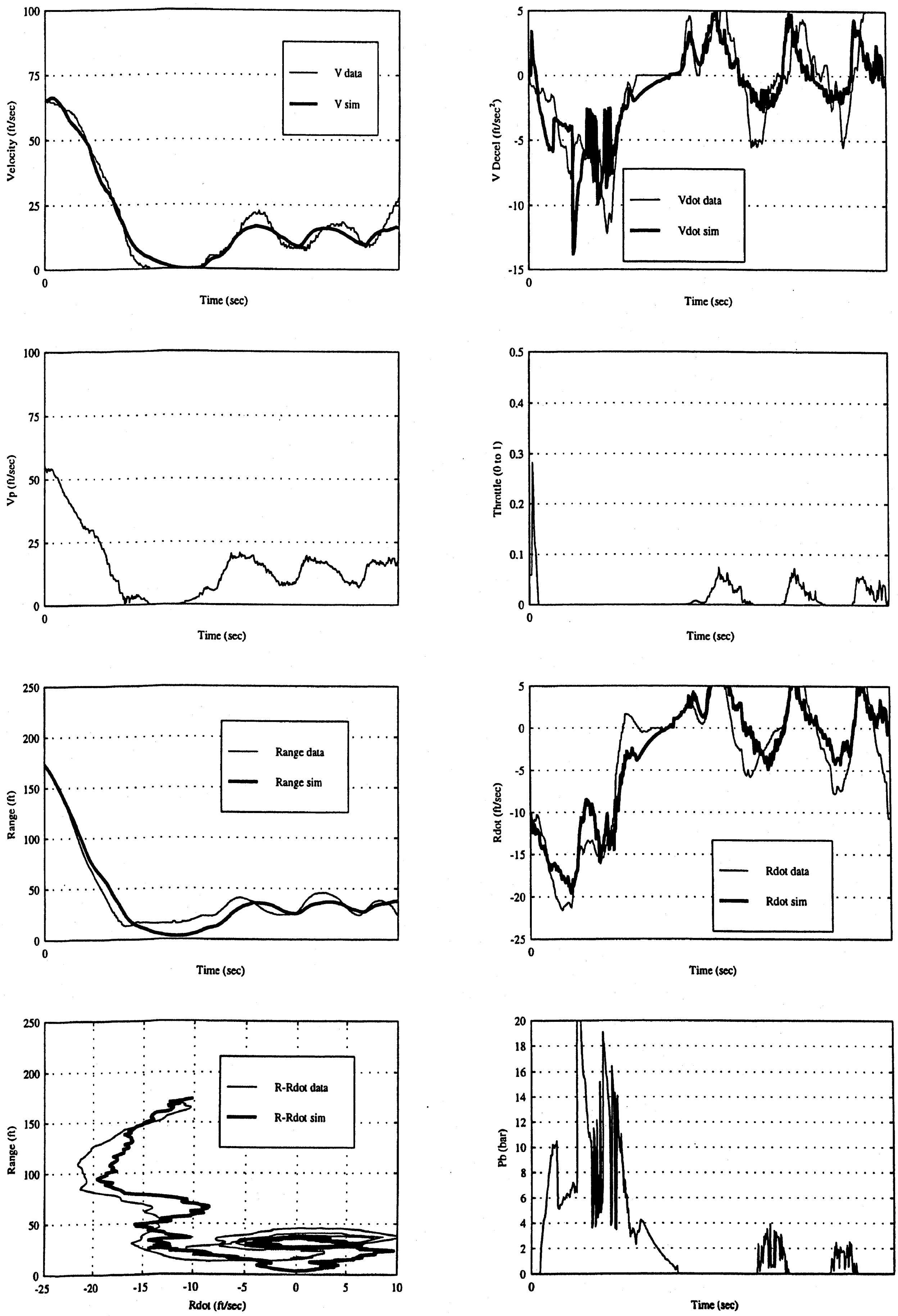
BMW Model, data vs. simulation (RunB).
Model 151, Th = 0.9, Tc = 2.8, T2 = 2.8, T3 = 0.9, rms = 6.83, meanRerr = 5.04
Driver: $z143_2 1$.txt



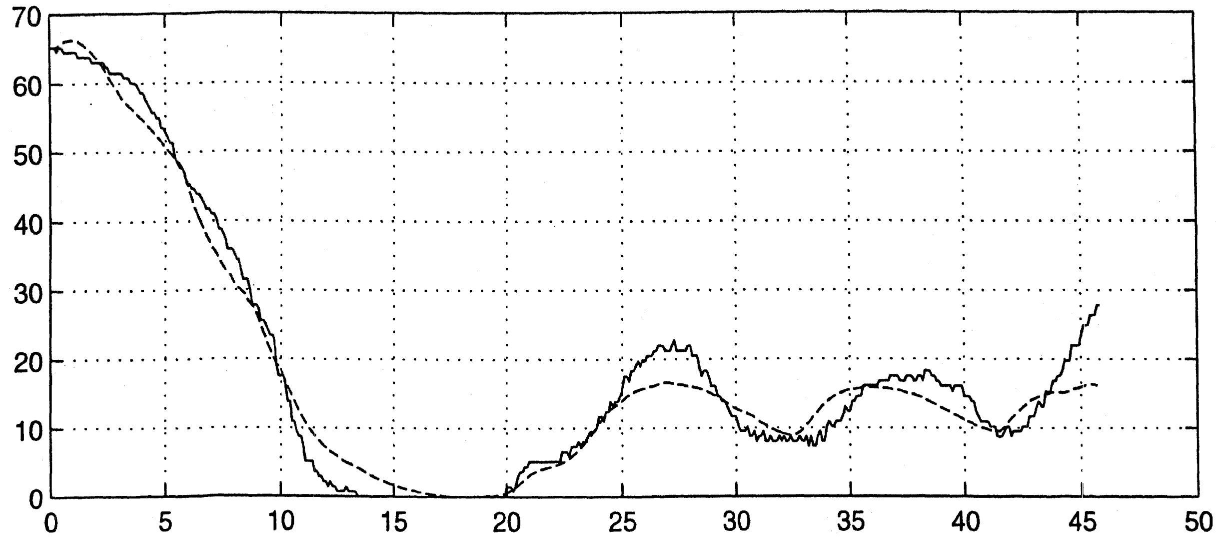




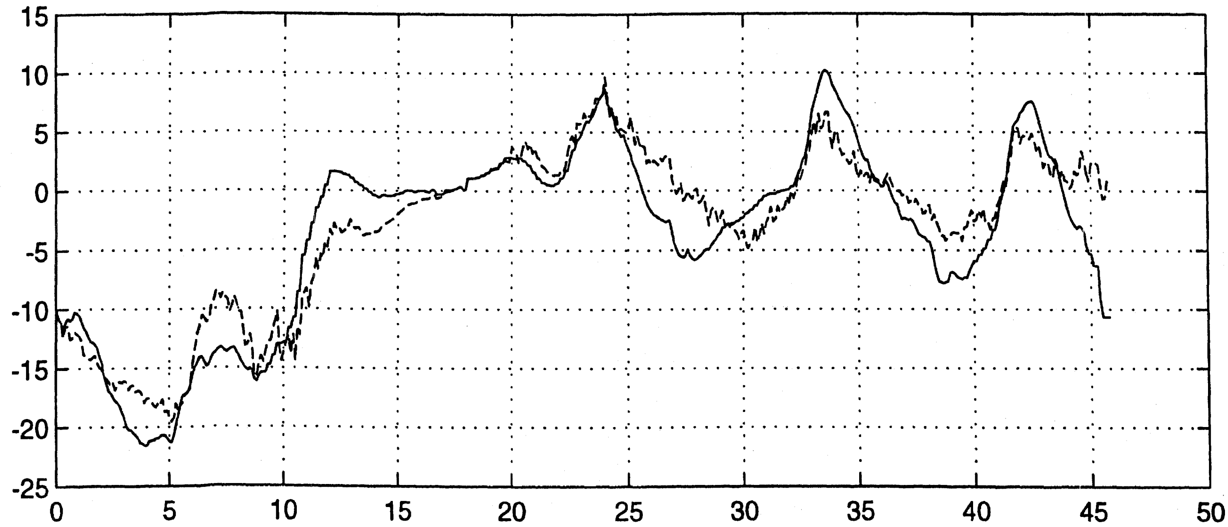
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9
Driver: z143$_4$0.txt



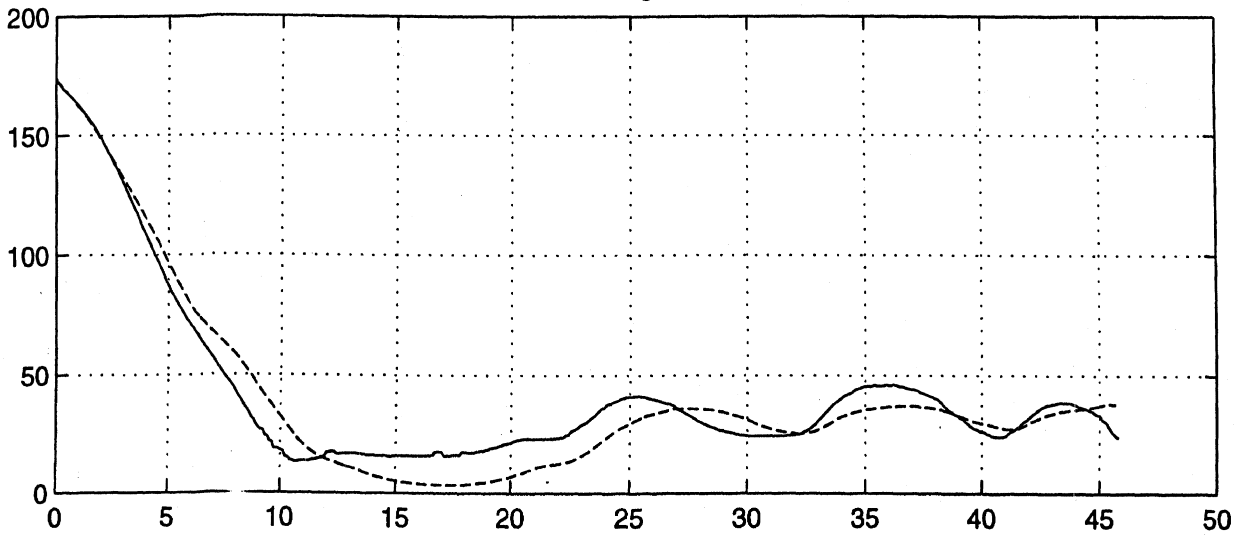
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9, rms = 8.90, meanRerr = 7.41
Driver: z143$_4$0.txt



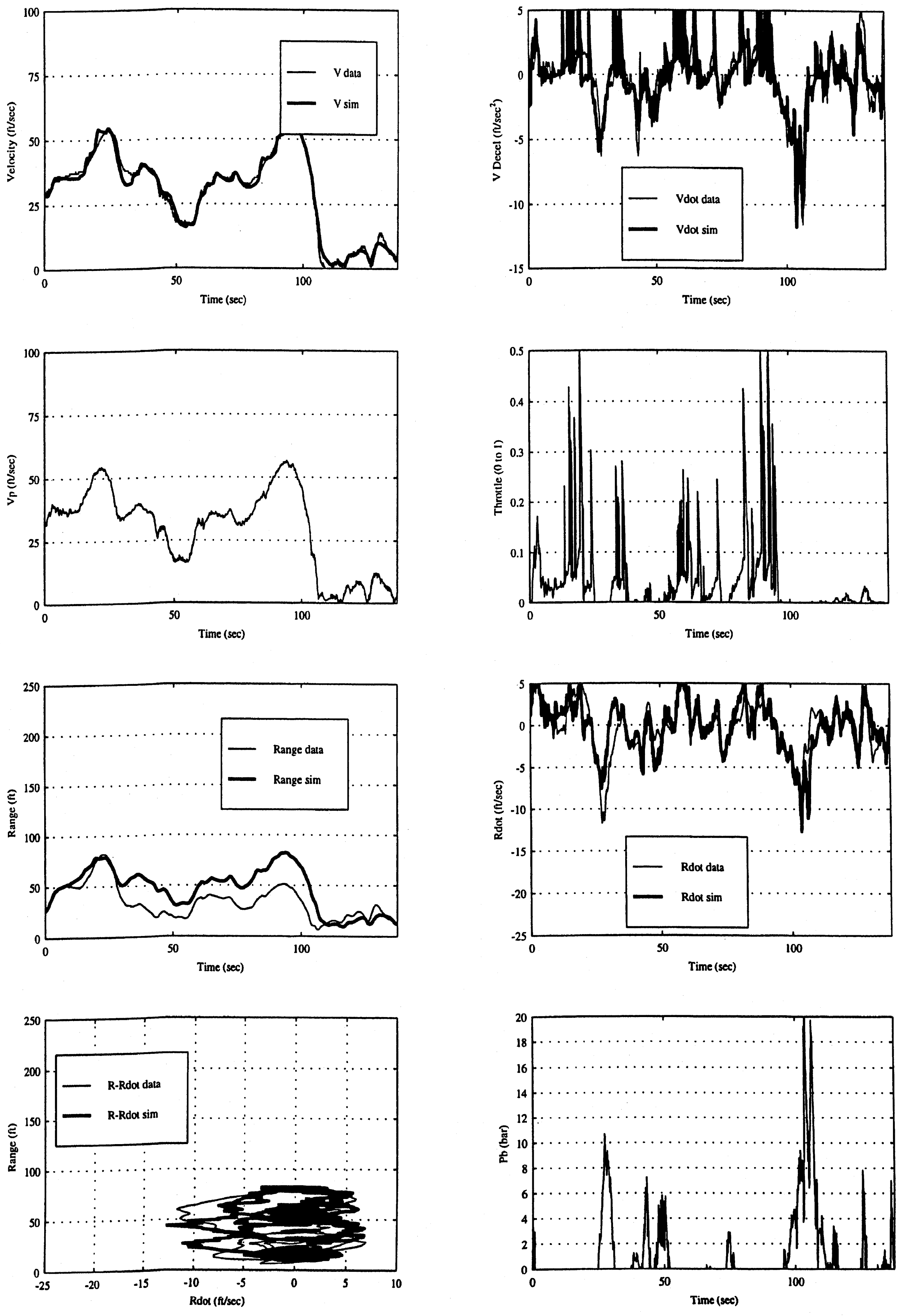
Rdot



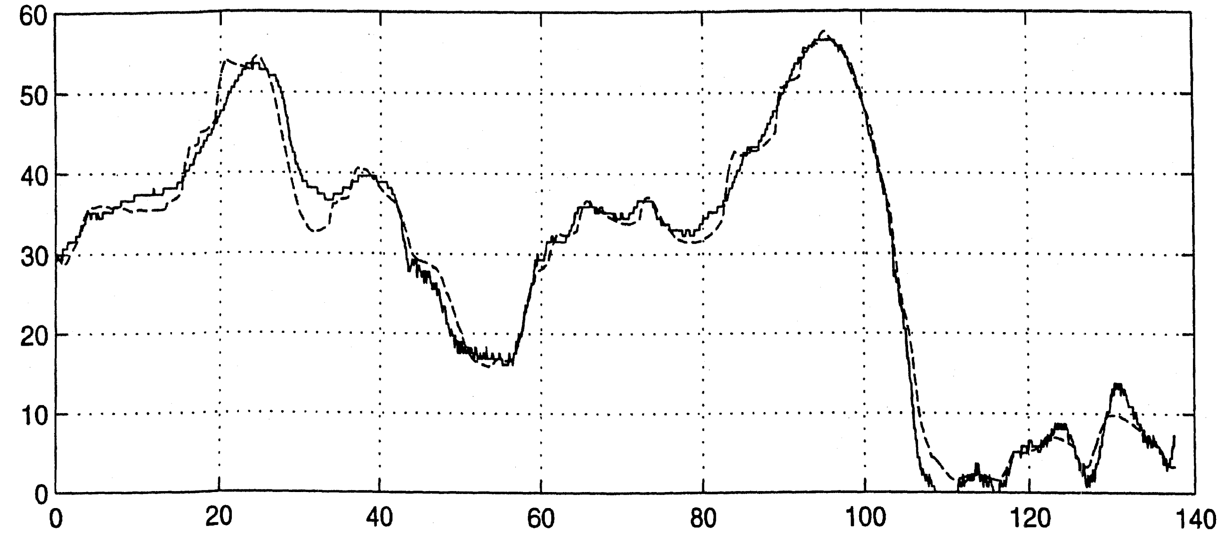
Range



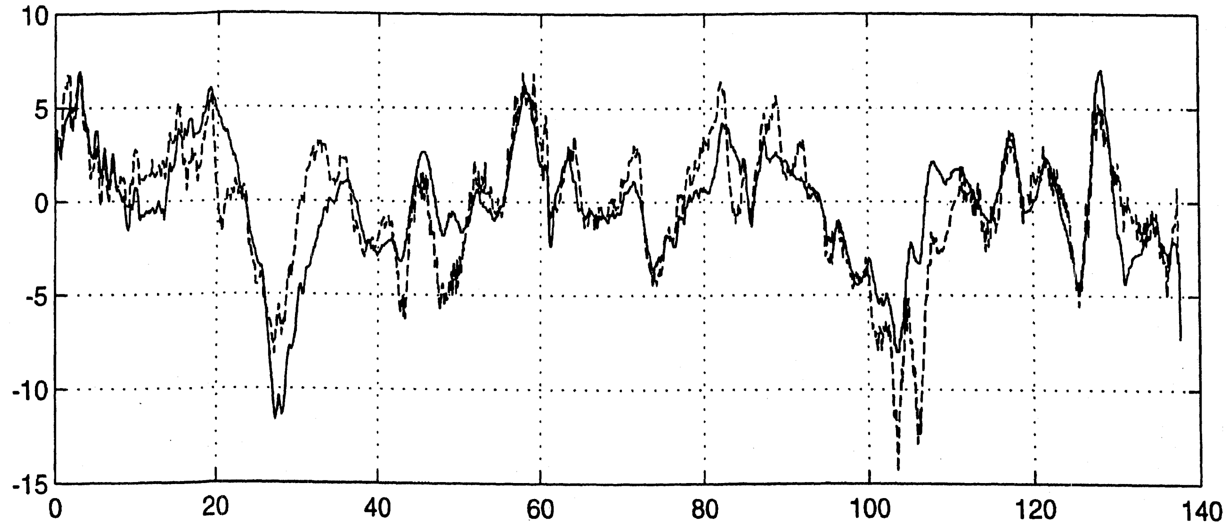
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.1, Tc = 2.8, T2 = 2.8, T3 = 1.1
Driver: z143$_4$5.txt



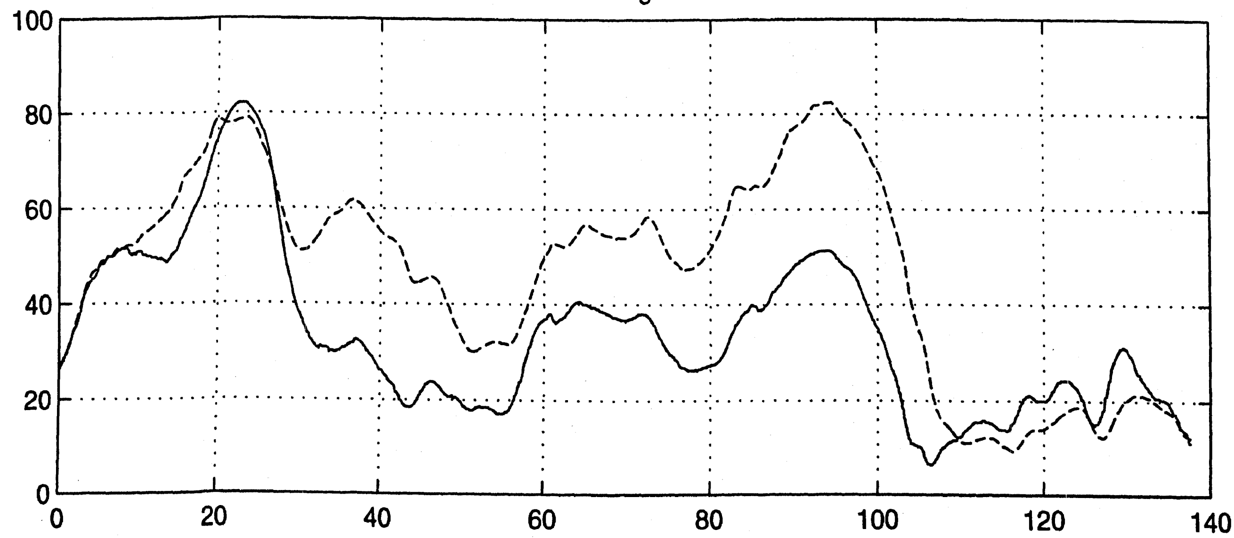
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.1, Tc = 2.8, T2 = 2.8, T3 = 1.1, rms = 18.38, meanRerr = 14.75
Driver: z143$_4$5.txt



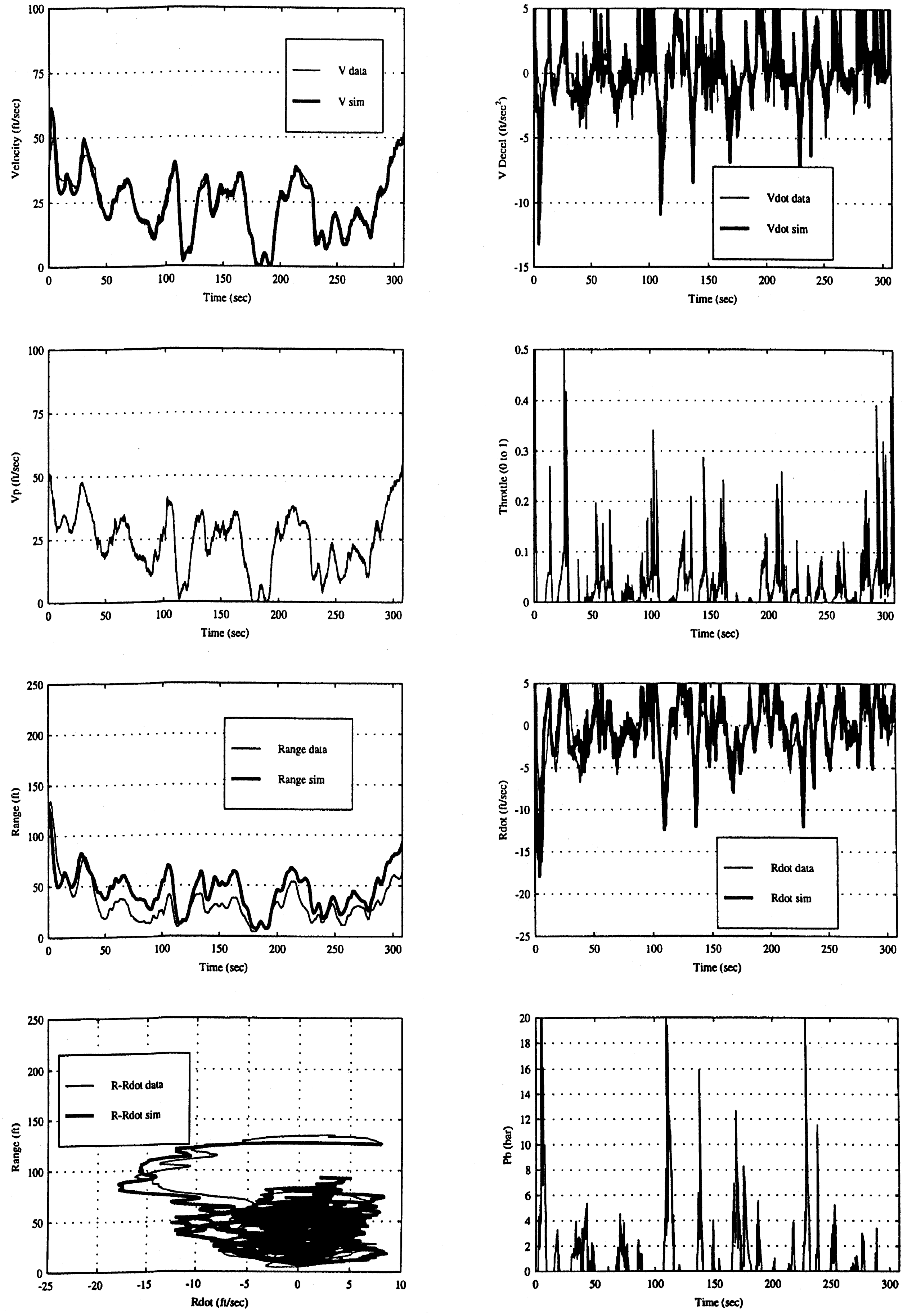
Rdot

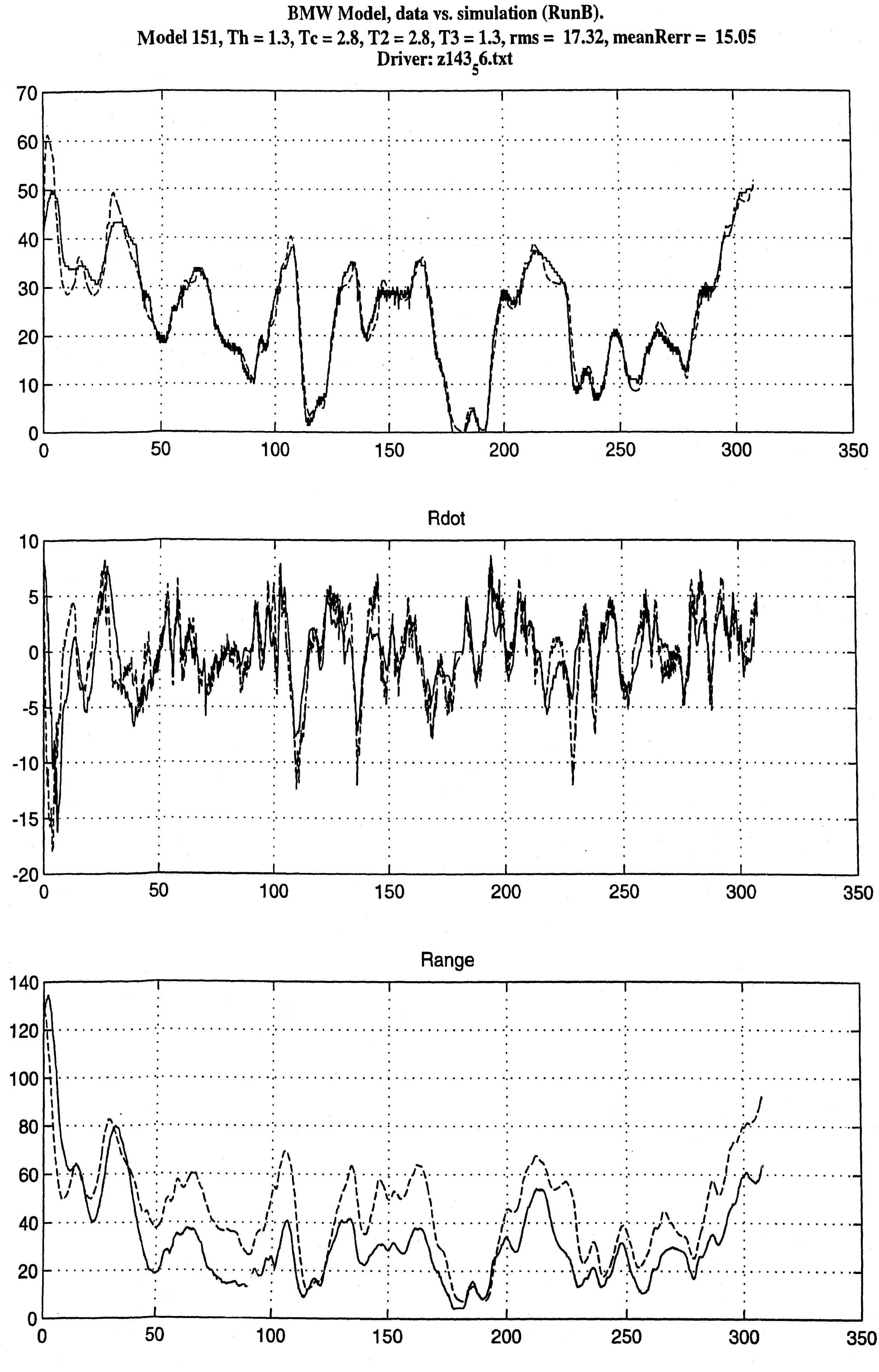


Range

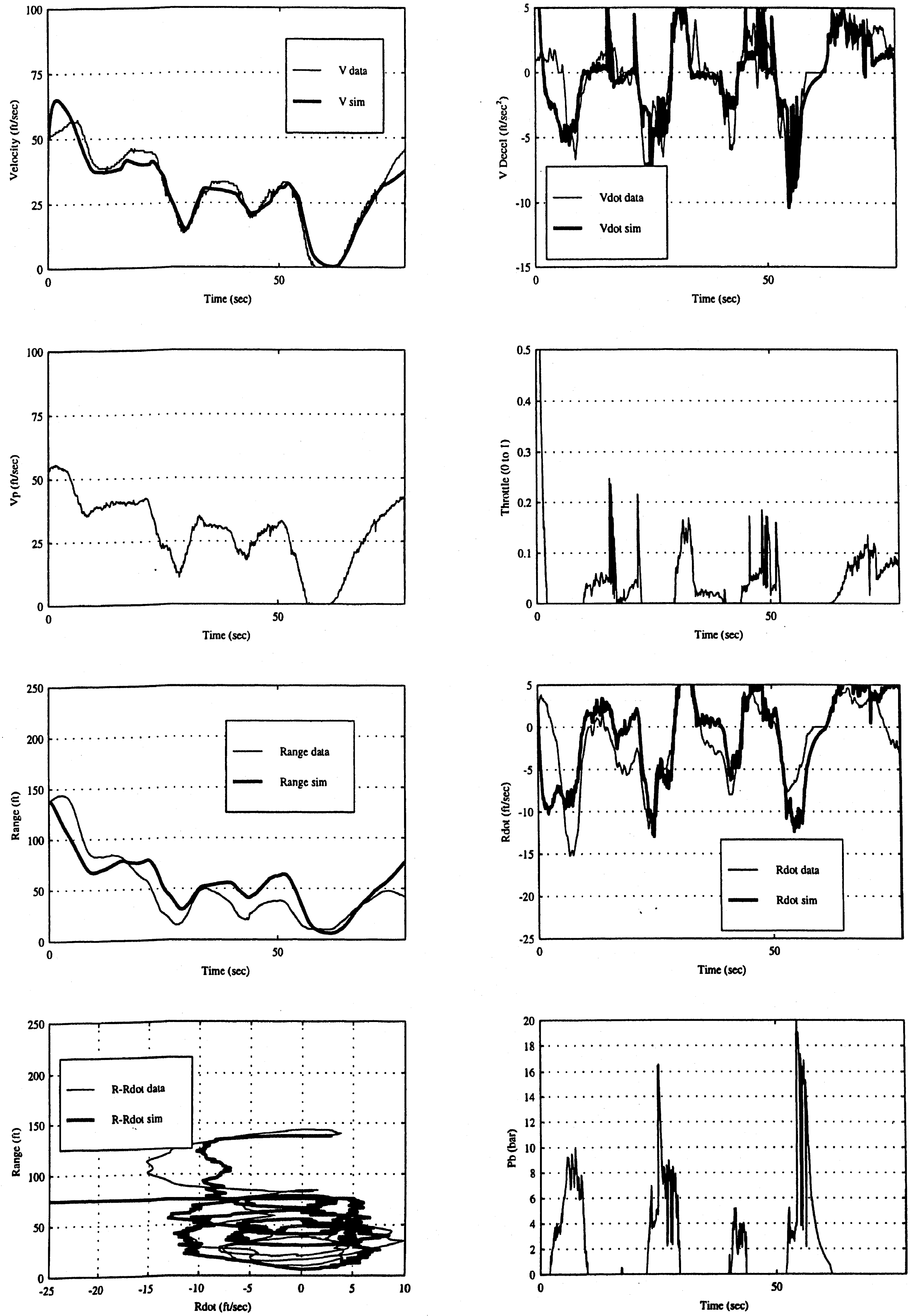


BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3
Driver: z143$_5$6.txt

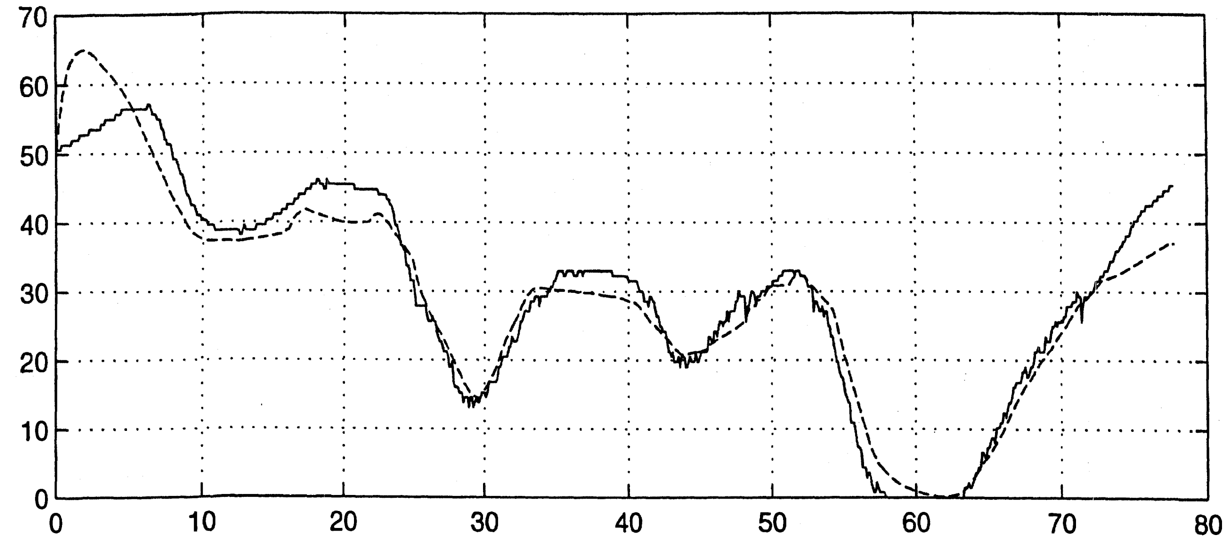


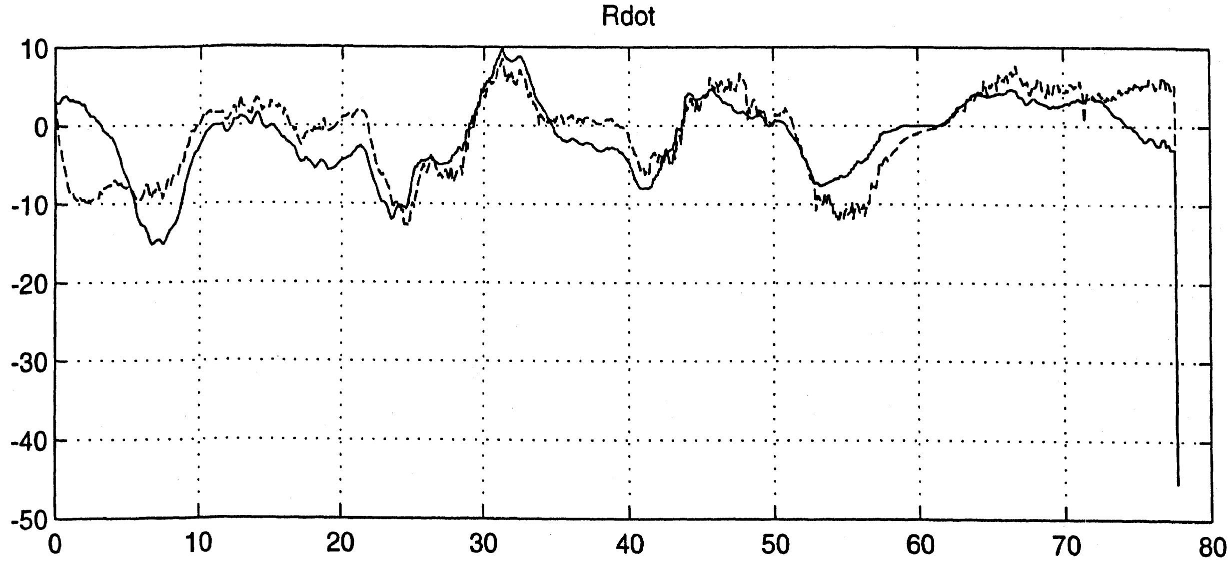

BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3, rms = 17.32, meanRerr = 15.05
Driver: z143_5 6.txt
Rdot
Range
0
50
100
150
200
250
300
350

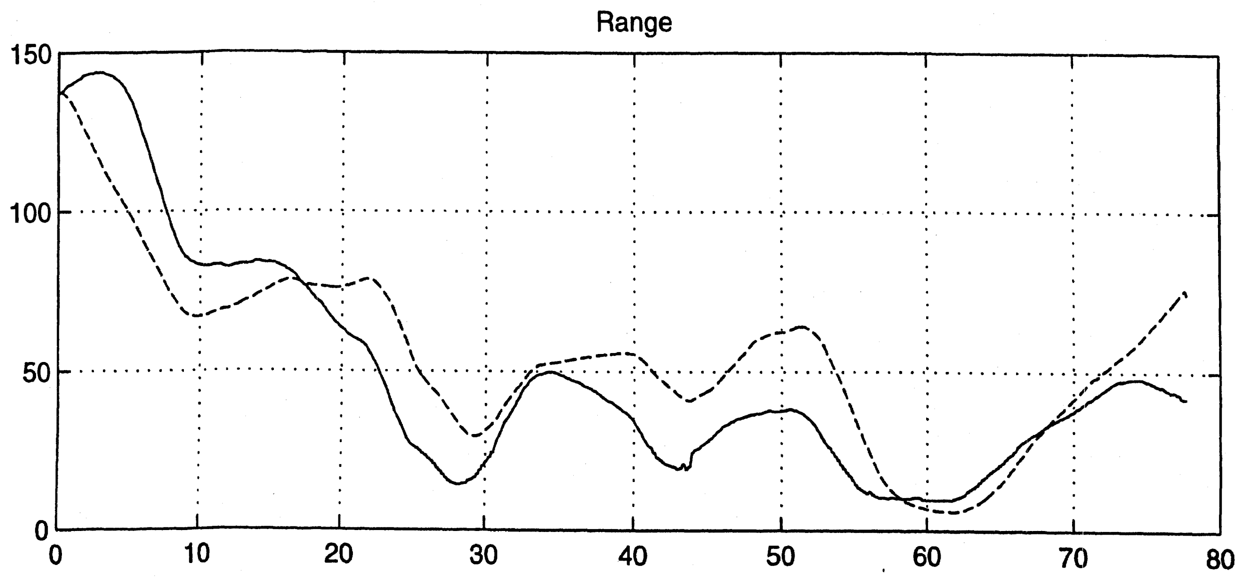
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.5, Tc = 2.8, T2 = 2.8, T3 = 1.5
Driver: z143$_{7}$2.txt



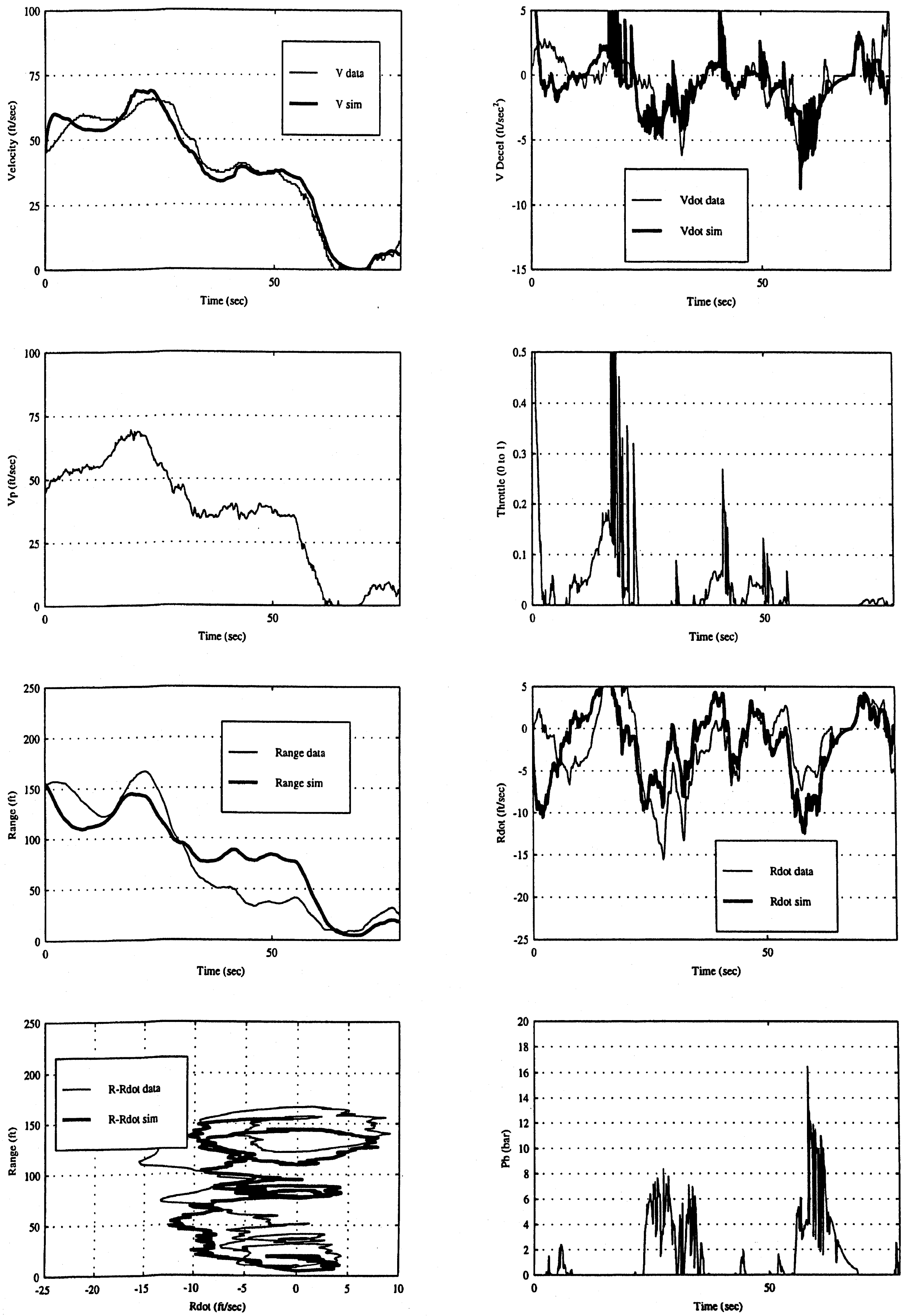
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.5, Tc = 2.8, T2 = 2.8, T3 = 1.5, rms = 17.62, meanRerr = 14.43
Driver: z143_7_2.txt



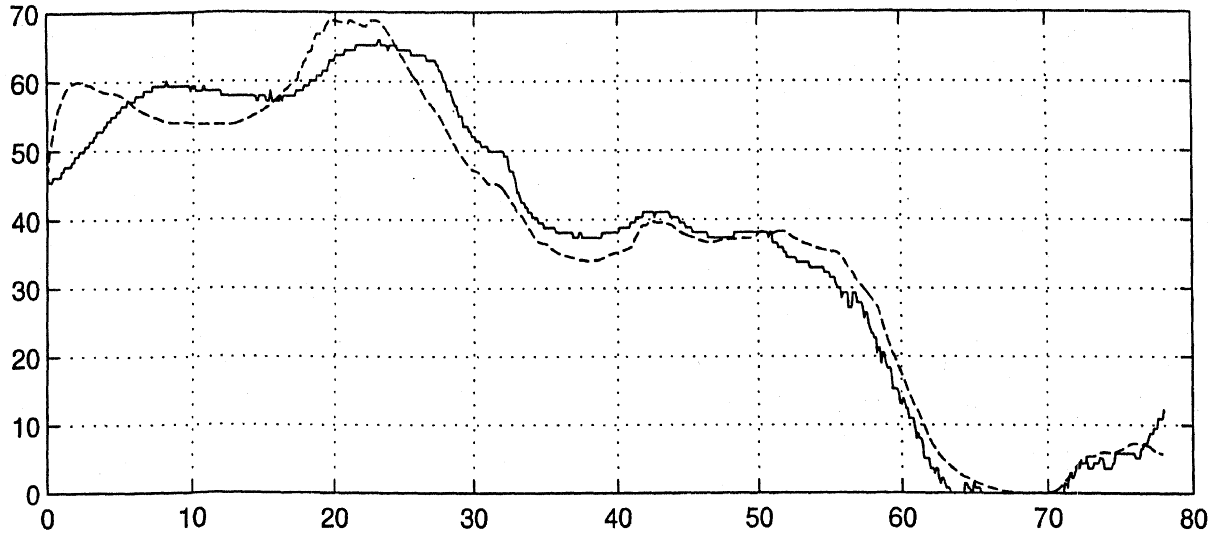




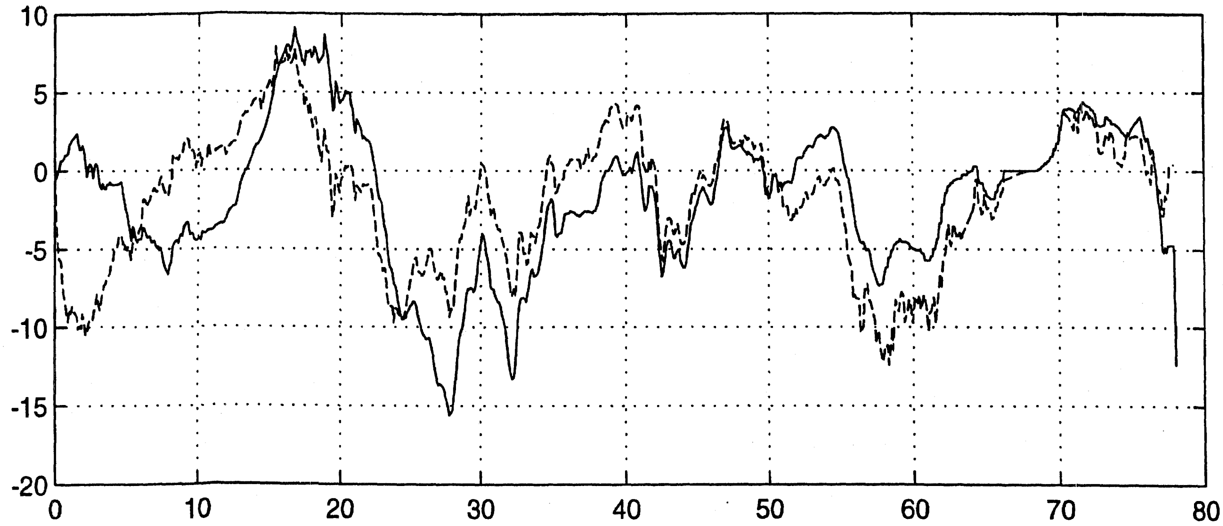
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.7, Tc = 2.8, T2 = 2.8, T3 = 1.7
Driver: z143$_9$7.txt



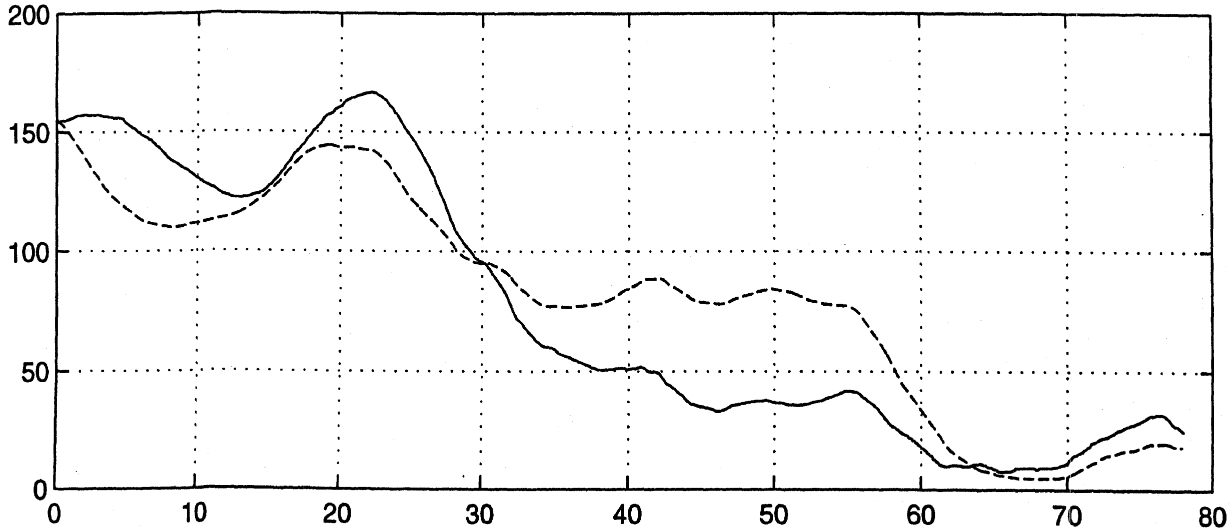
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.7, Tc = 2.8, T2 = 2.8, T3 = 1.7, rms = 25.06, meanRerr = 20.48
Driver: z143$_9$7.txt



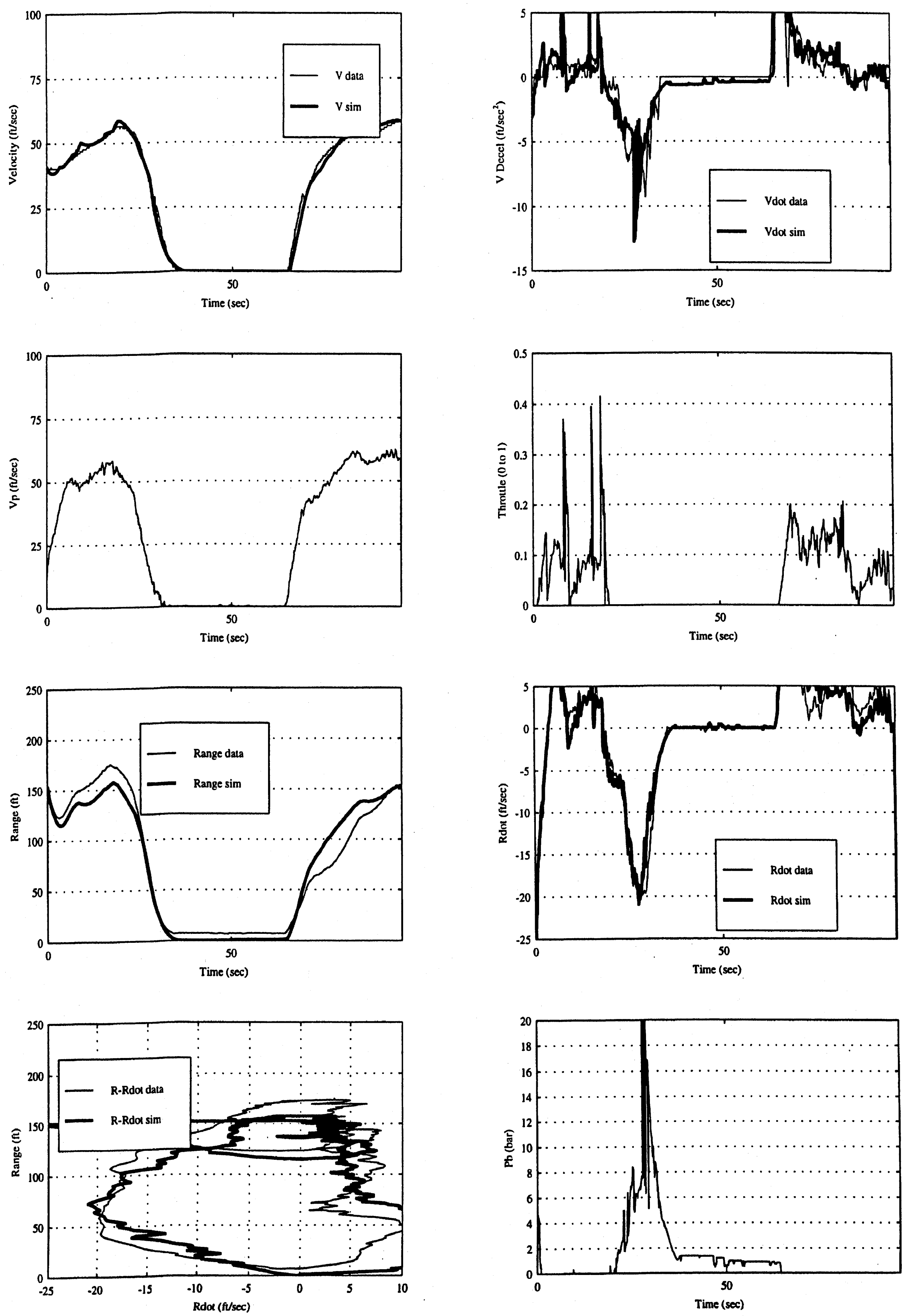
Rdot



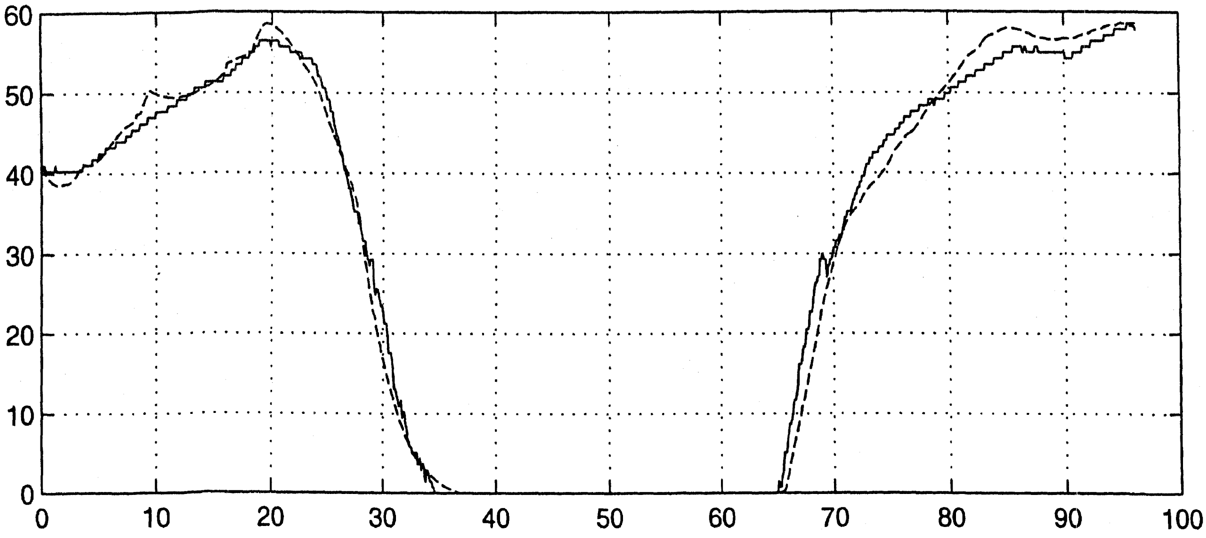
Range



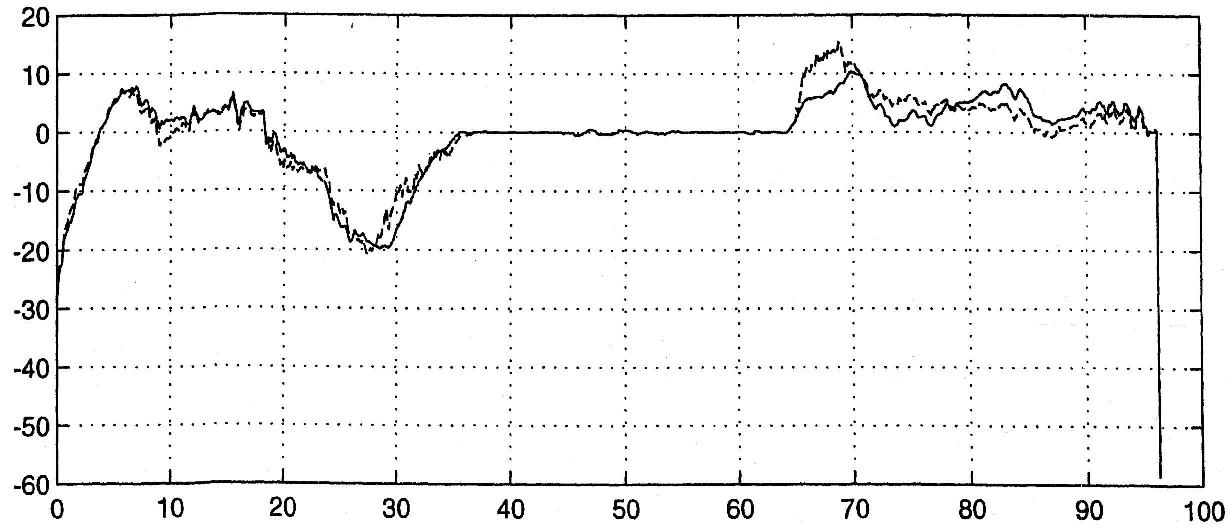
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.3, Tc = 2.8, T2 = 2.8, T3 = 2.3
Driver: z150_1 17.txt



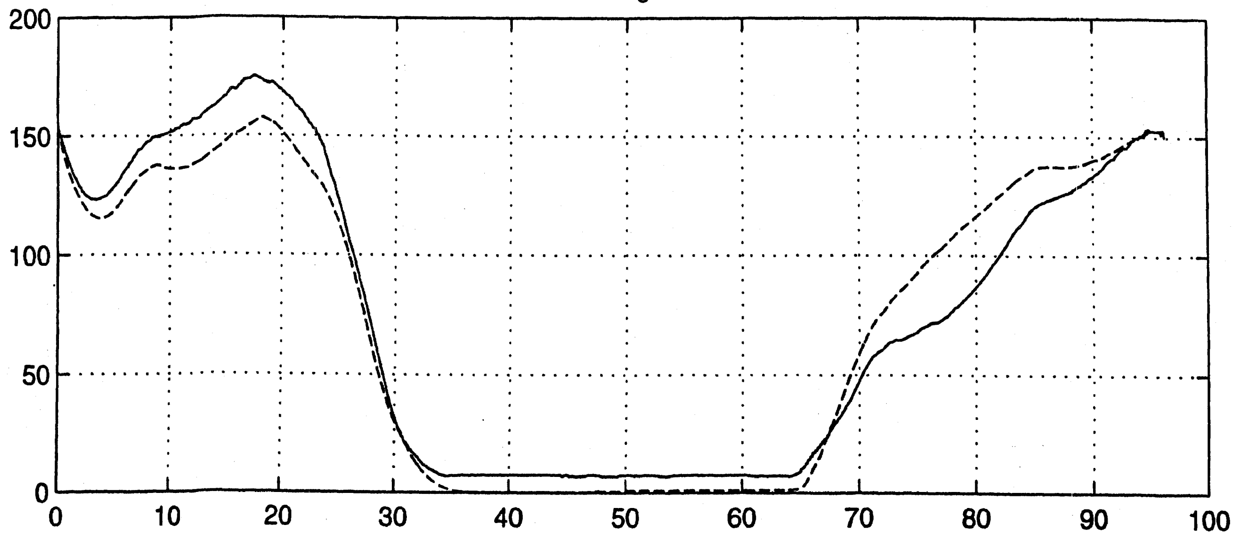
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.3, Tc = 2.8, T2 = 2.8, T3 = 2.3, rms = 13.32, meanRerr = 10.96
Driver: z150$_1$17.txt



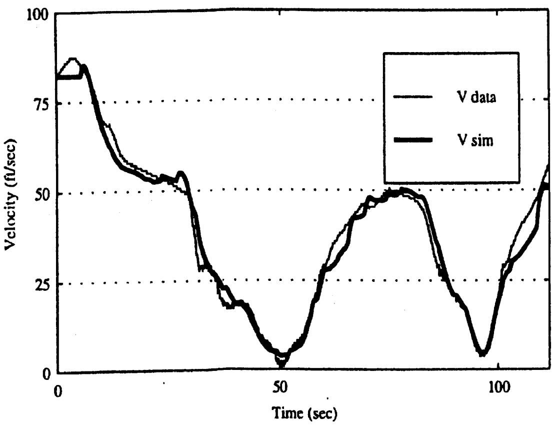
Rdot

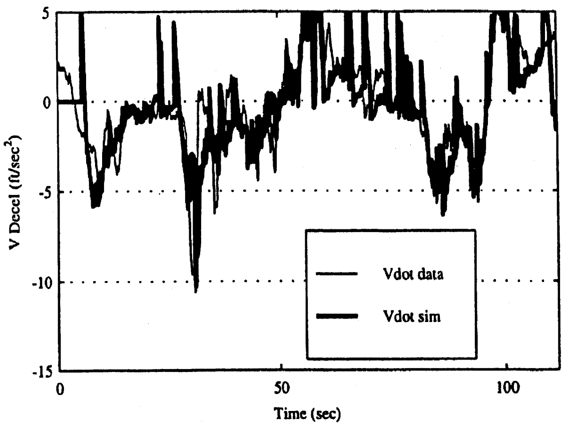


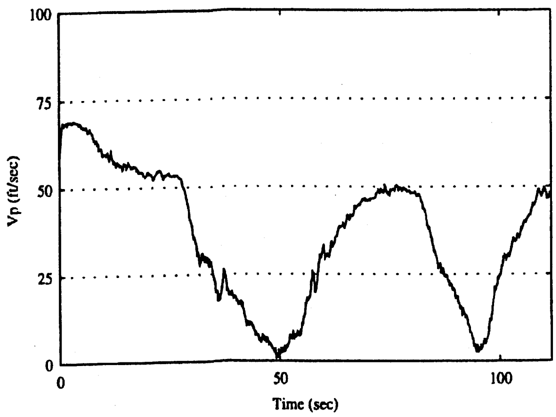
Range

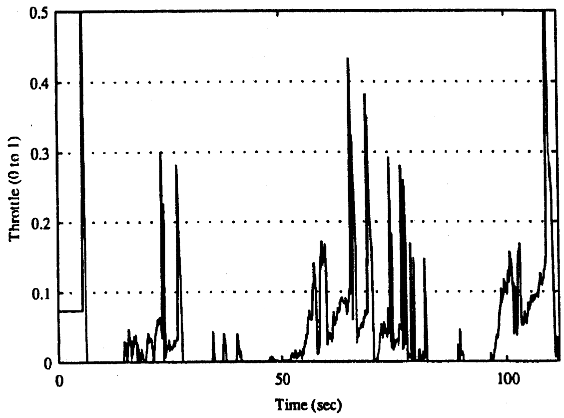


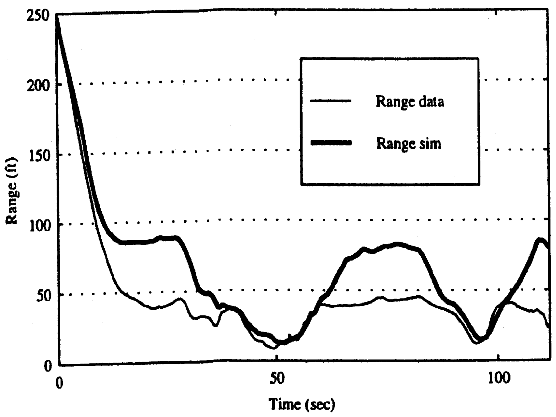
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3
Driver: $z150_1 22.txt$

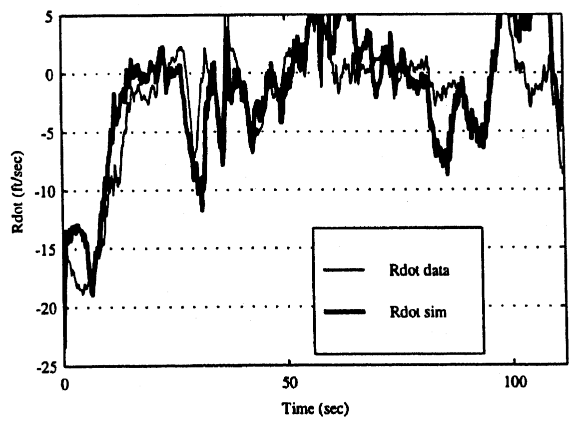


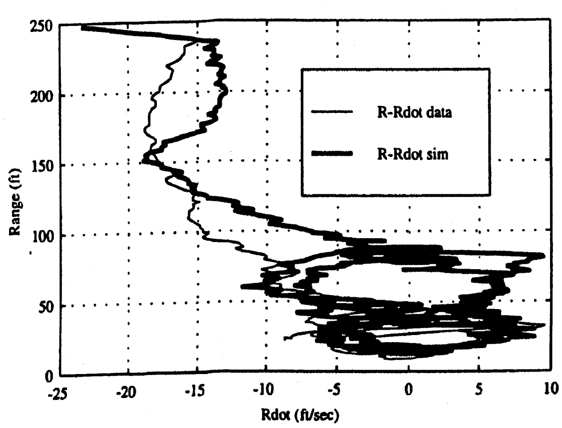


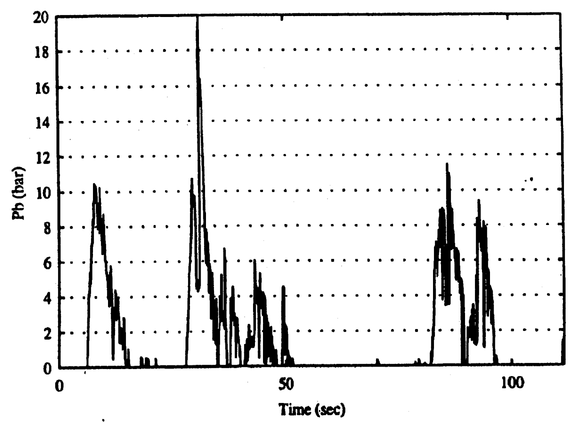




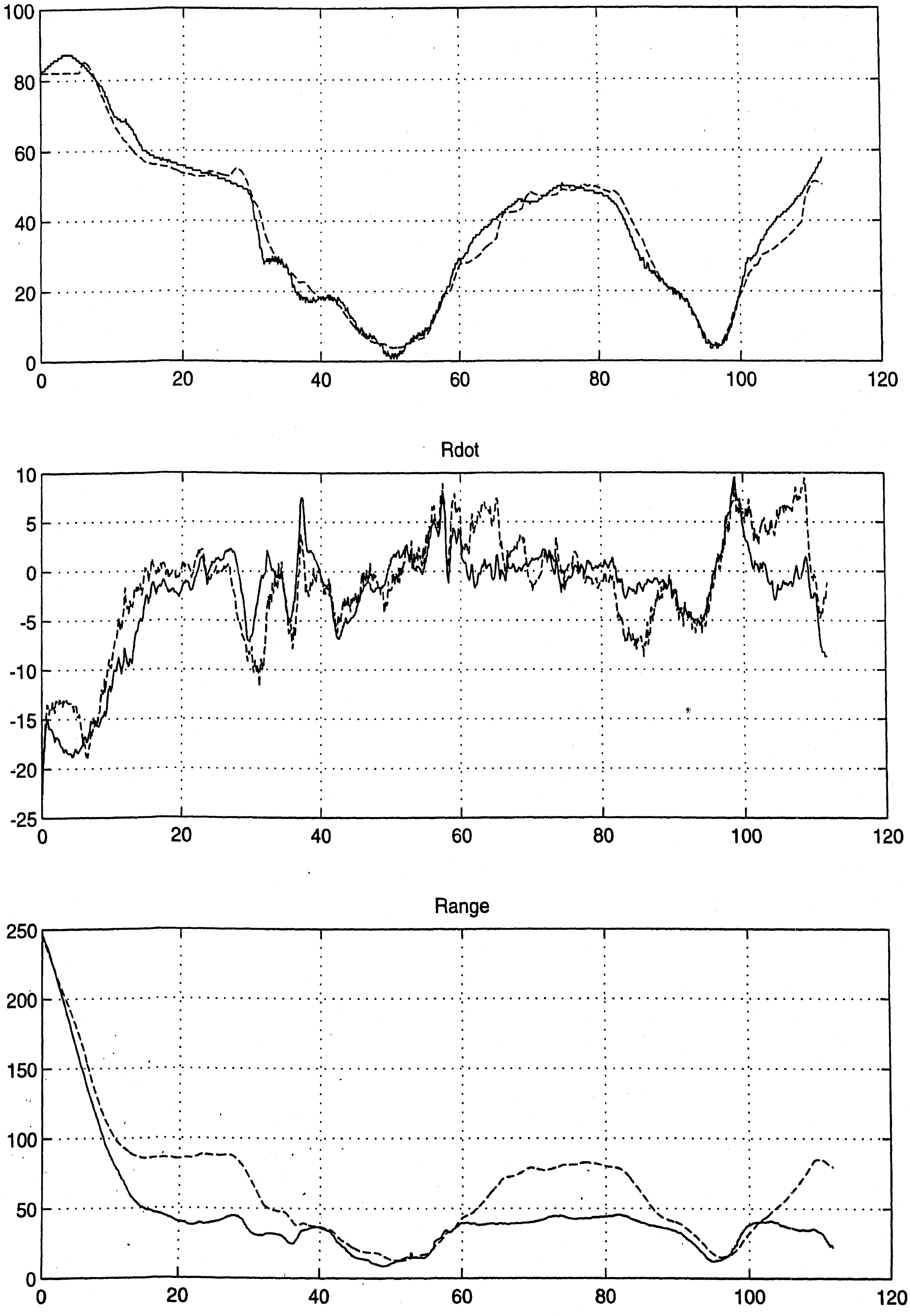




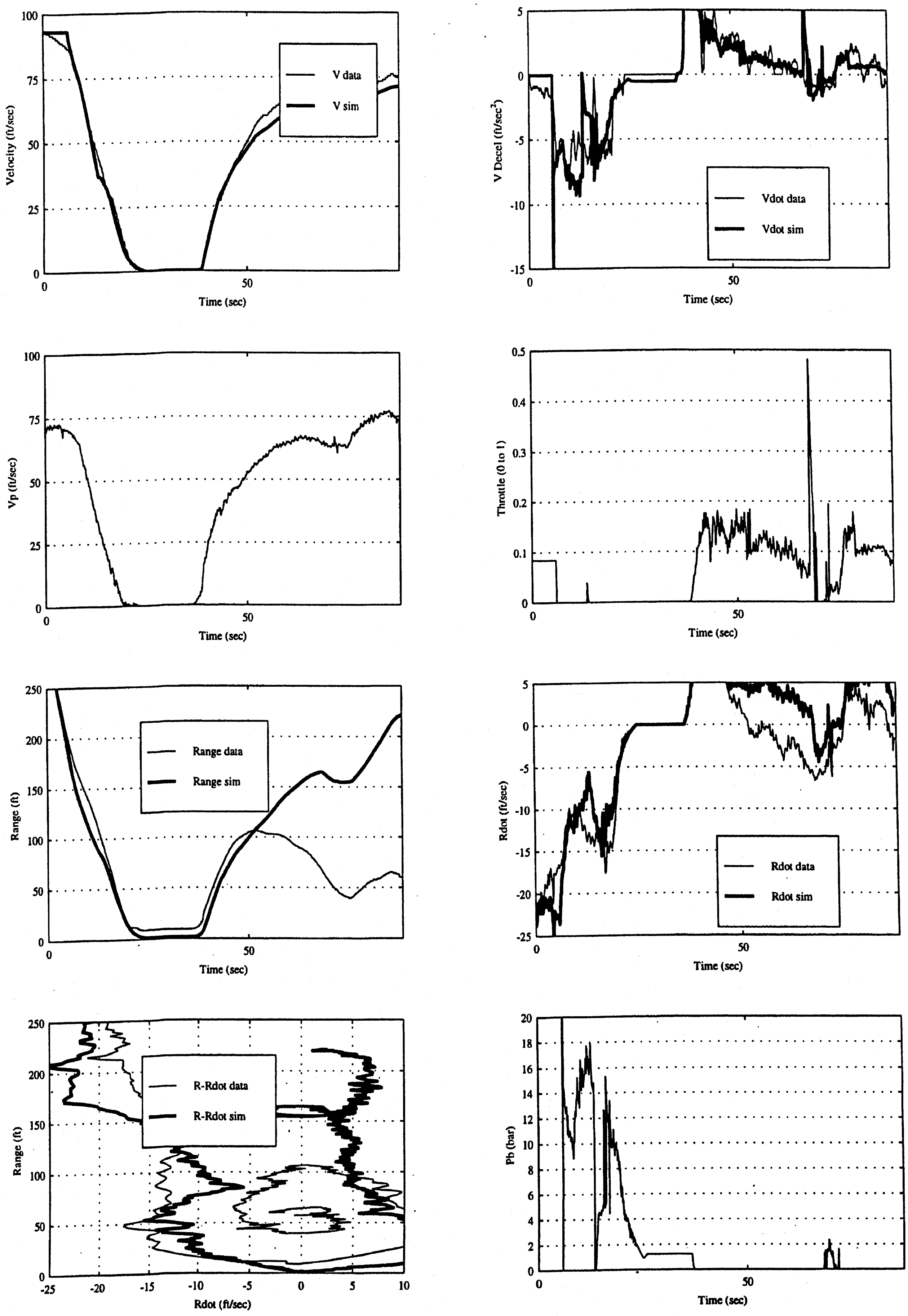




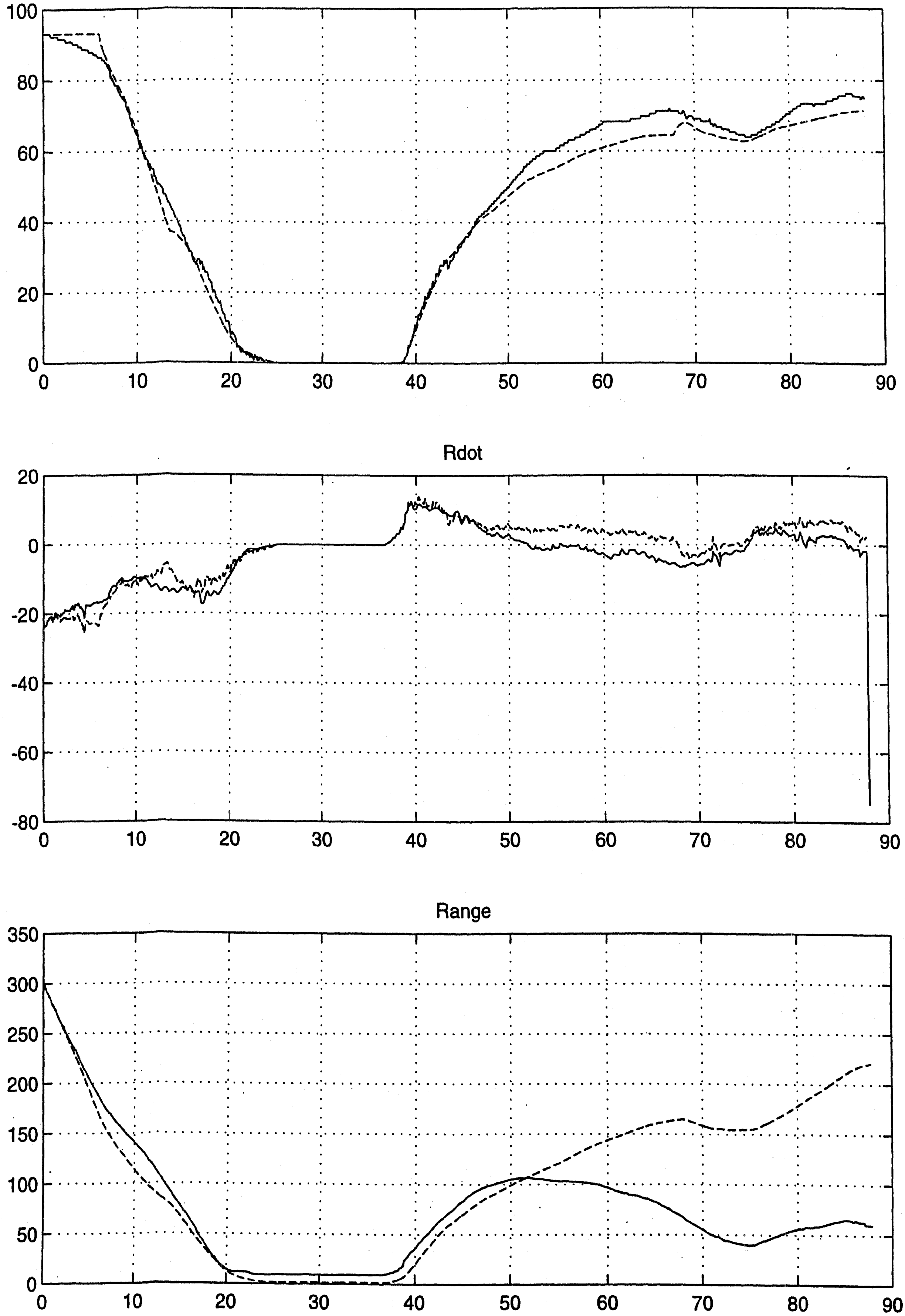
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3, rms = 26.49, meanRerr = 20.44
Driver: z150$_1$22.txt



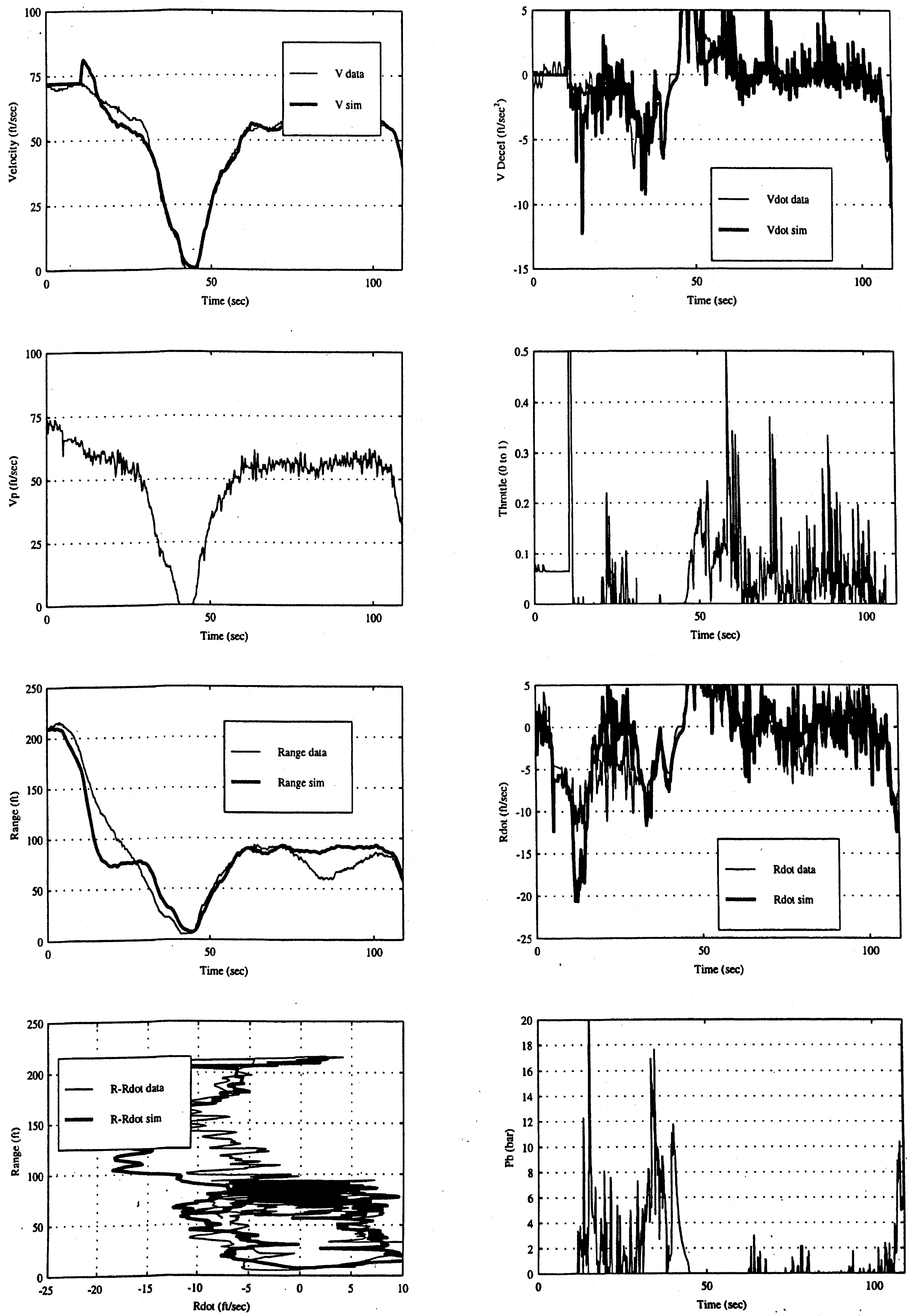
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.1, Tc = 2.8, T2 = 2.8, T3 = 2.1
Driver: z150_1 24.txt



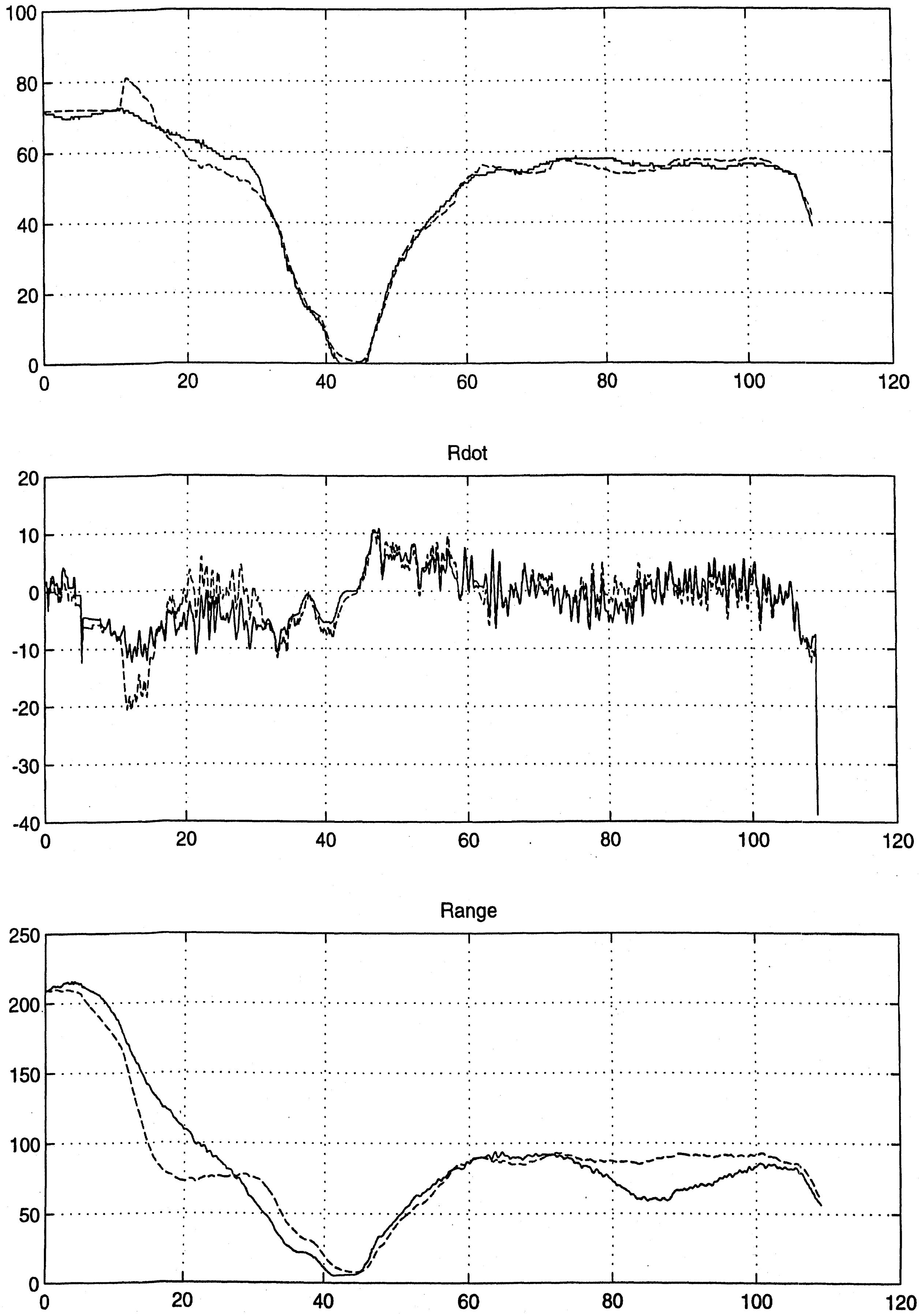
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.1, Tc = 2.8, T2 = 2.8, T3 = 2.1, rms = 64.33, meanRerr = 41.91
Driver: z150_1 24.txt



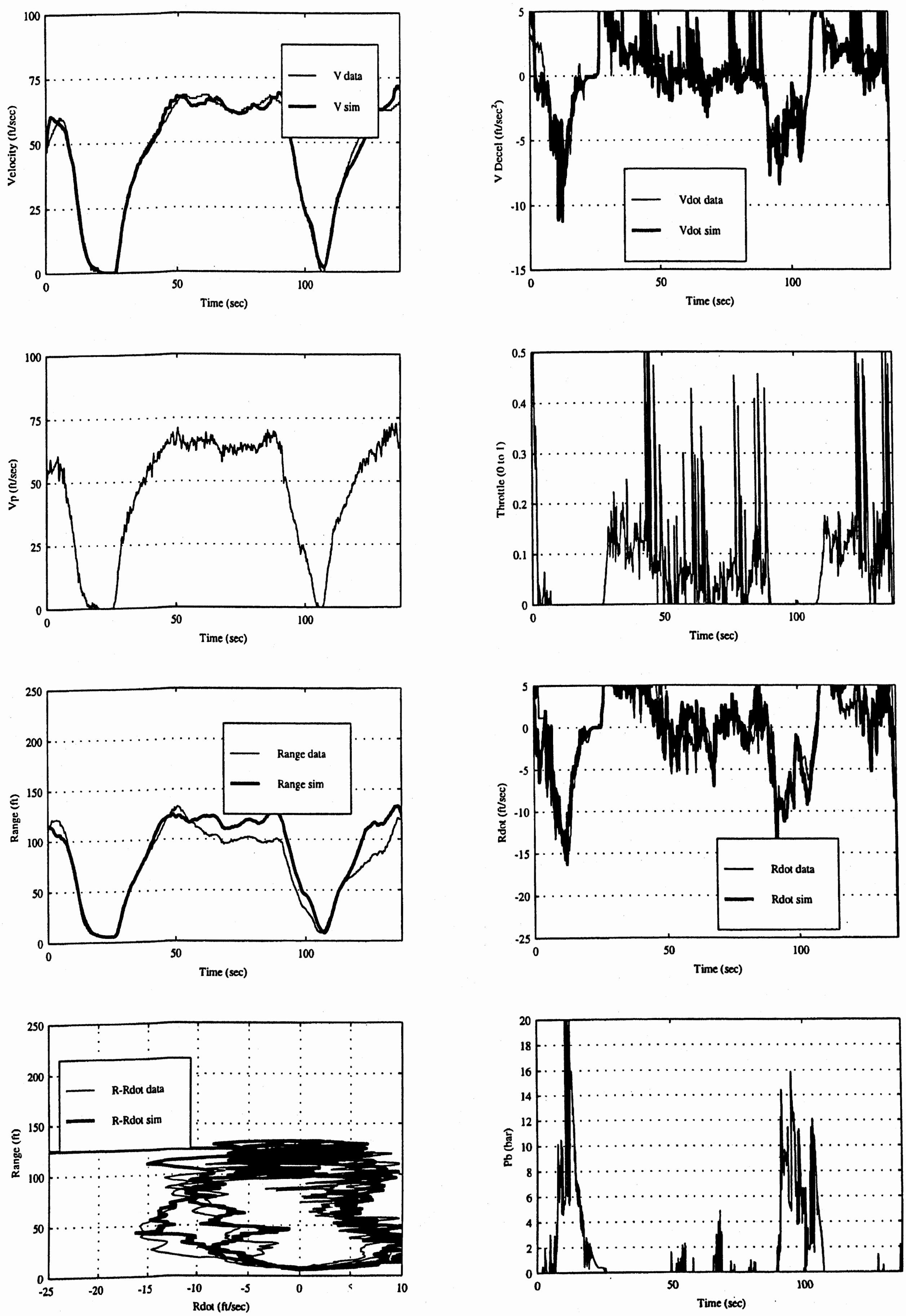
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3
Driver: z150_1 25.txt



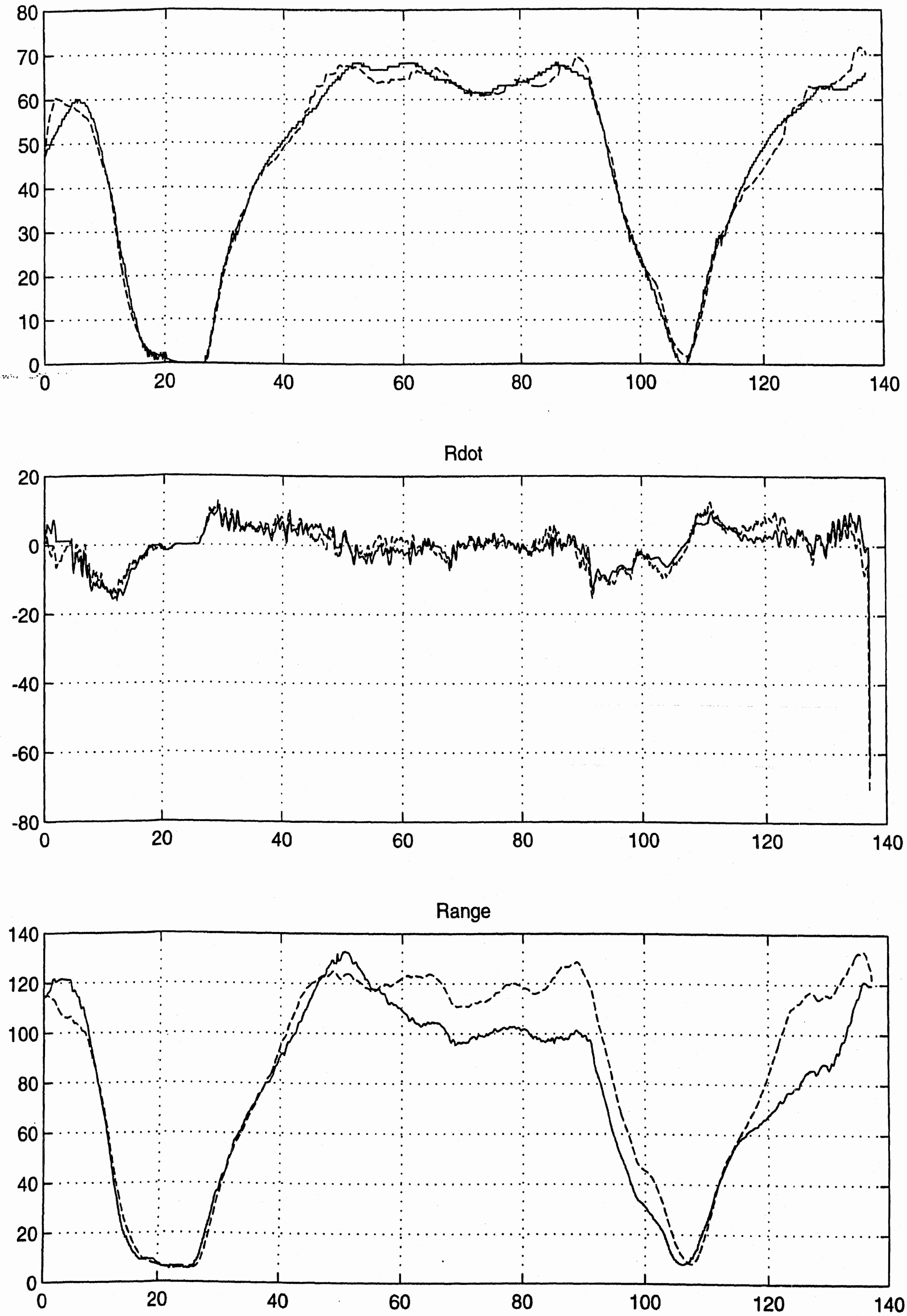
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3, rms = 16.74, meanRerr = 12.54
Driver: $z150_1 25$.txt



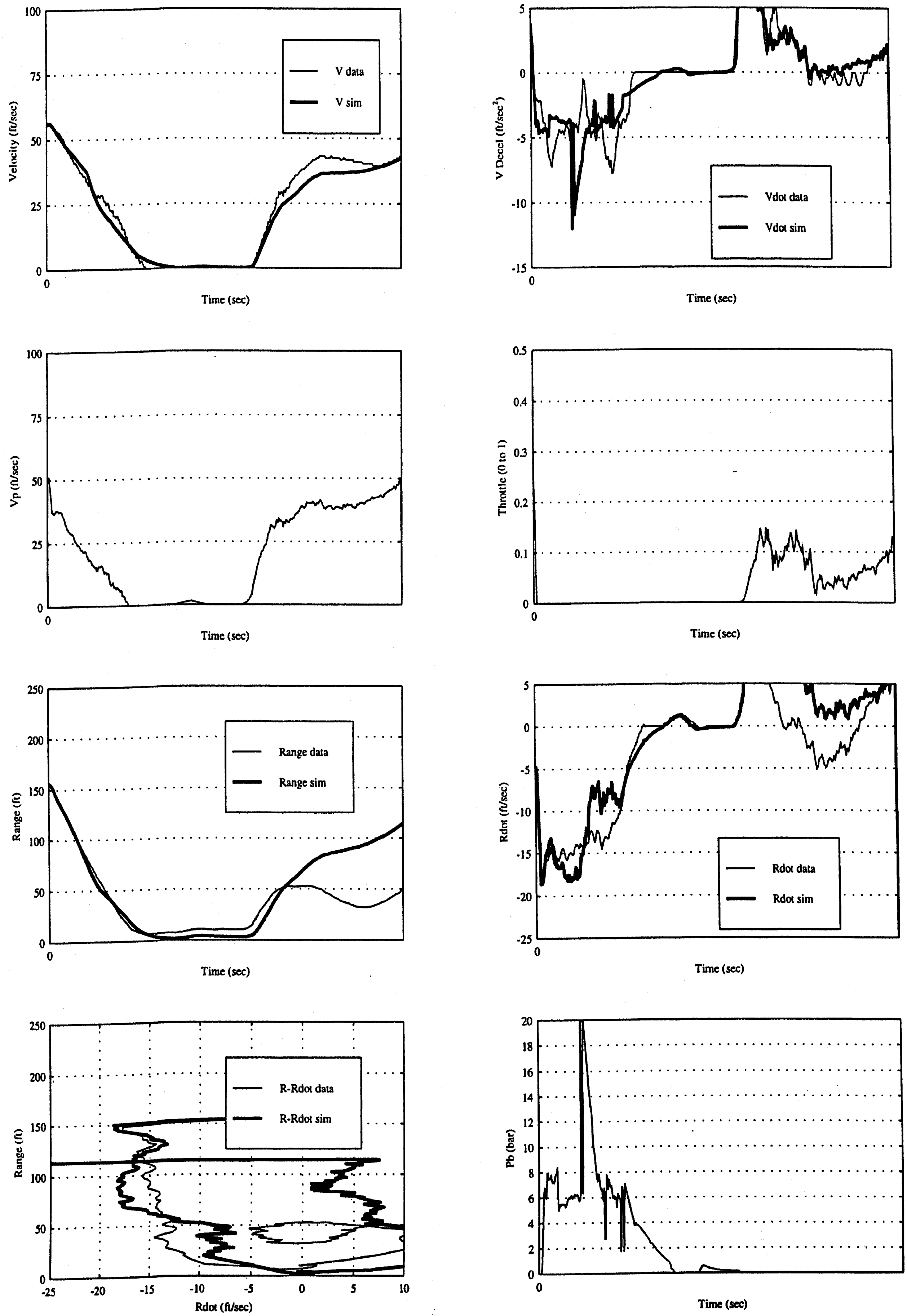
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.5, Tc = 2.8, T2 = 2.8, T3 = 1.5
Driver: $z150_1 28$.txt



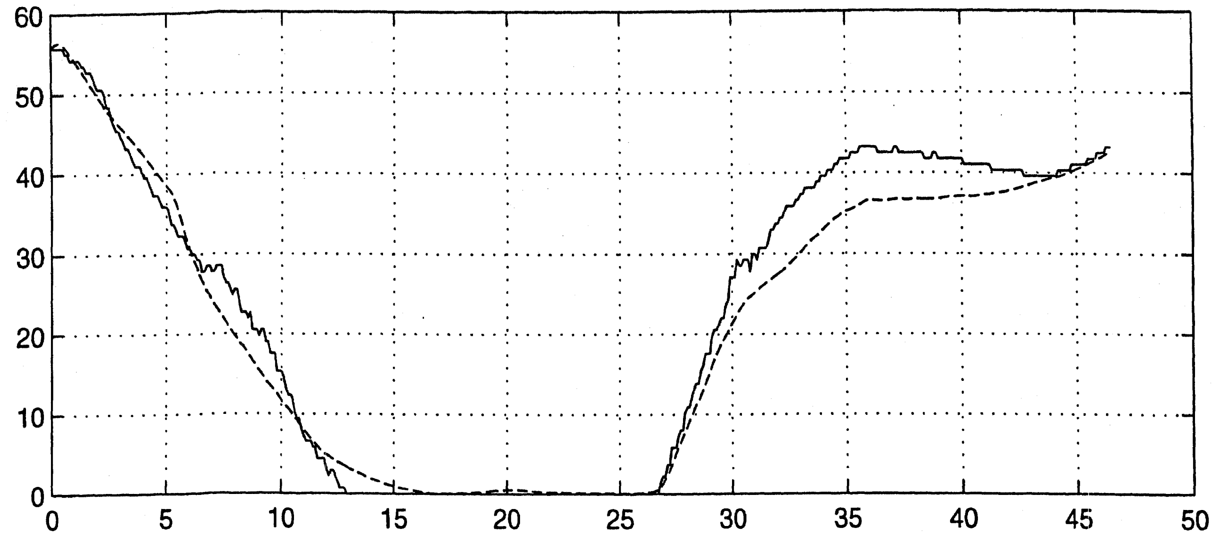
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.5, Tc = 2.8, T2 = 2.8, T3 = 1.5, rms = 14.62, meanRerr = 11.23
Driver: z150_1 28.txt



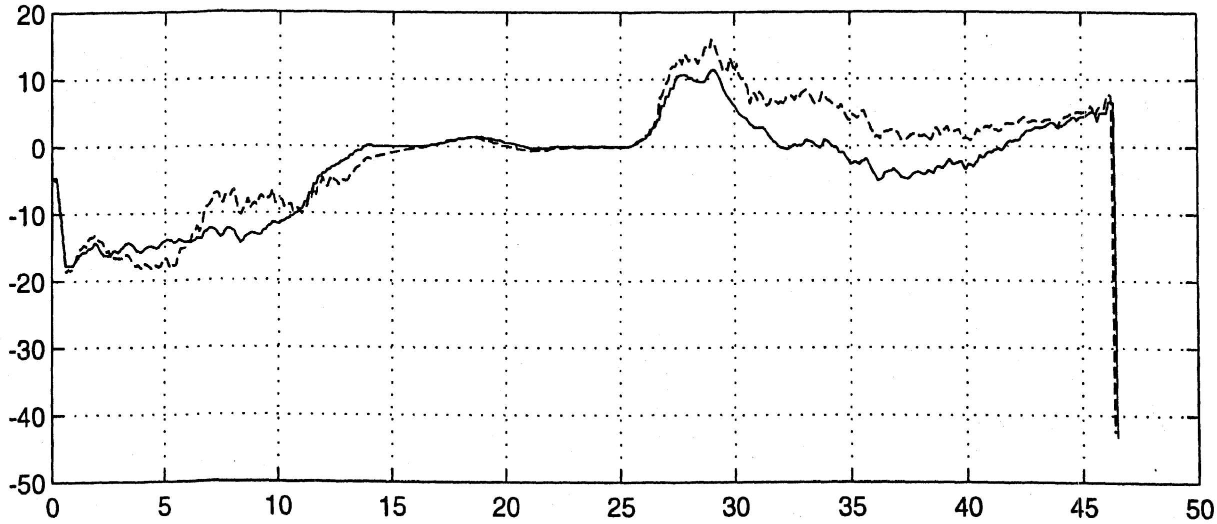
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.3, Tc = 2.8, T2 = 2.8, T3 = 2.3
Driver: z150$_1$38.txt



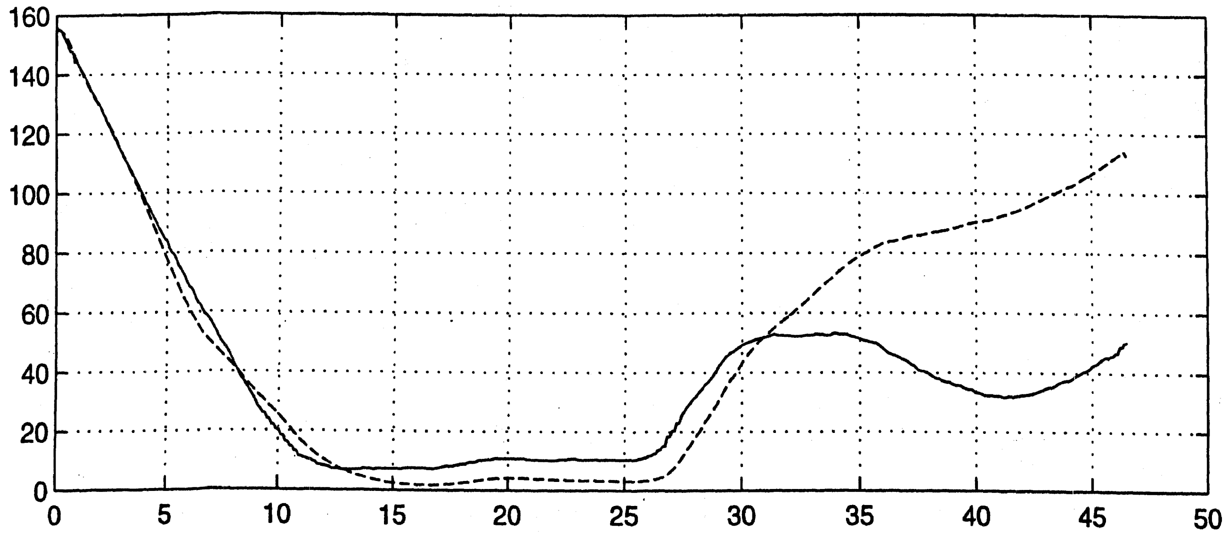
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.3, Tc = 2.8, T2 = 2.8, T3 = 2.3, rms = 28.50, meanRerr = 17.68
Driver: z150_1 38.txt



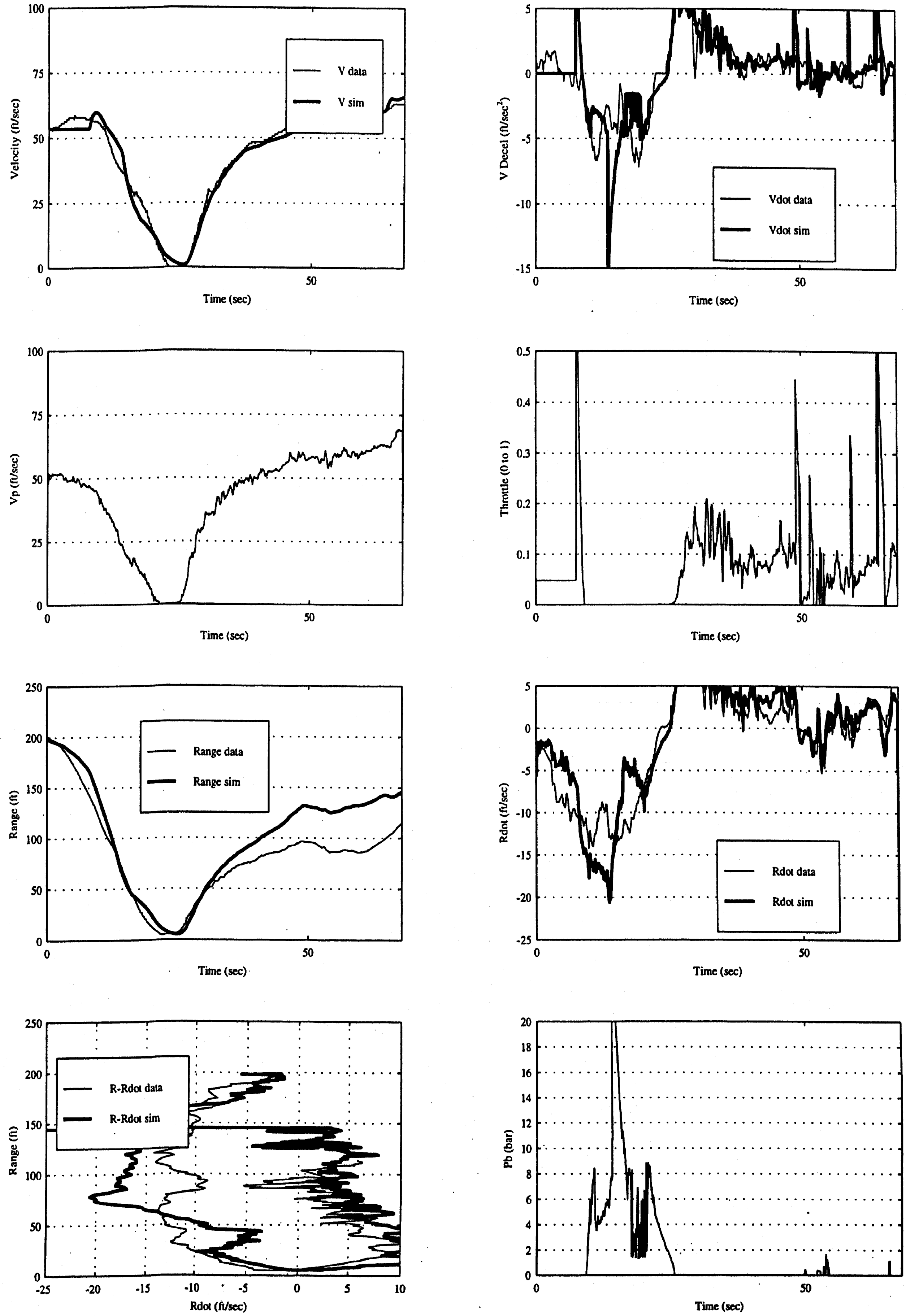
Rdot



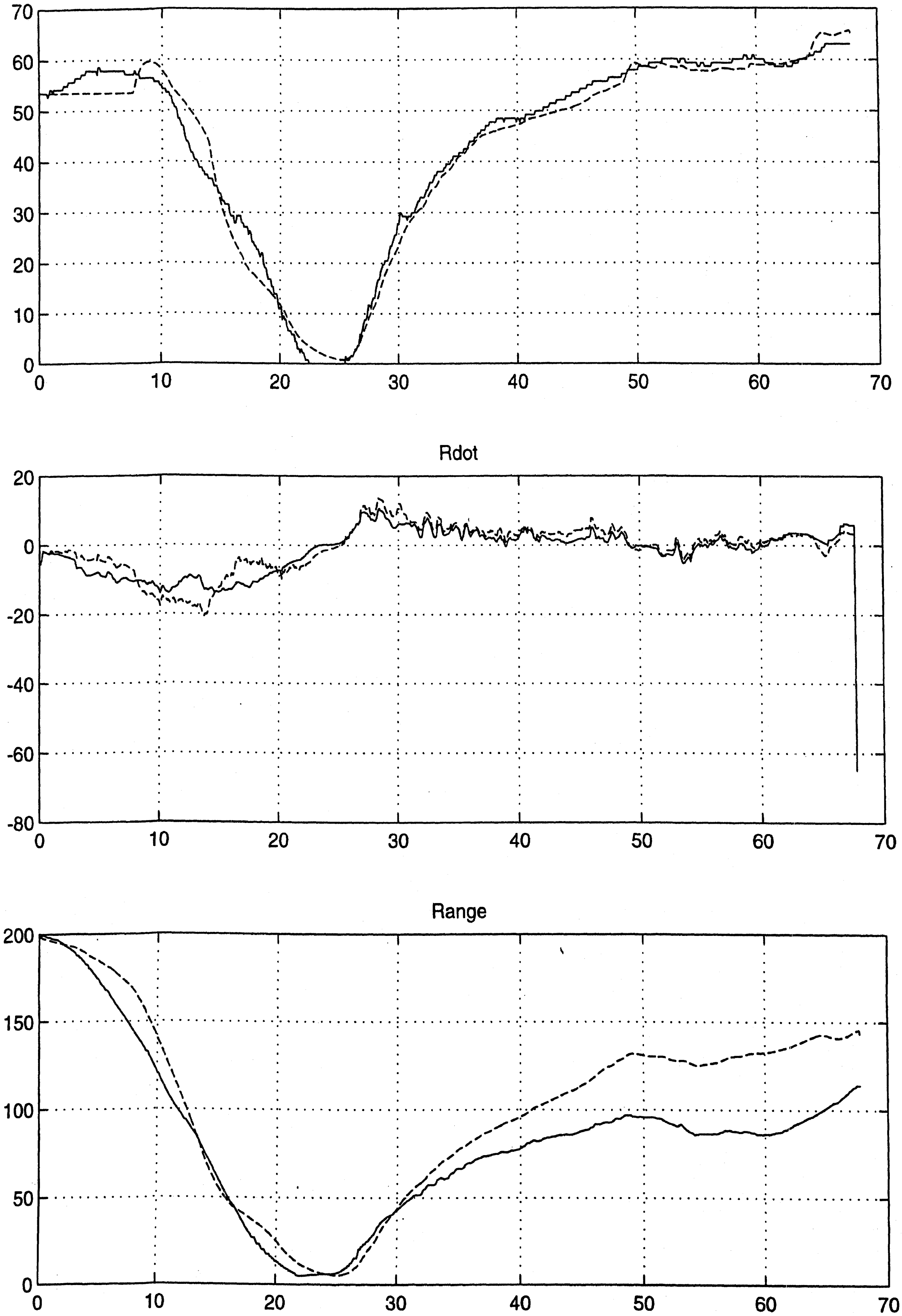
Range



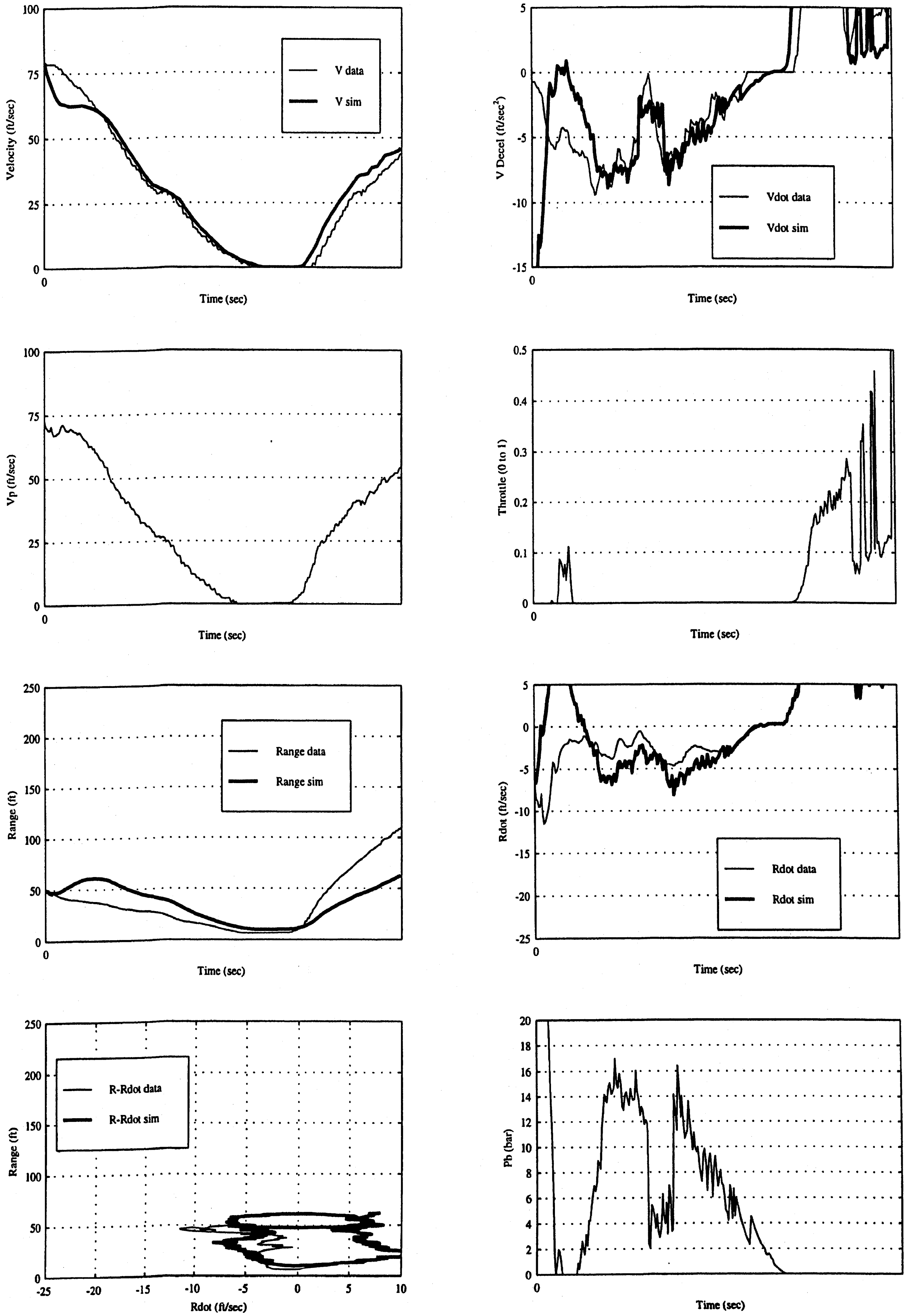
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.8, Tc = 2.8, T2 = 2.8, T3 = 1.8
Driver: z150$_1$39.txt



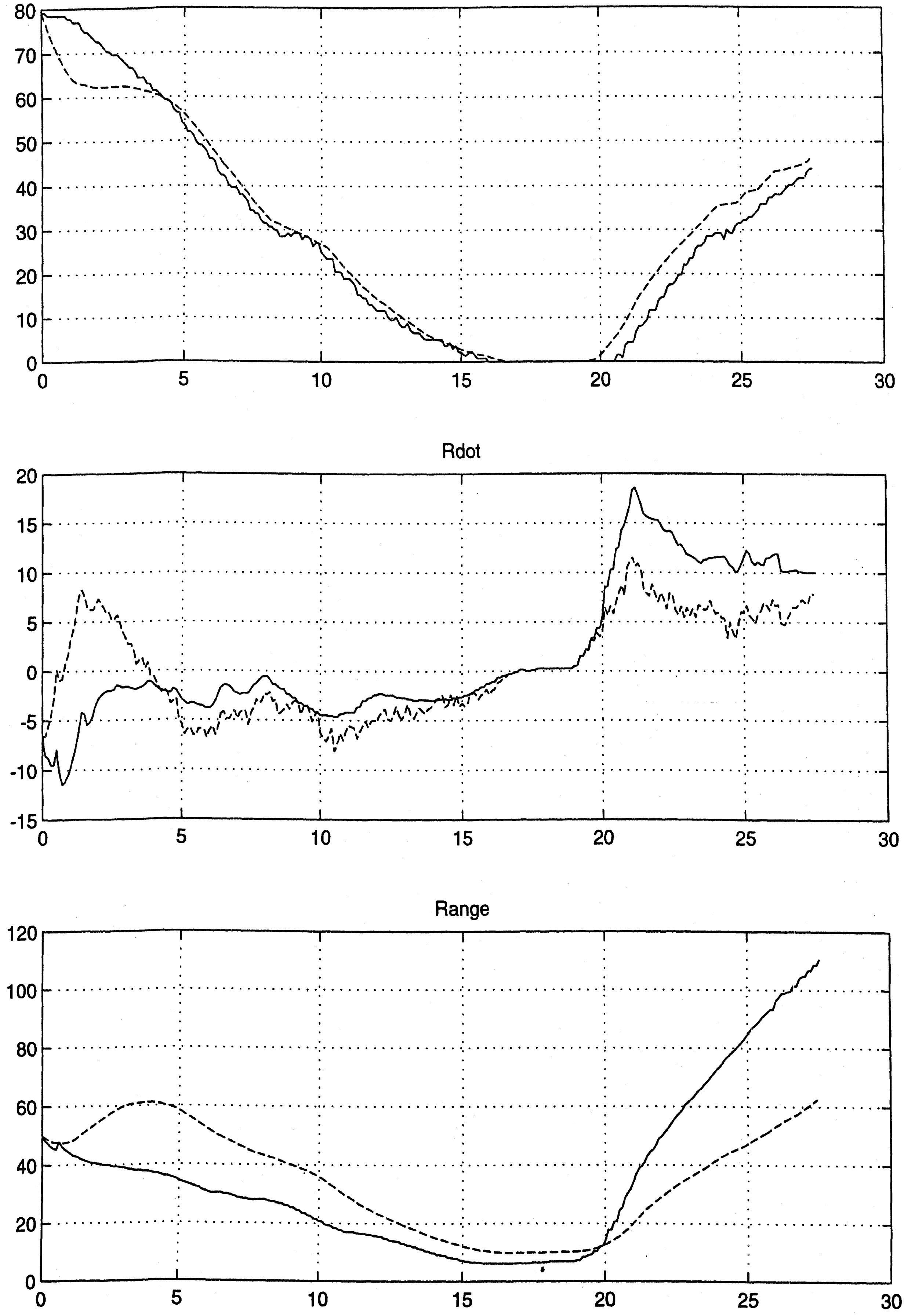
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.8, Tc = 2.8, T2 = 2.8, T3 = 1.8, rms = 24.73, meanRerr = 19.39
Driver: z150_1 39.txt



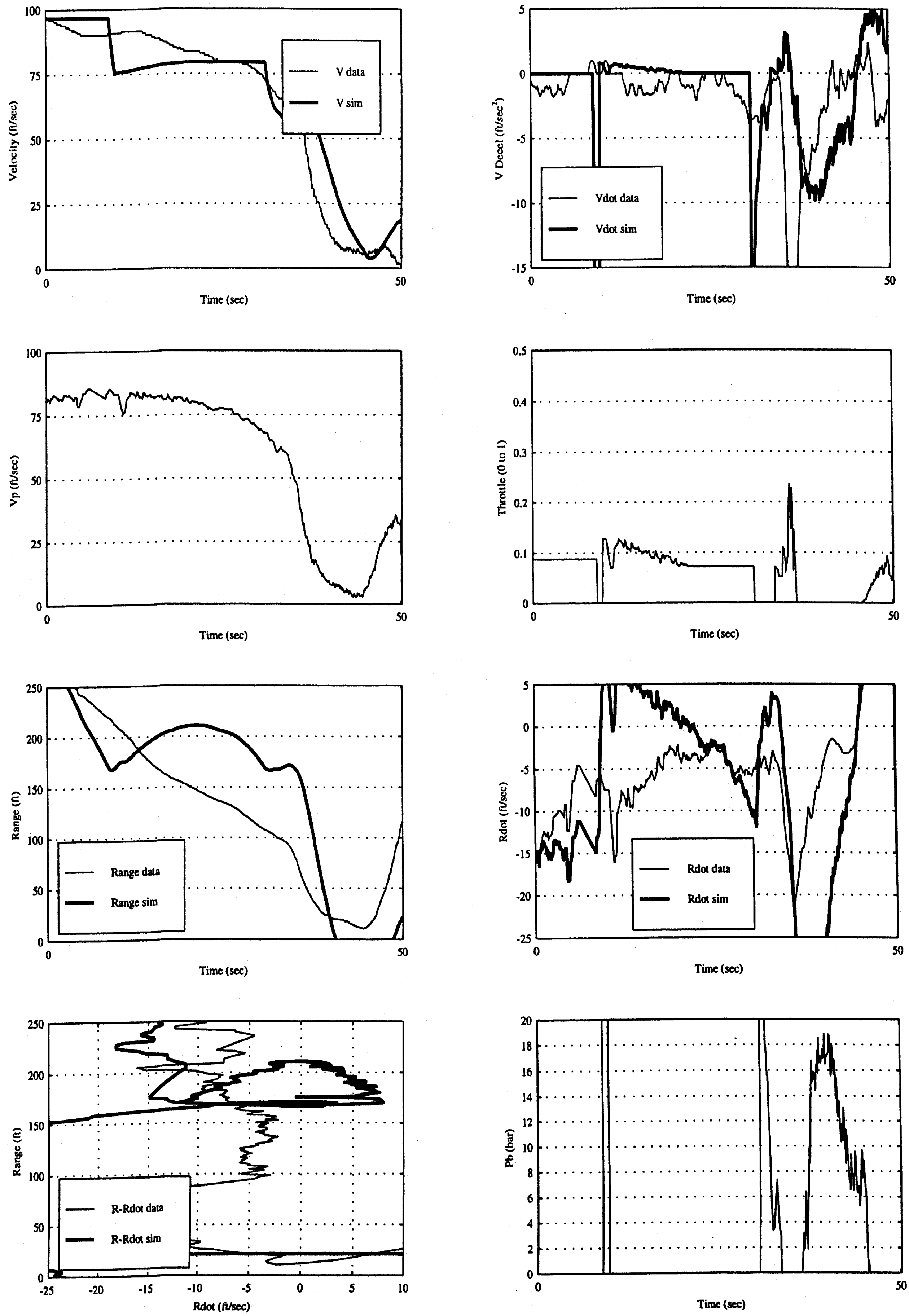
BMW Model, data vs. simulation (RunB).
Model 151, Th = 0.9, Tc = 2.8, T2 = 2.8, T3 = 0.9
Driver: z150$_1$41.txt



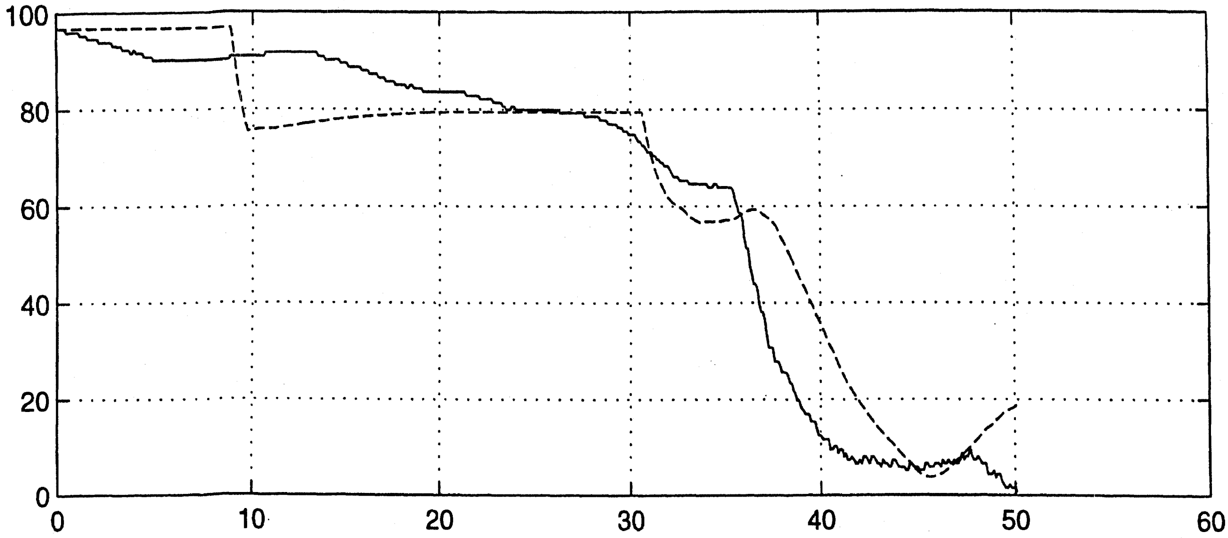
BMW Model, data vs. simulation (RunB).
Model 151, Th = 0.9, Tc = 2.8, T2 = 2.8, T3 = 0.9, rms = 20.00, meanRerr = 15.19
Driver: z150_1 41.txt



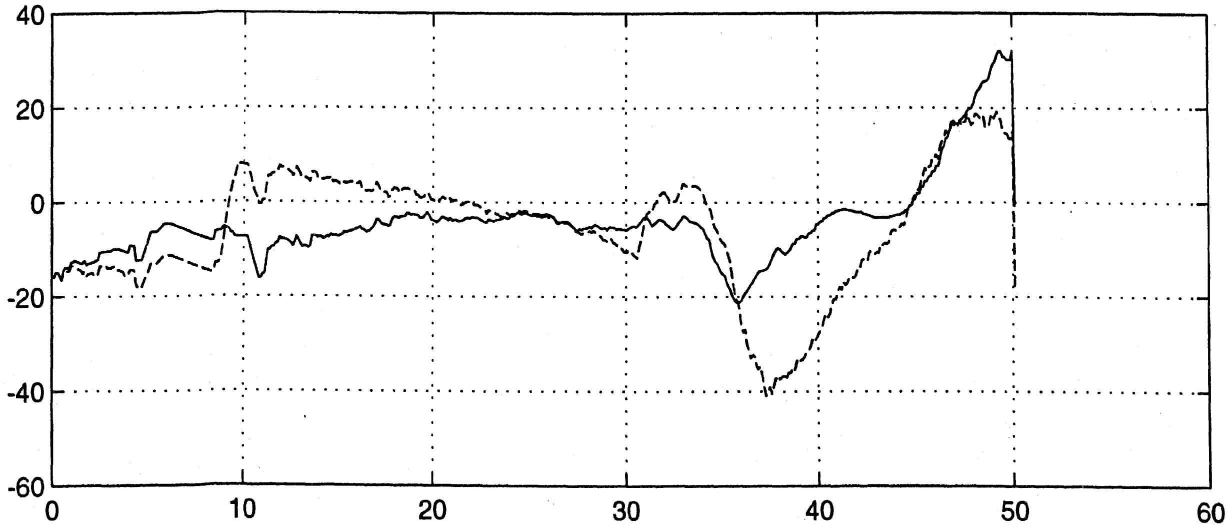
BMW Model, data vs. simulation (RunB).
Model 151, Th = 5.4, Tc = 2.8, T2 = 2.8, T3 = 5.4
Driver: $z150_1 43$.txt



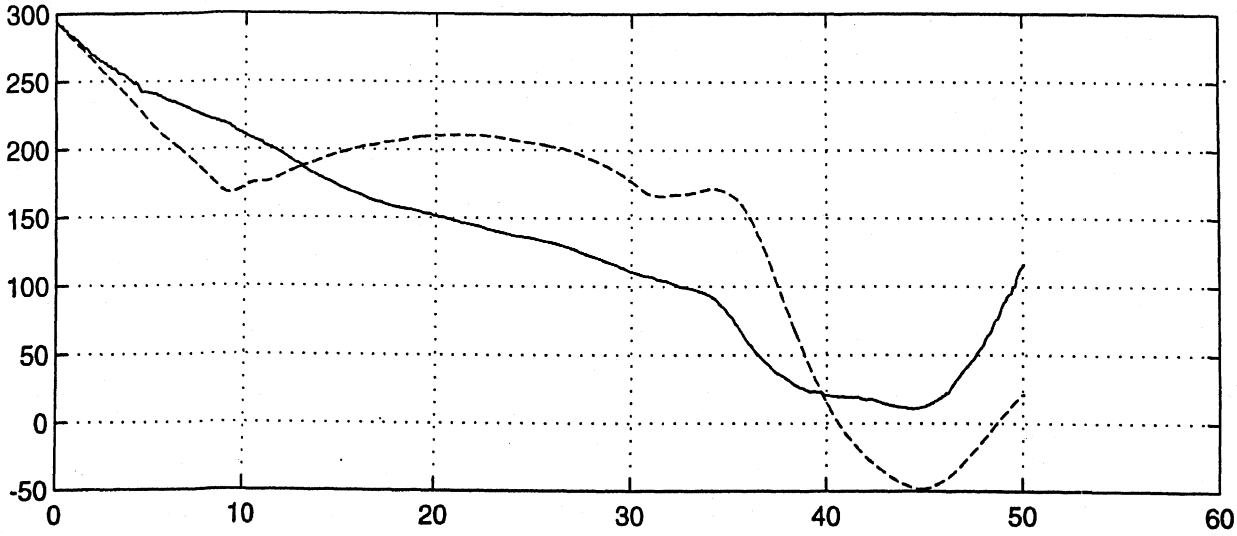
BMW Model, data vs. simulation (RunB).
Model 151, Th = 5.4, Tc = 2.8, T2 = 2.8, T3 = 5.4, rms = 54.93, meanRerr = 47.94
Driver: z150$_1$43.txt



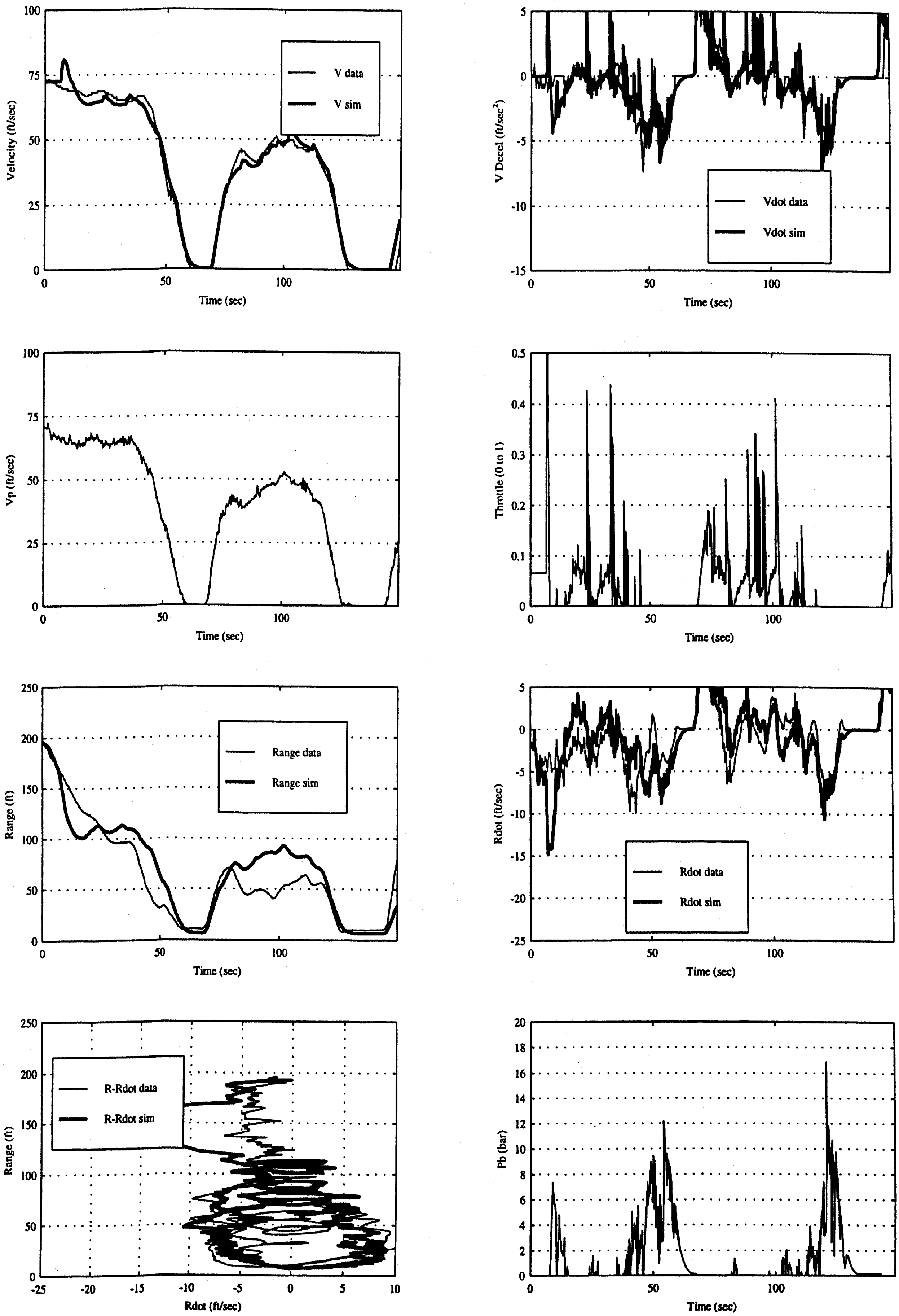
Rdot



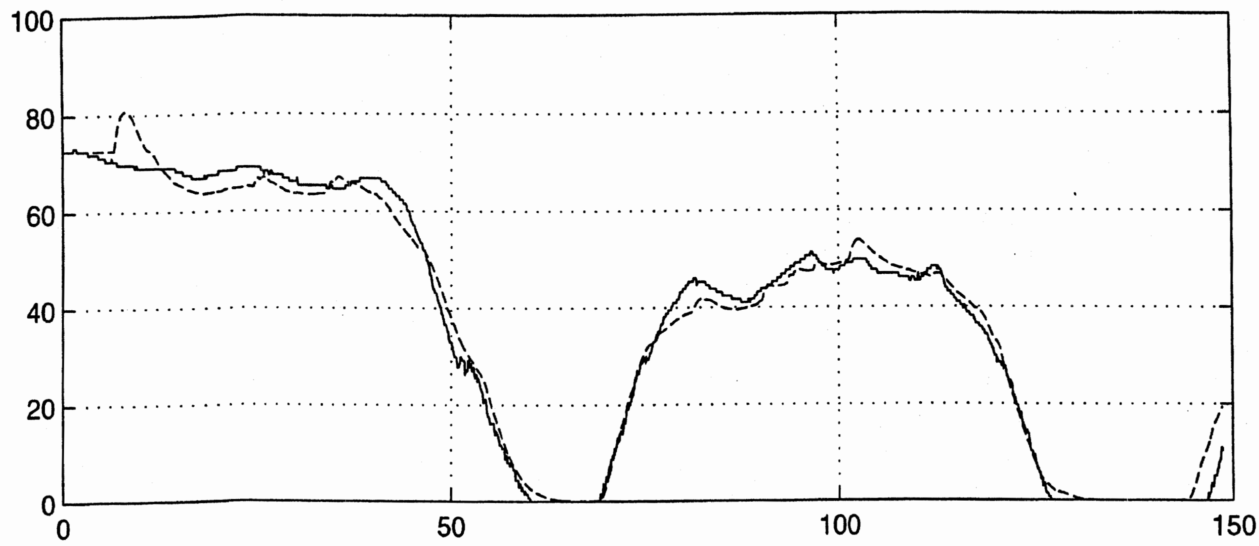
Range



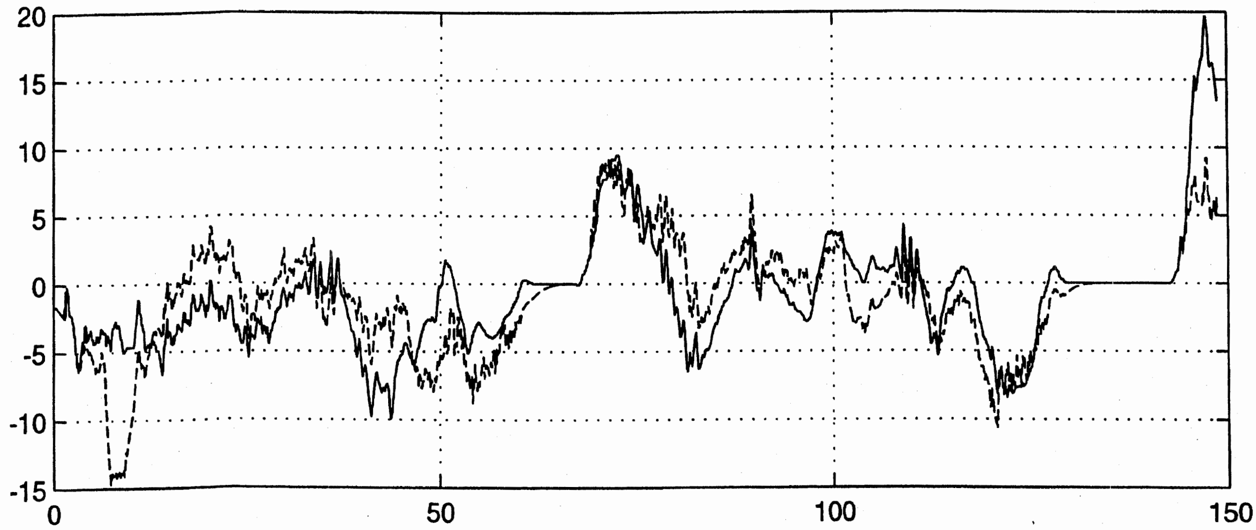
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.4, Tc = 2.8, T2 = 2.8, T3 = 1.4
Driver: z150$_1$47.txt



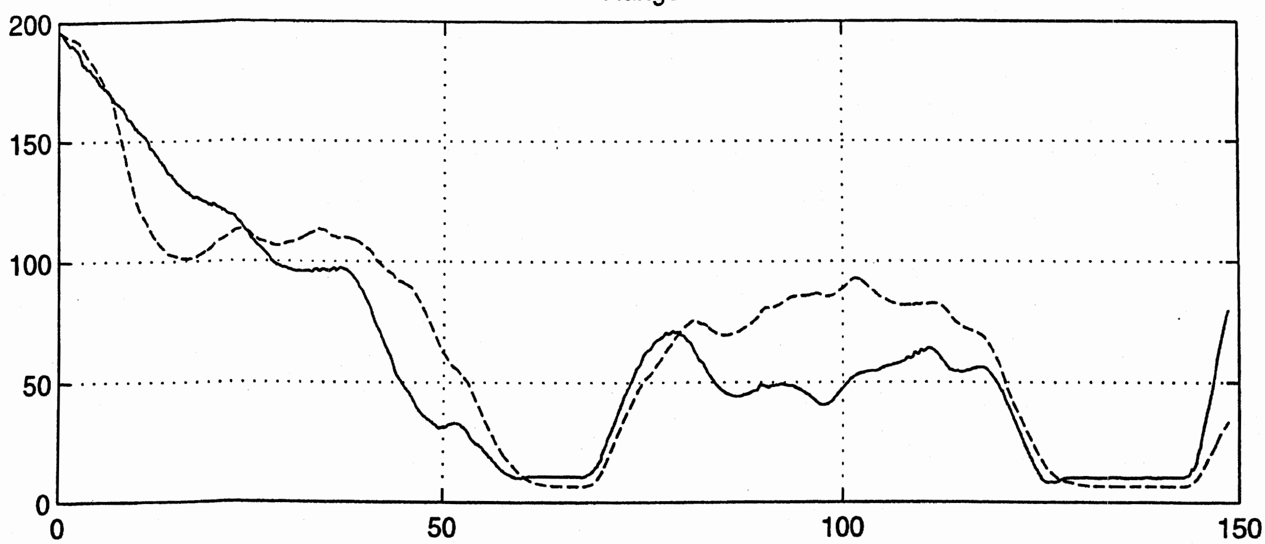
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.4, Tc = 2.8, T2 = 2.8, T3 = 1.4, rms = 21.38, meanRerr = 16.69
Driver: $z150_1 47$.txt



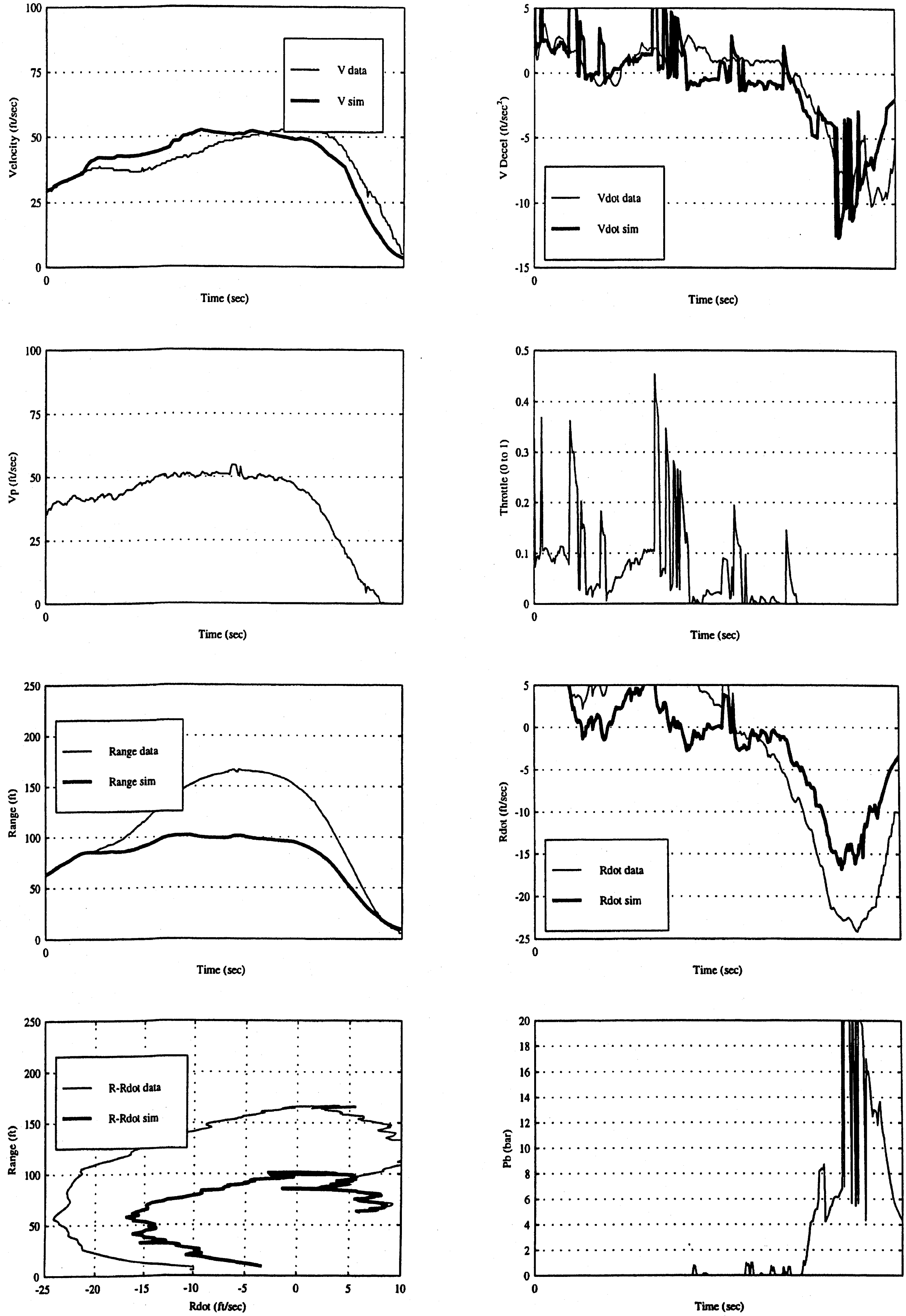
Rdot



Range



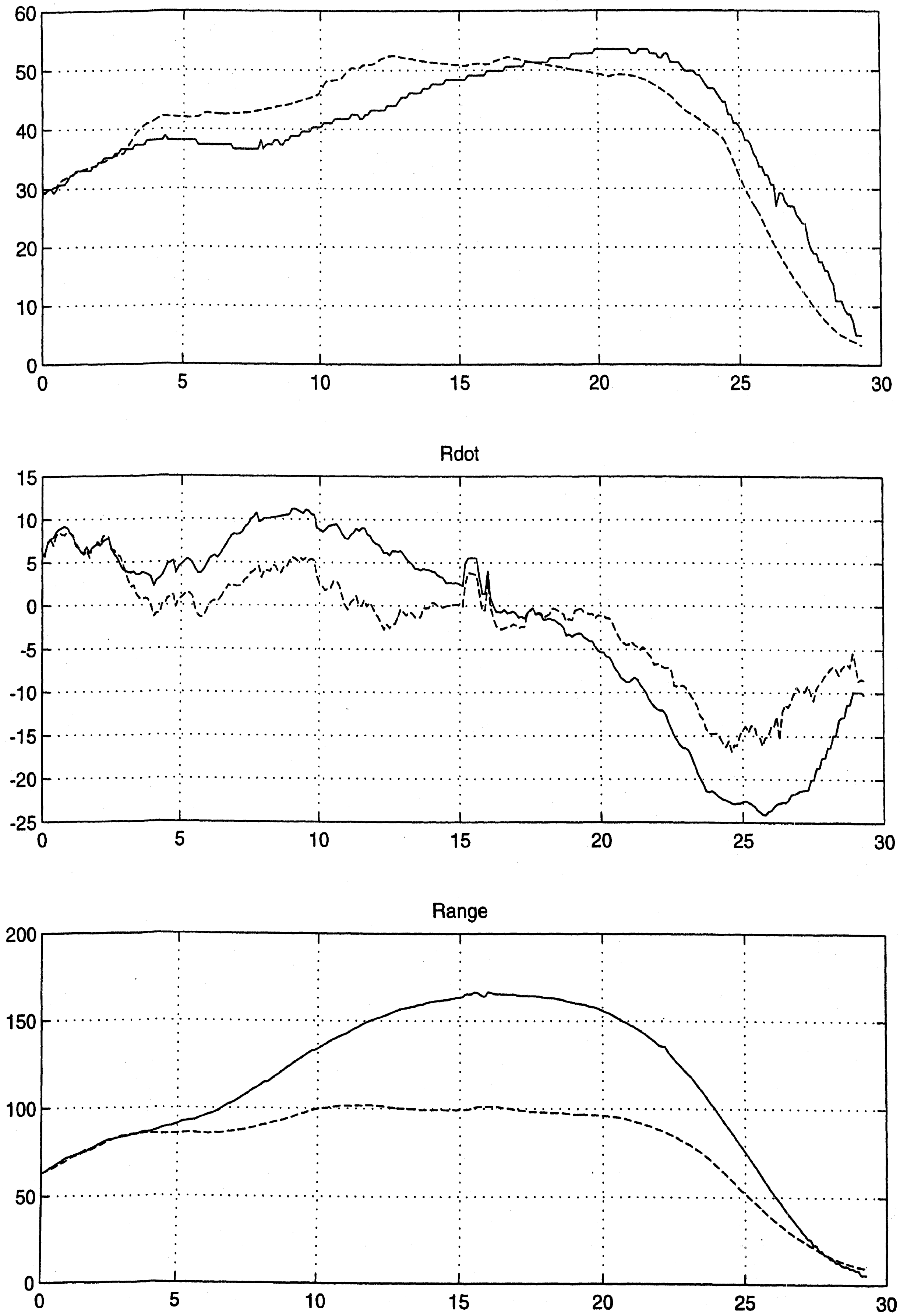
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6
Driver: z150_1 54.txt



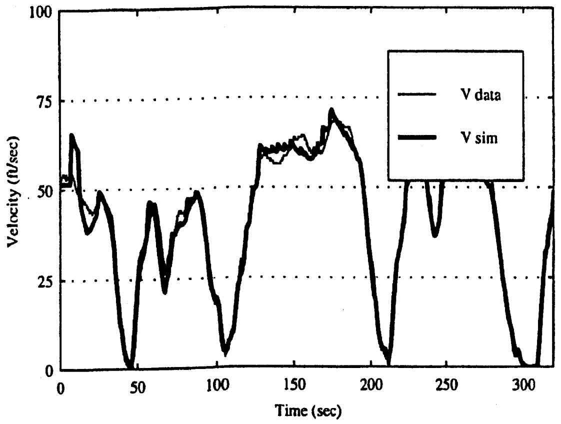
BMW Model, data vs. simulation (RunB).

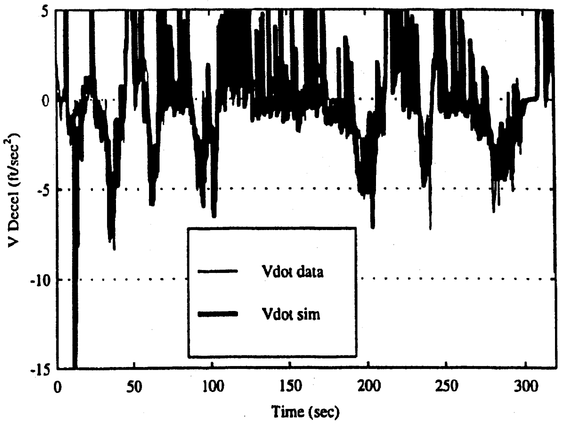
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6, rms = 40.18, meanRerr = 31.85

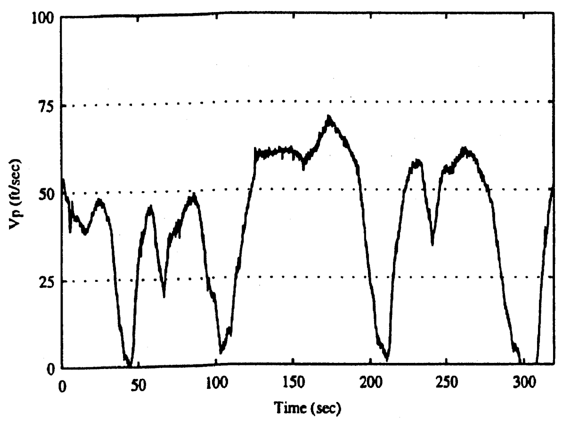
Driver: z150_1 54.txt

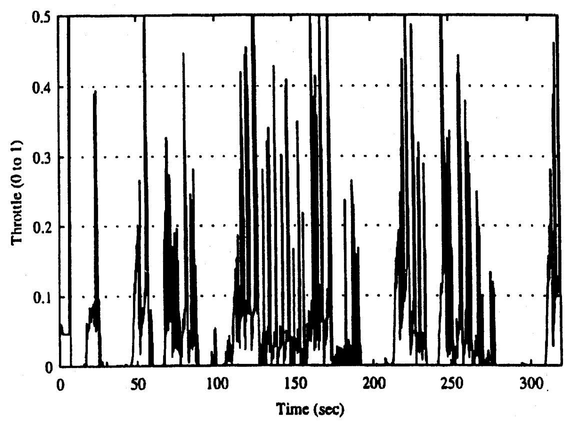


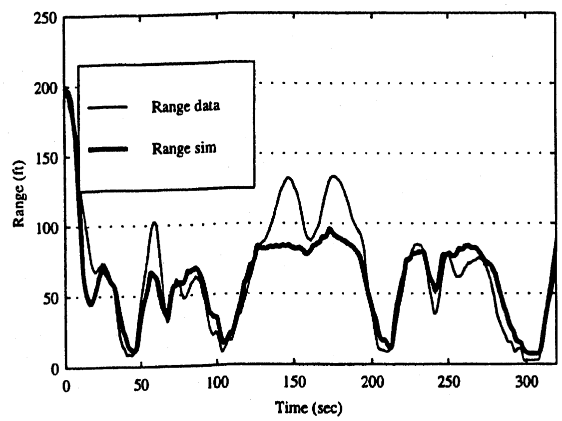
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.1, Tc = 2.8, T2 = 2.8, T3 = 1.1
Driver: z150$_1$57.txt

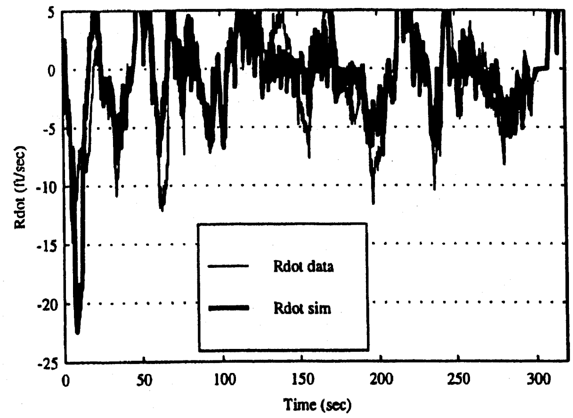


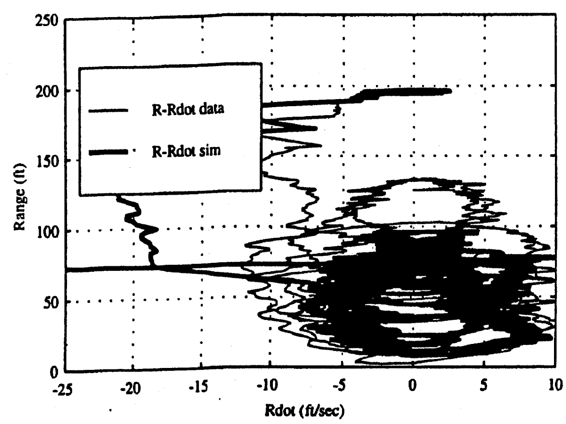


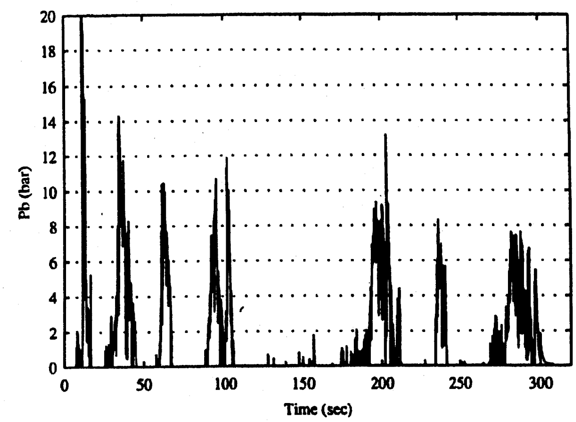




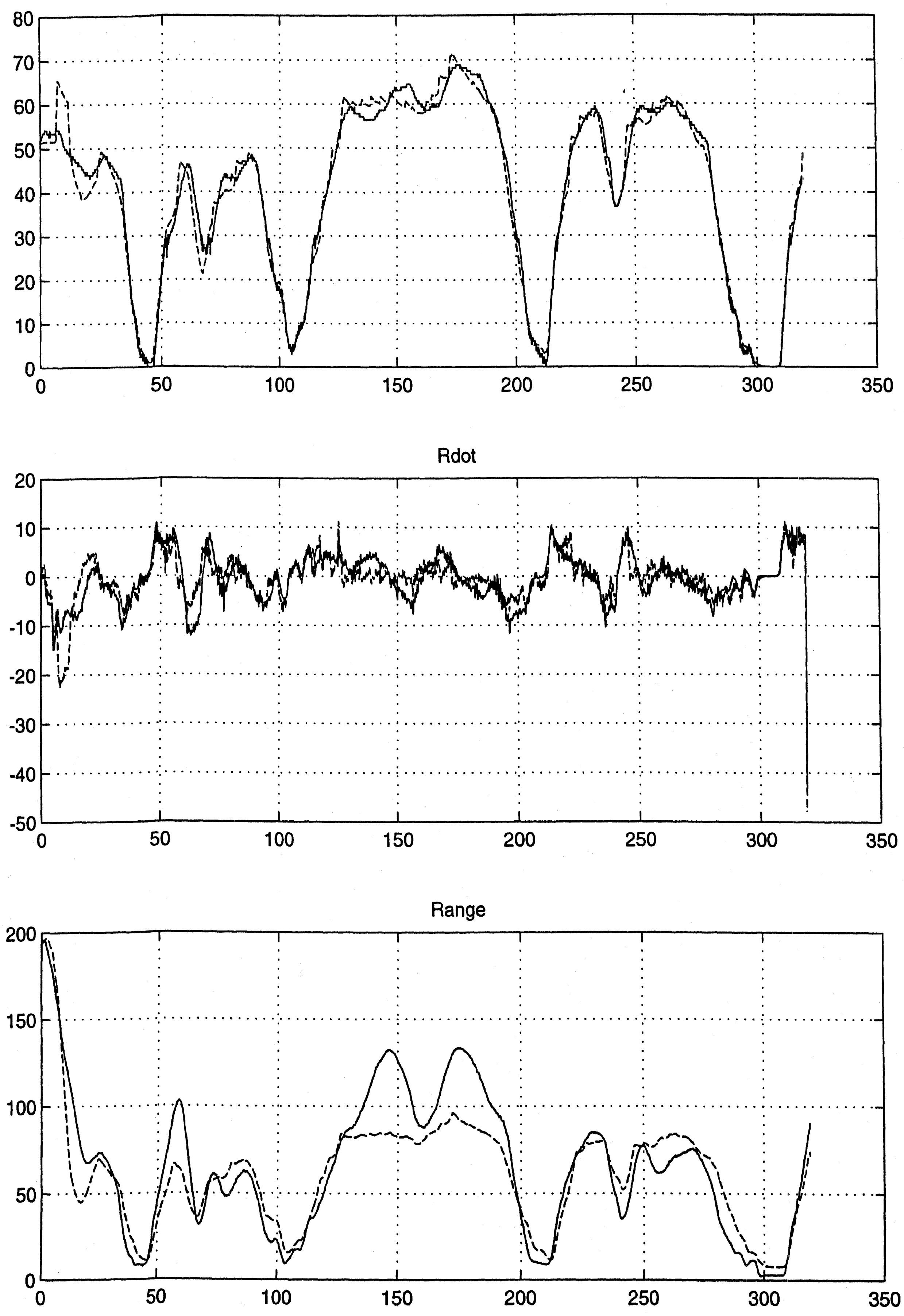




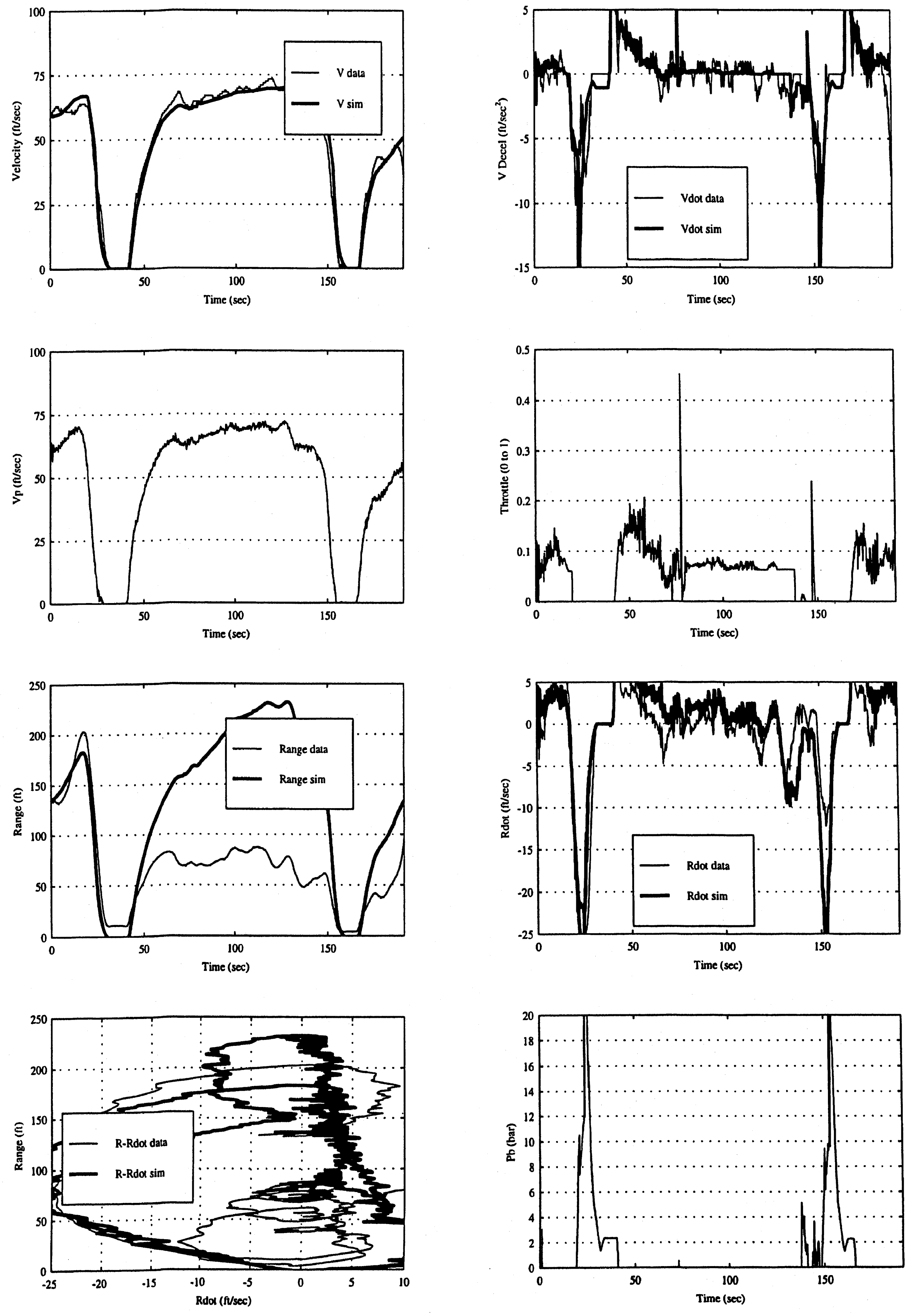




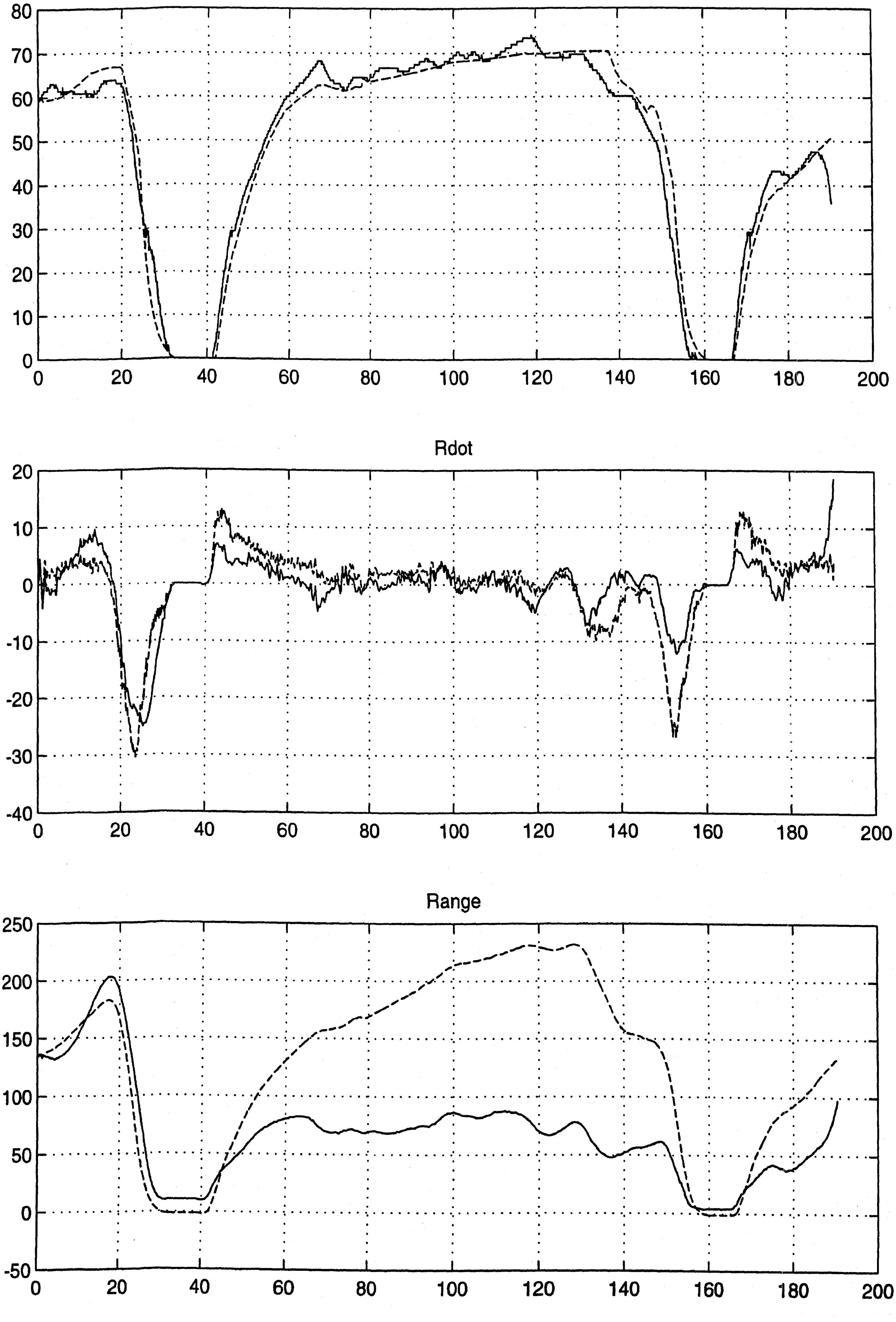
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.1, Tc = 2.8, T2 = 2.8, T3 = 1.1, rms = 17.82, meanRerr = 13.38
Driver: z150_1 57.txt



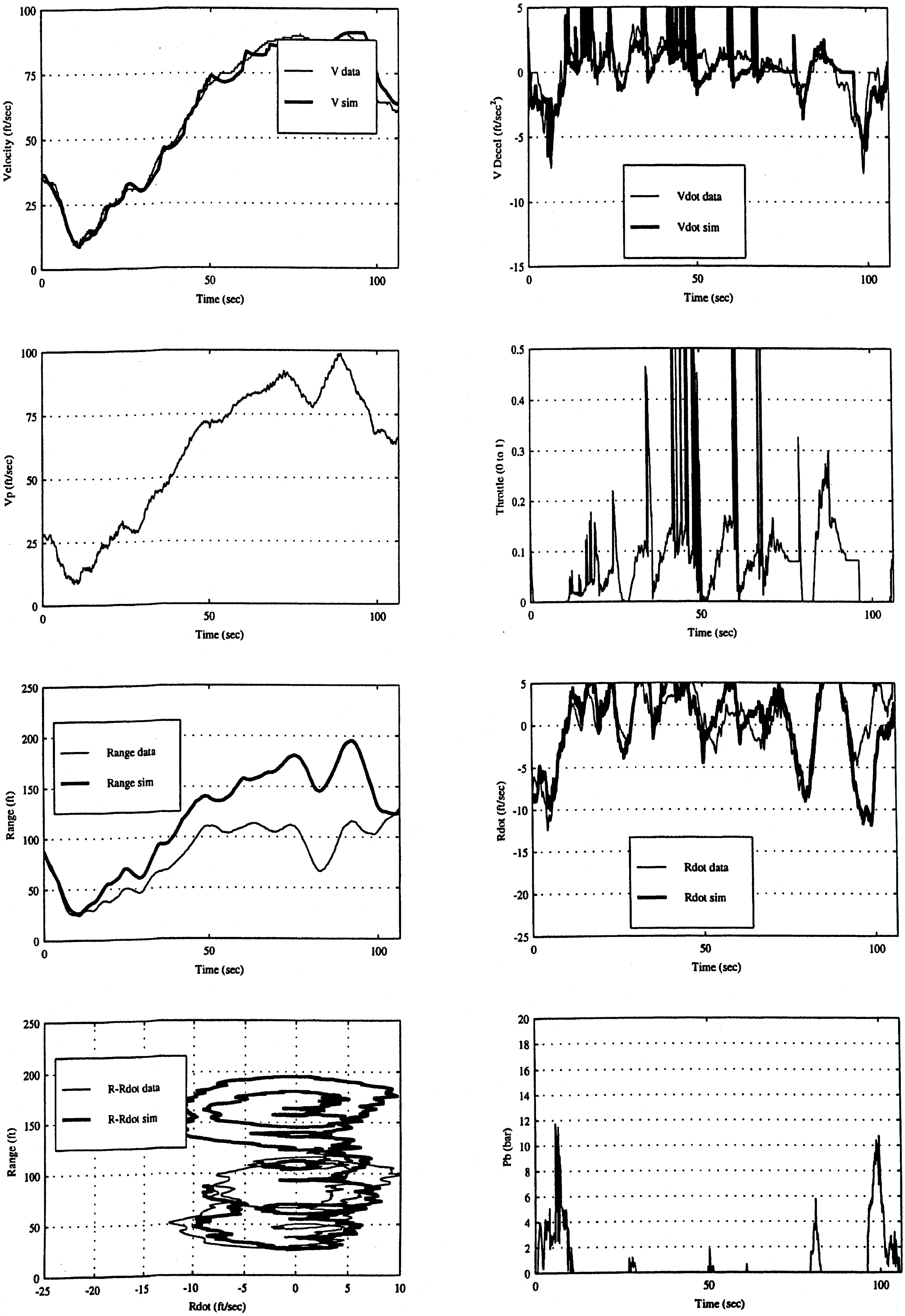
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.2, Tc = 2.8, T2 = 2.8, T3 = 2.2
Driver: z150_1 79.txt



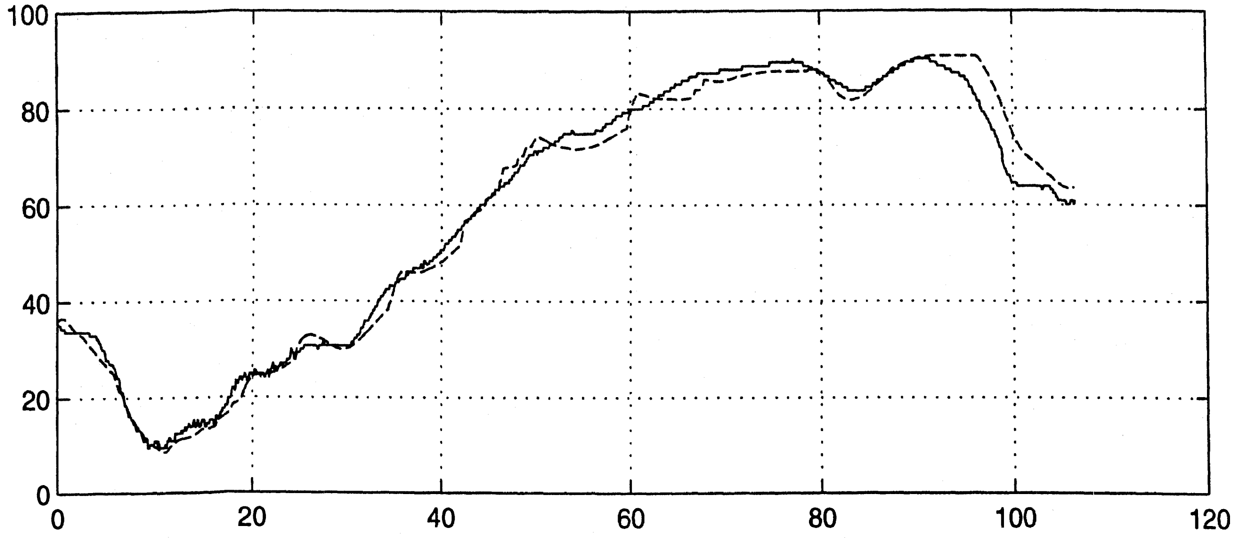
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.2, Tc = 2.8, T2 = 2.8, T3 = 2.2, rms = 85.66, meanRerr = 67.41
Driver: $z150_1 79$.txt

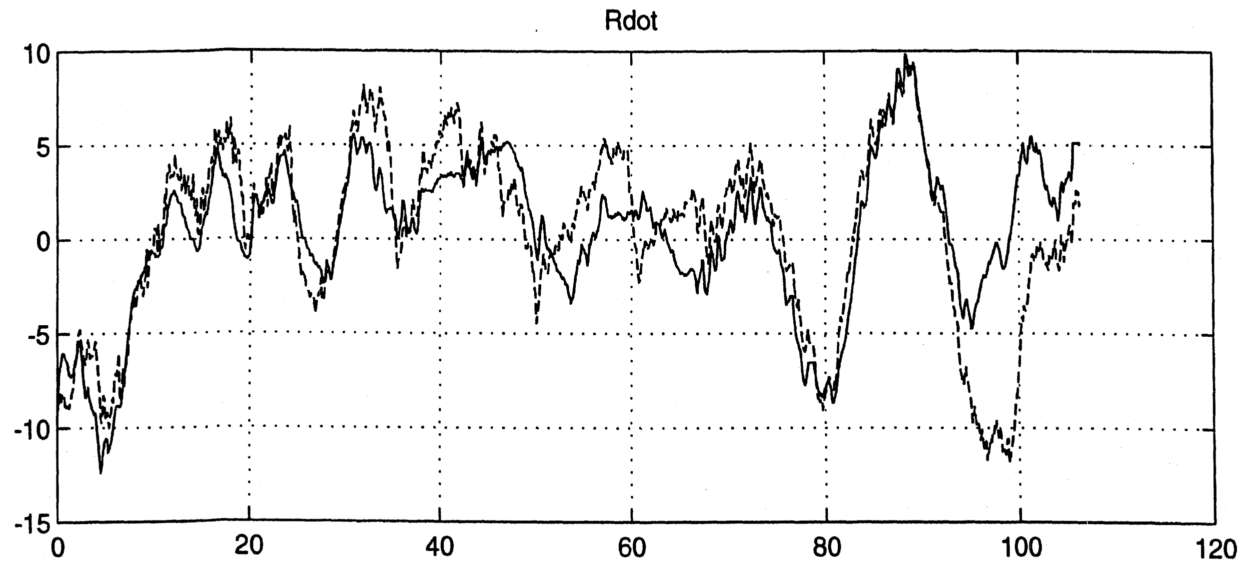


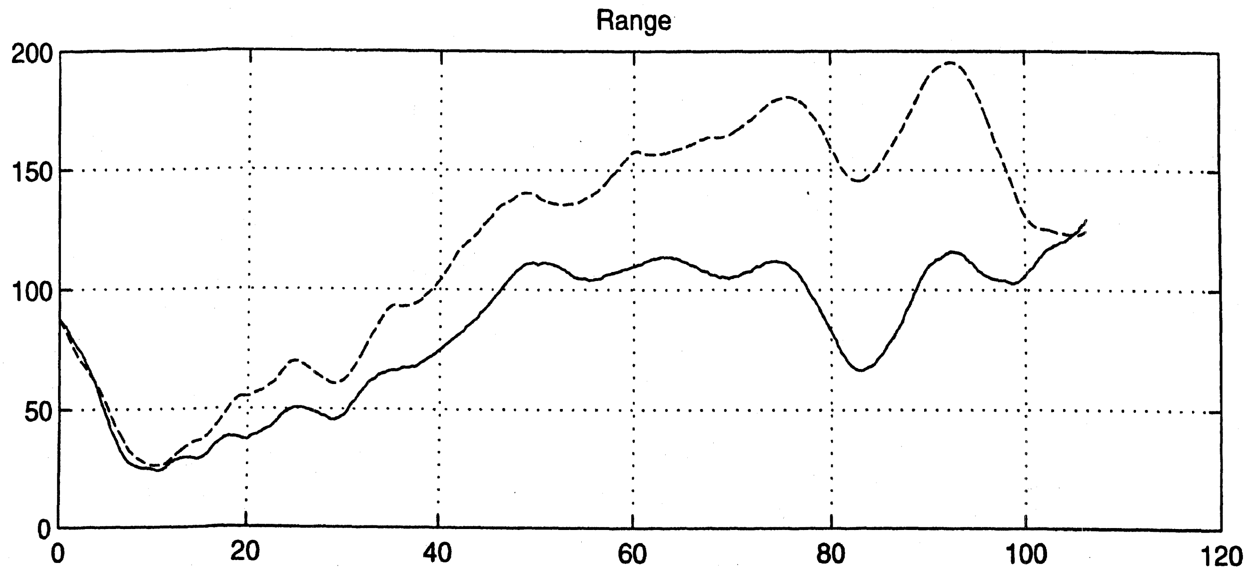
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6
Driver: z150_5 1.txt



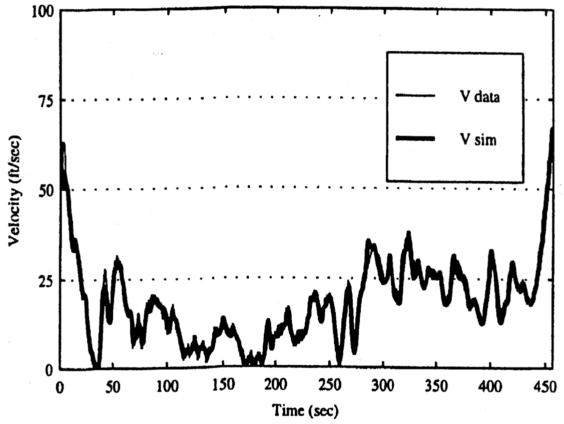
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.6, Tc = 2.8, T2 = 2.8, T3 = 1.6, rms = 44.96, meanRerr = 36.33
Driver: z150_5 1.txt

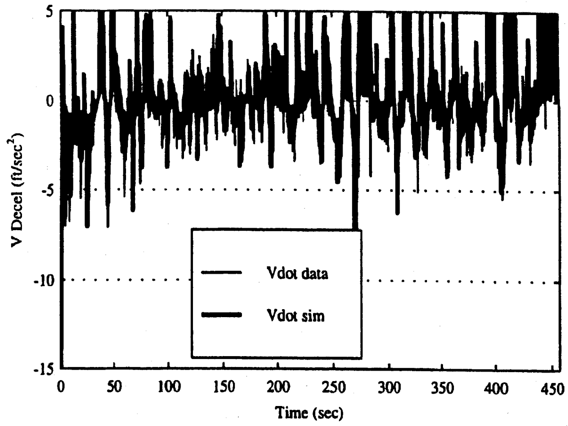


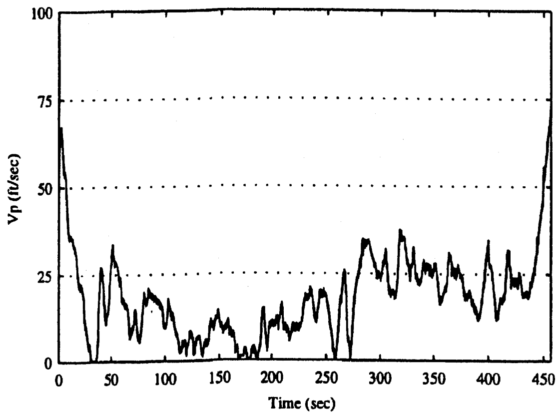


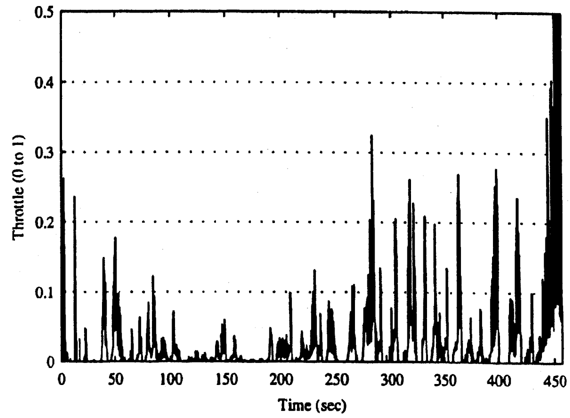


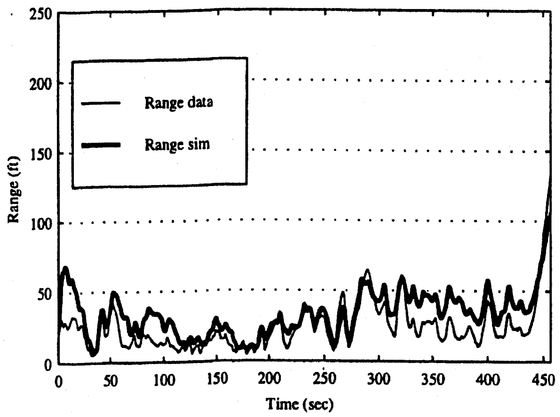
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.2, Tc = 2.8, T2 = 2.8, T3 = 1.2
Driver: z150$_5$6.txt

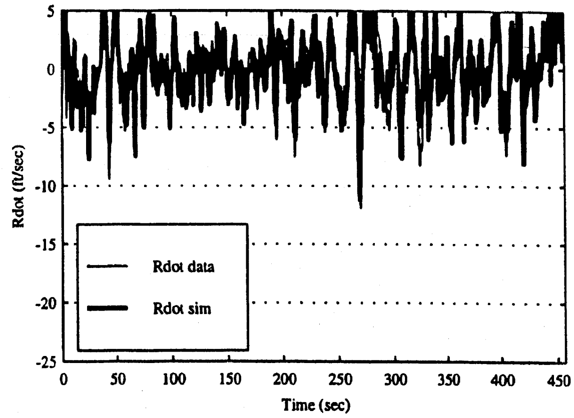


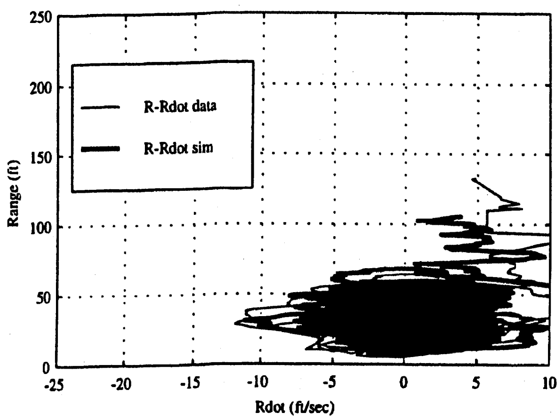


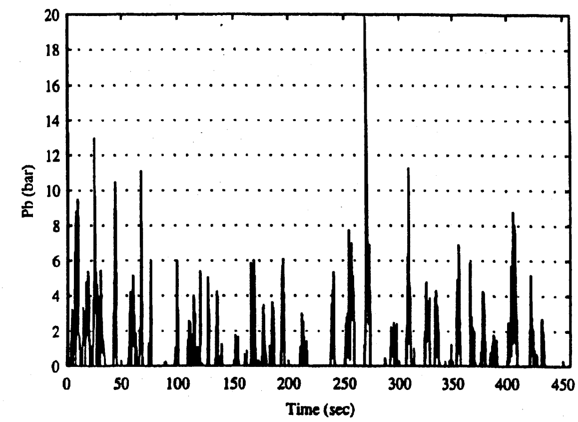




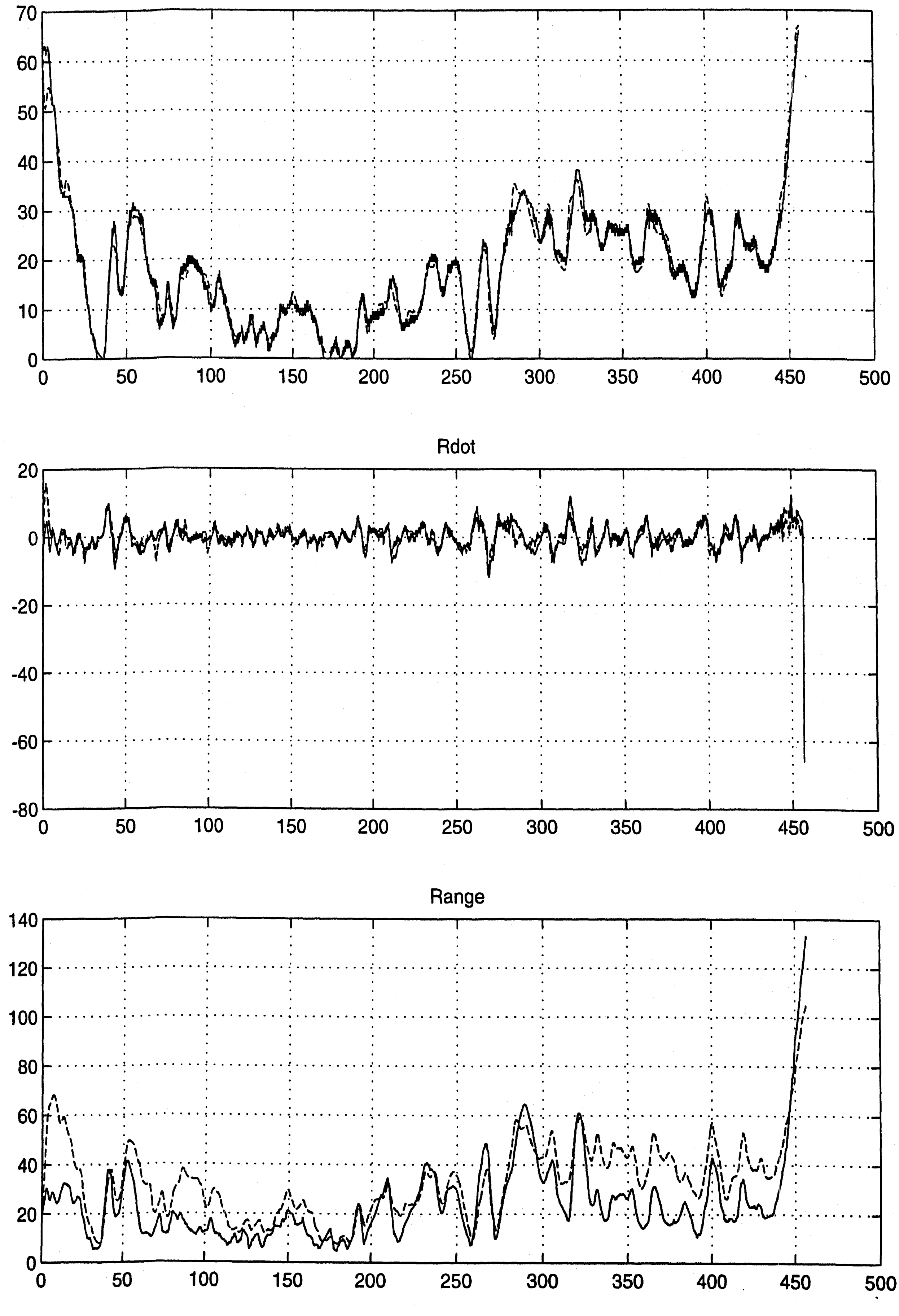




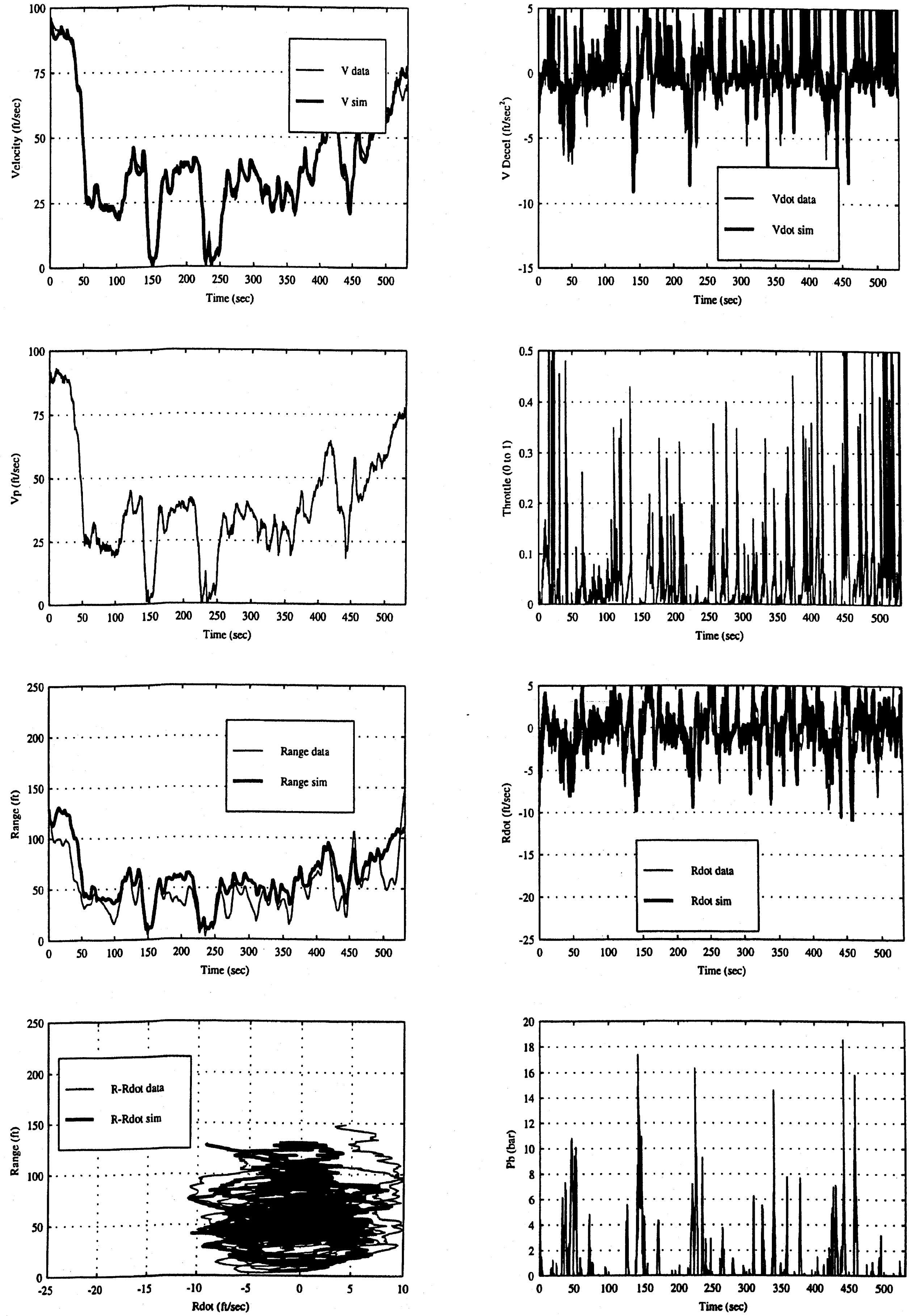




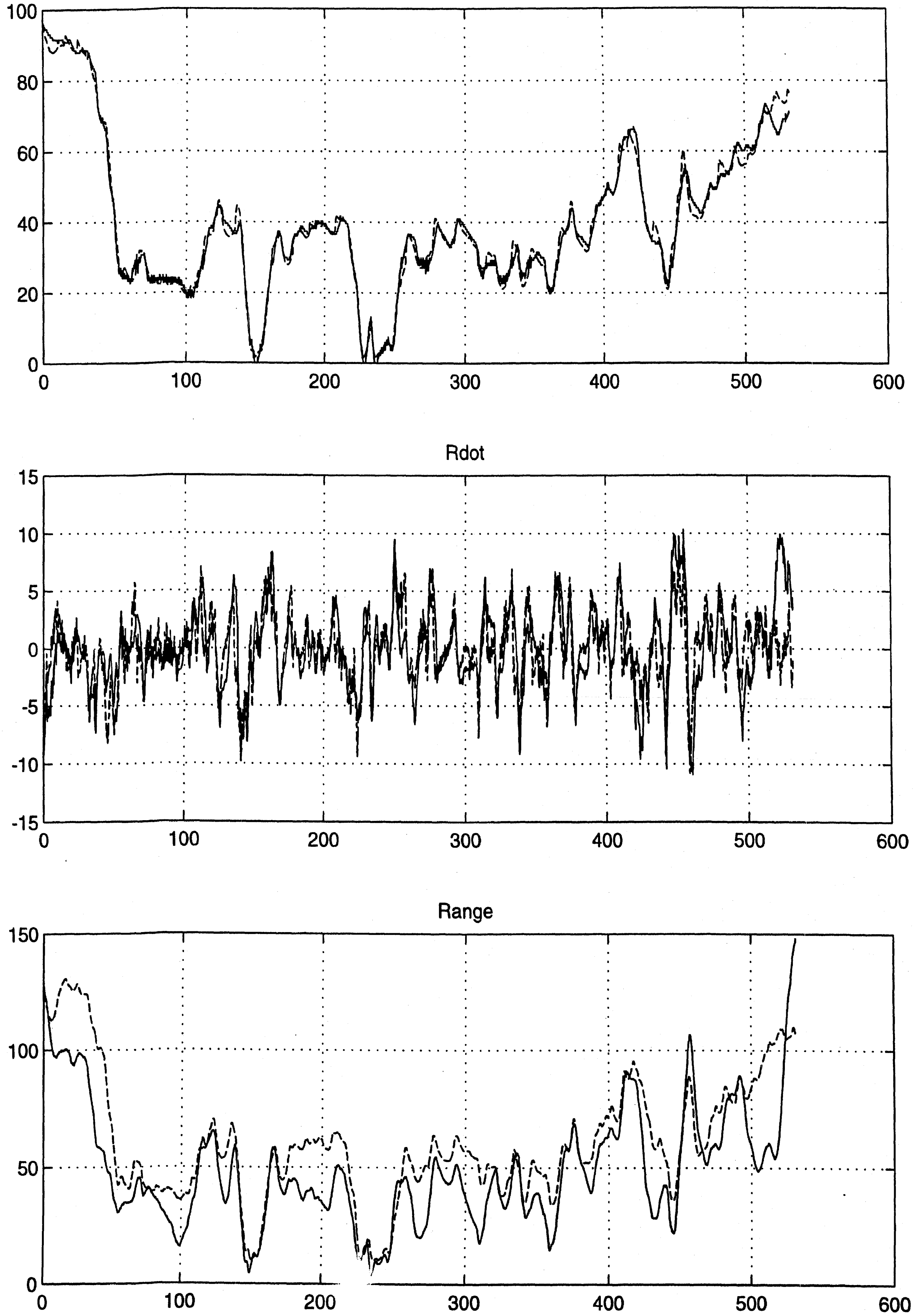
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.2, Tc = 2.8, T2 = 2.8, T3 = 1.2, rms = 13.39, meanRerr = 10.94
Driver: z150_5 6.txt



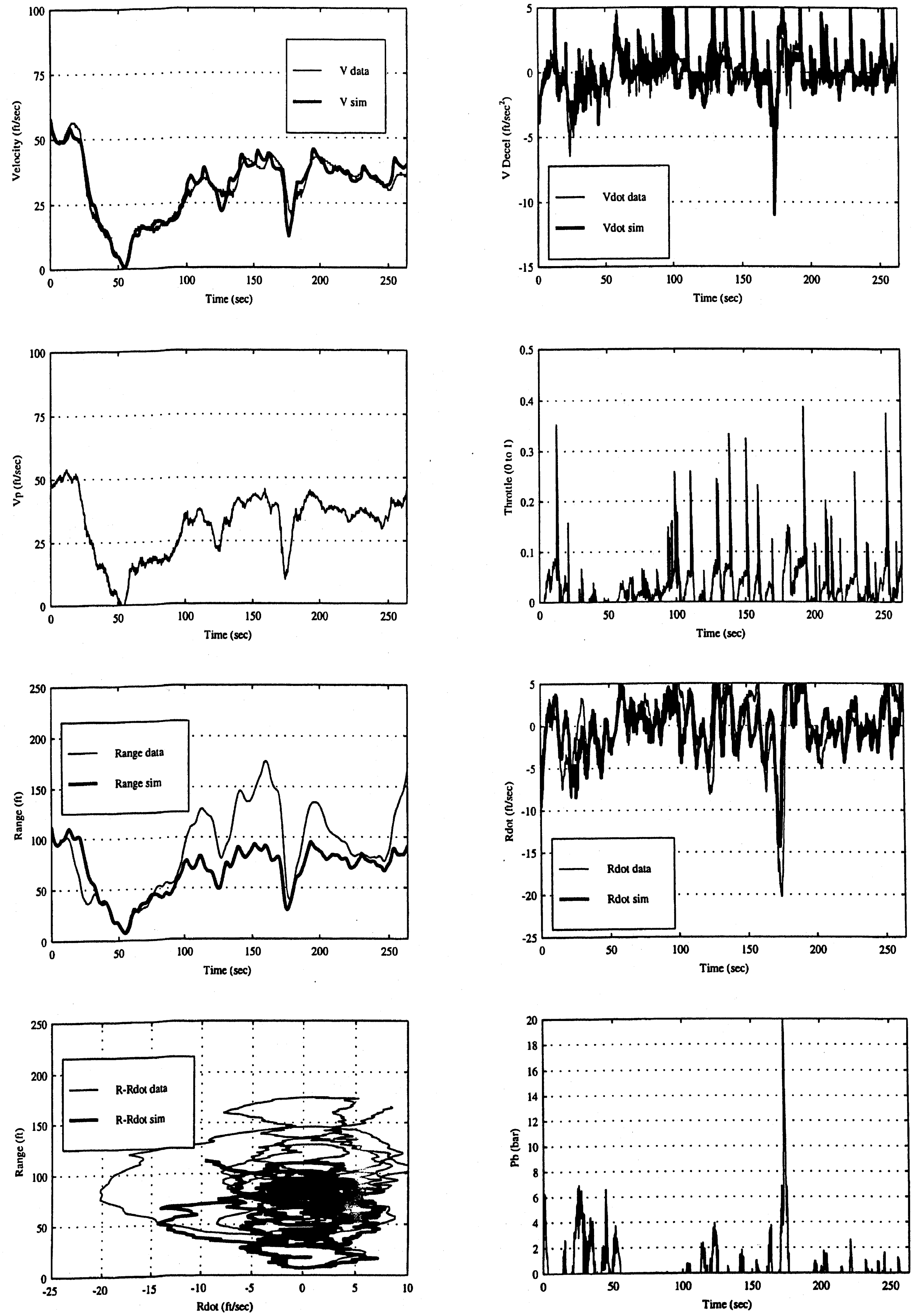
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.2, Tc = 2.8, T2 = 2.8, T3 = 1.2
Driver: $z150_9 0.txt$



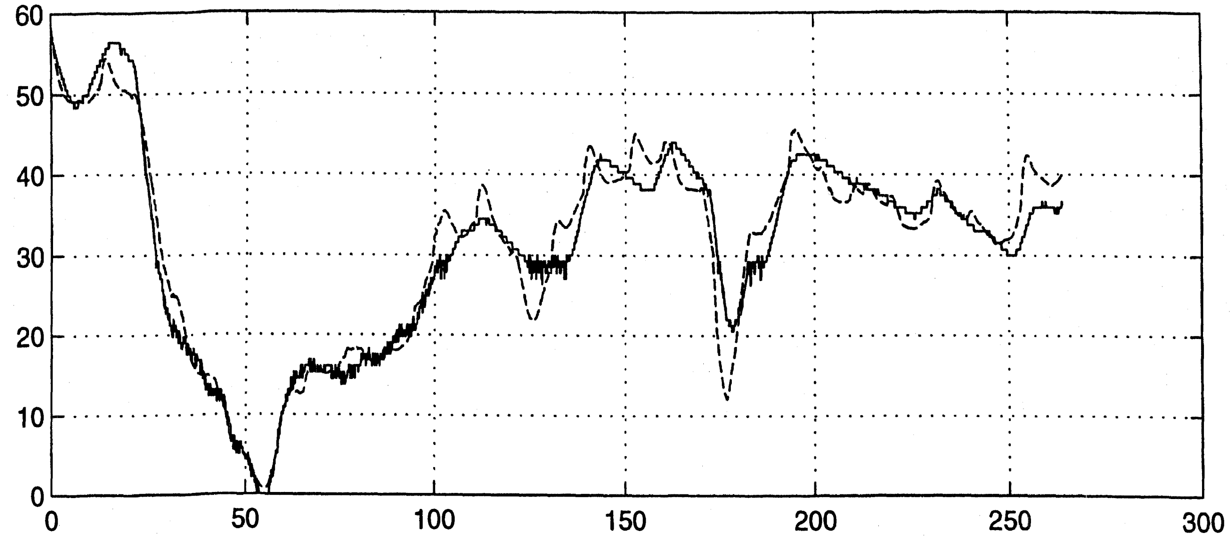
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.2, Tc = 2.8, T2 = 2.8, T3 = 1.2, rms = 17.75, meanRerr = 13.81
Driver: z150$_9$0.txt



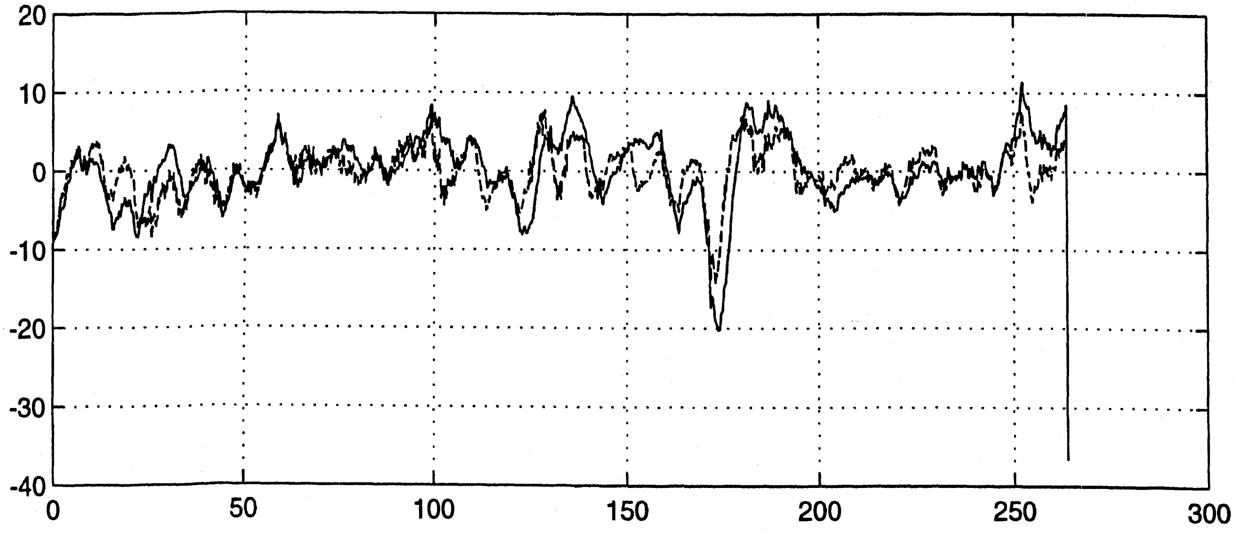
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.7, Tc = 2.8, T2 = 2.8, T3 = 1.7
Driver: $z151_4 0$.txt



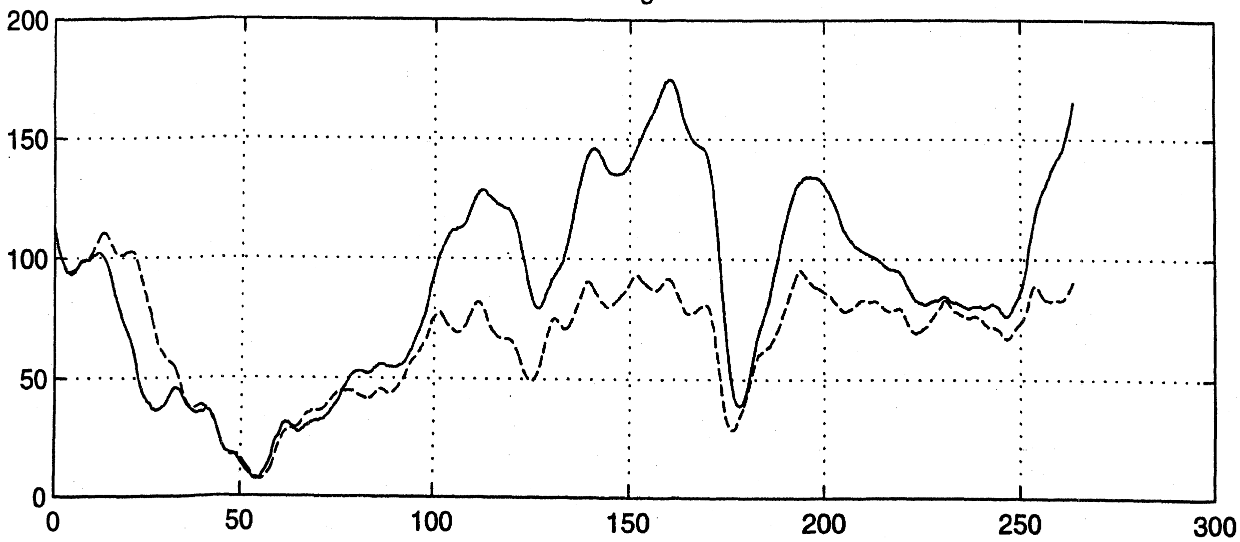
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.7, Tc = 2.8, T2 = 2.8, T3 = 1.7, rms = 34.27, meanRerr = 25.31
Driver: z151$_4$0.txt



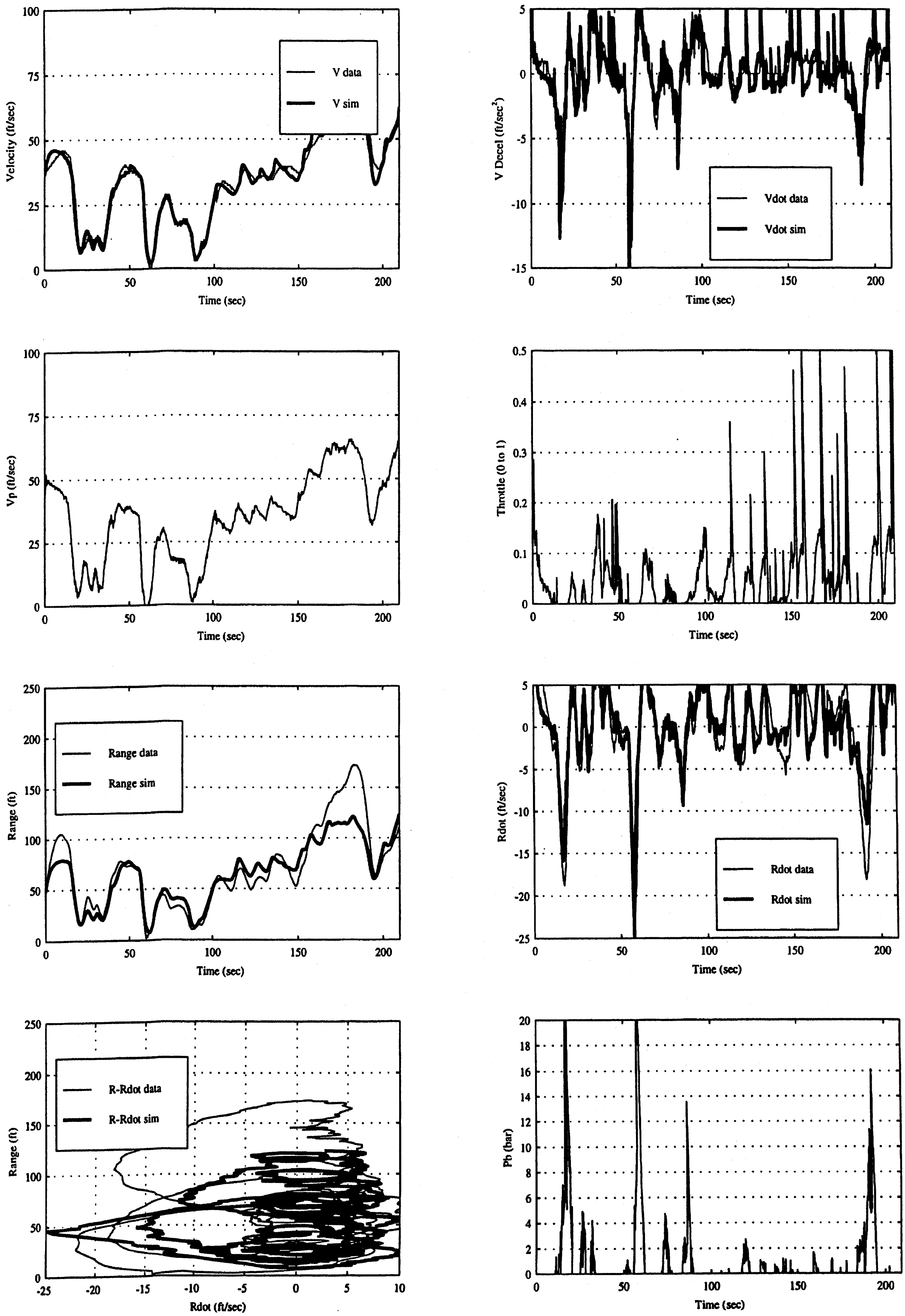
Rdot



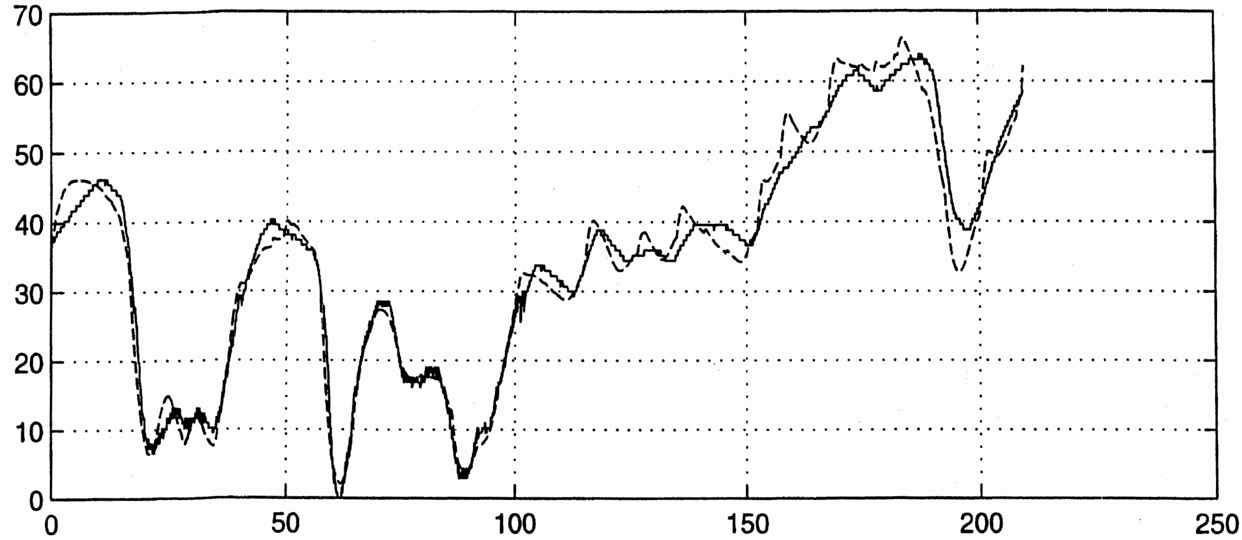
Range

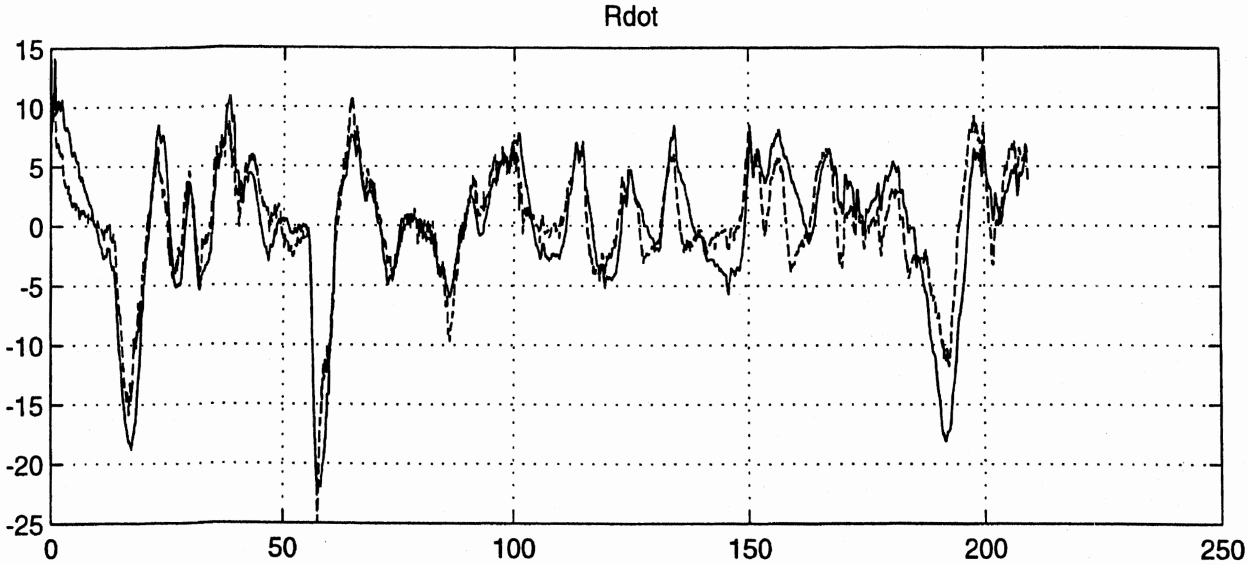


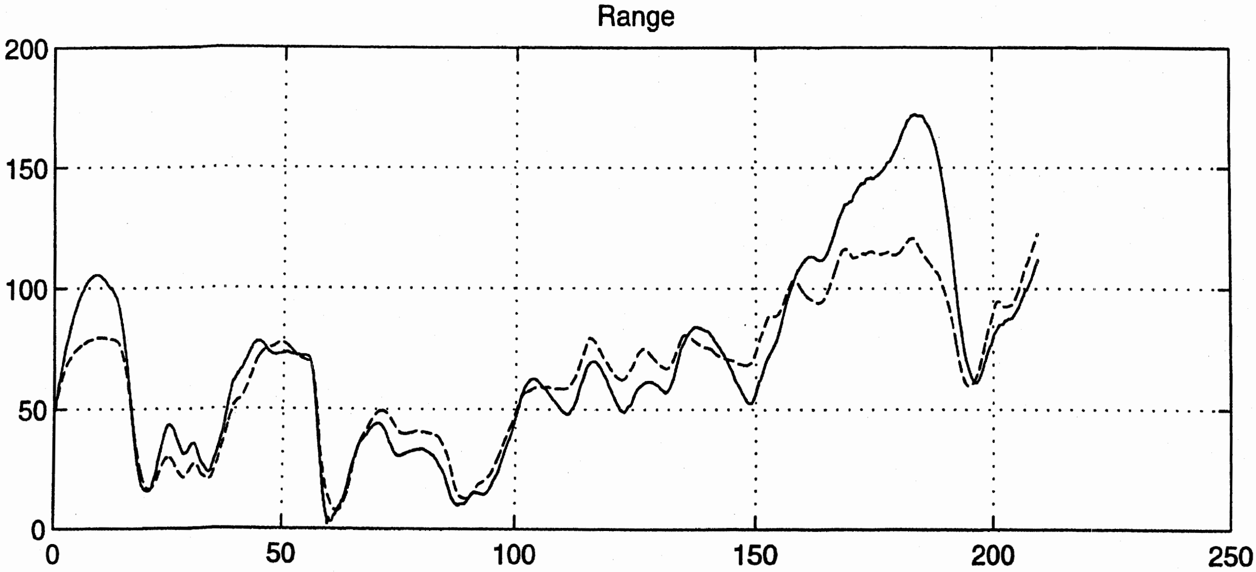
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.5, Tc = 2.8, T2 = 2.8, T3 = 1.5
Driver: $z151_4 2$.txt



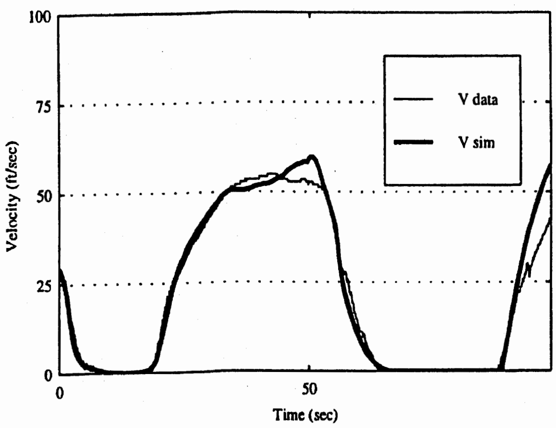
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.5, Tc = 2.8, T2 = 2.8, T3 = 1.5, rms = 16.74, meanRerr = 11.80
Driver: $z151_4 2.txt$

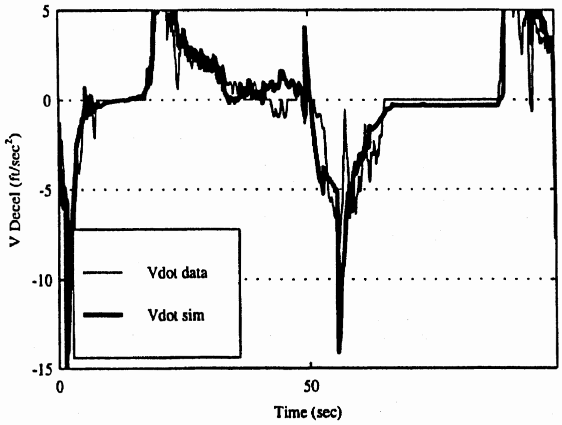


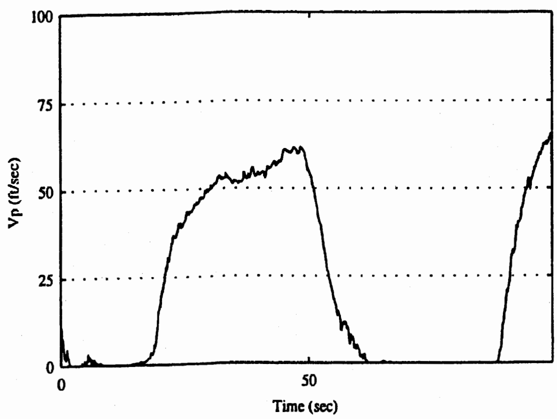


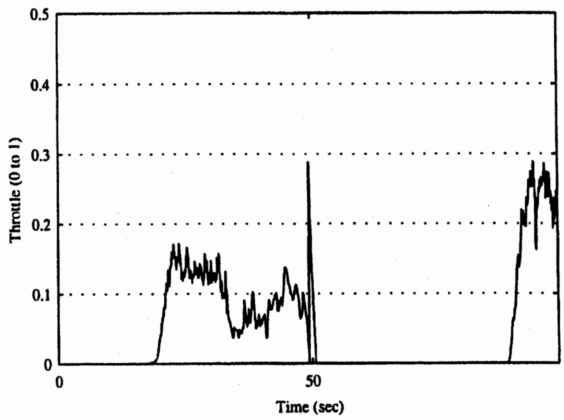


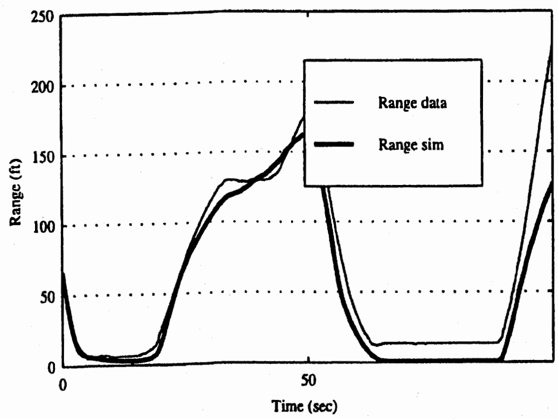
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.3, Tc = 2.8, T2 = 2.8, T3 = 2.3
Driver: z151$_5$7.txt

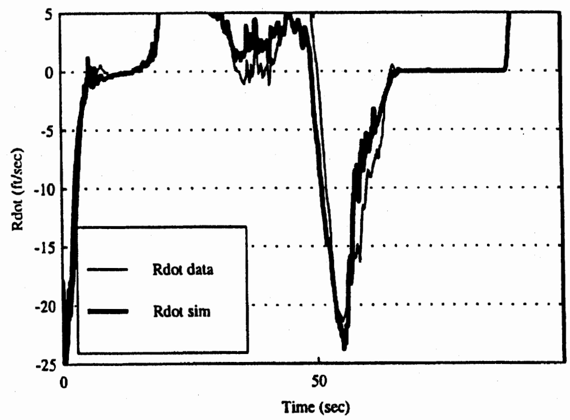


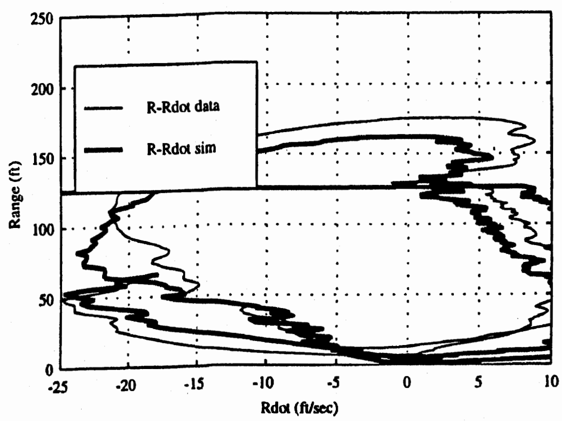


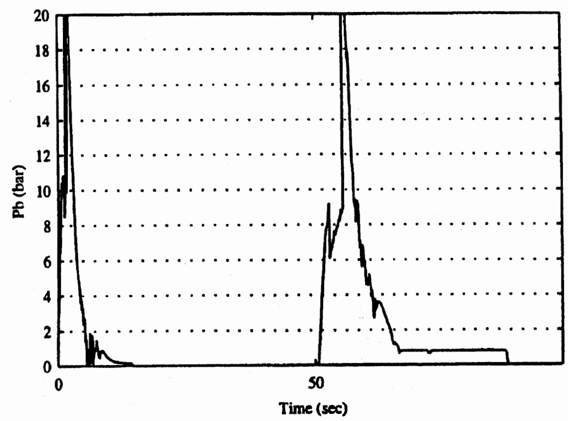




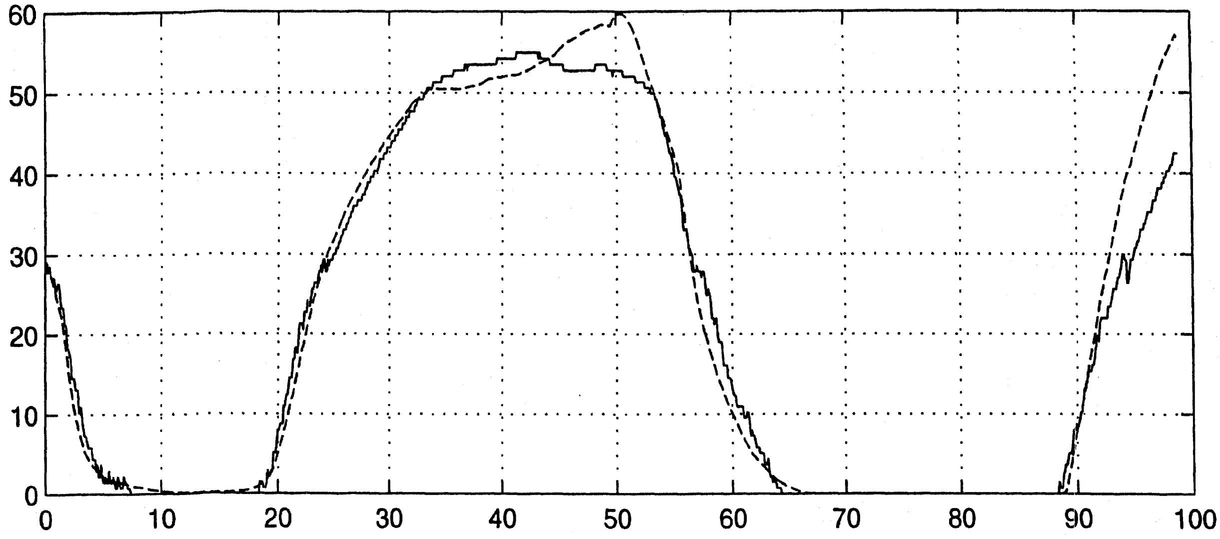


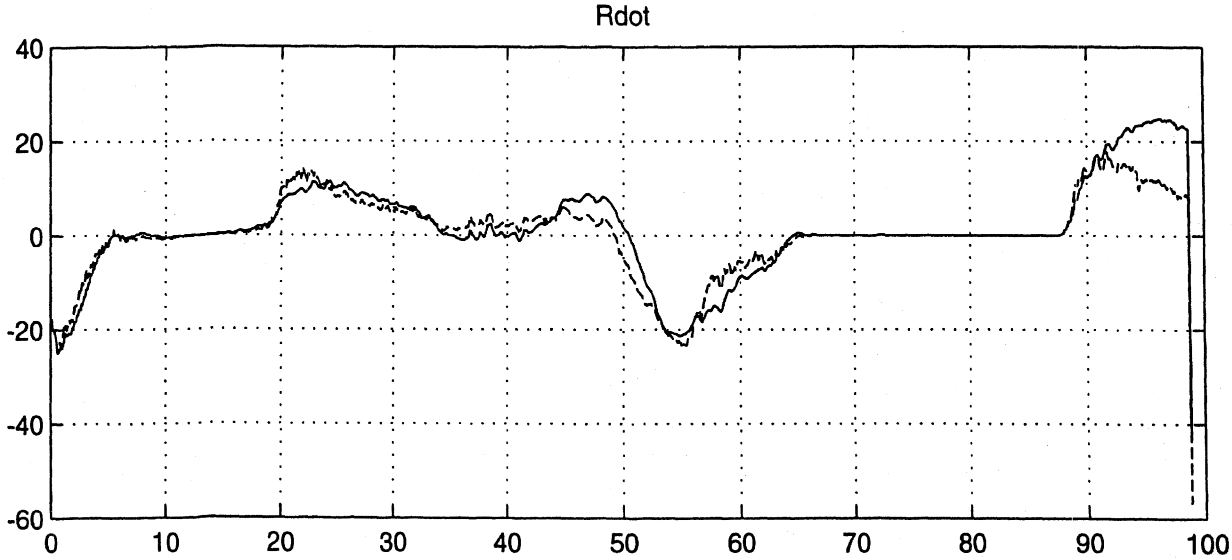


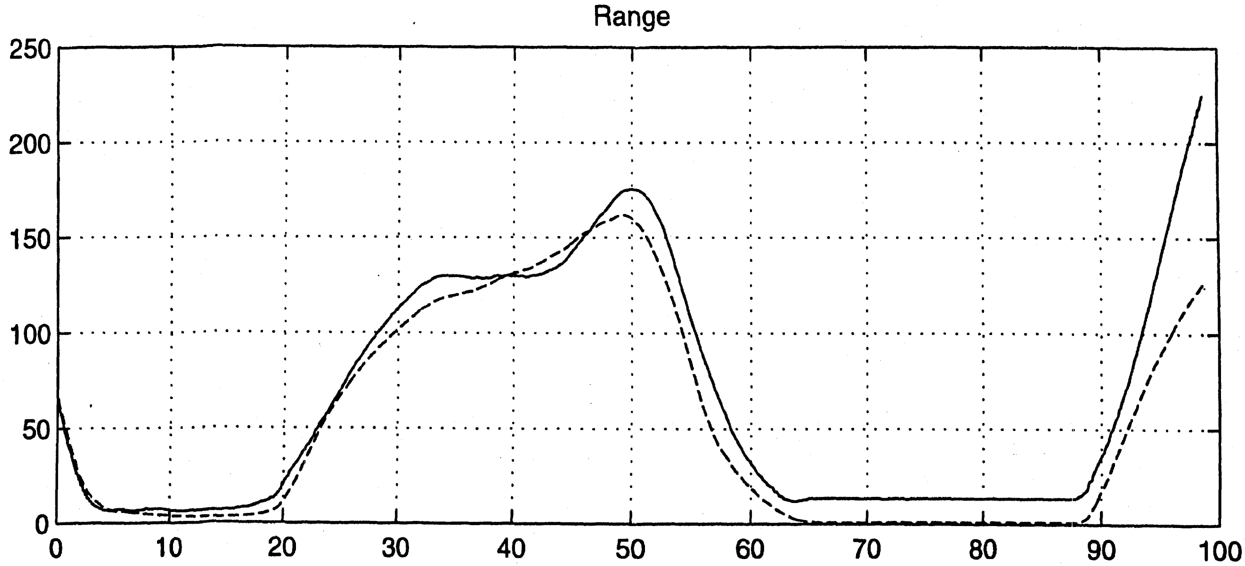




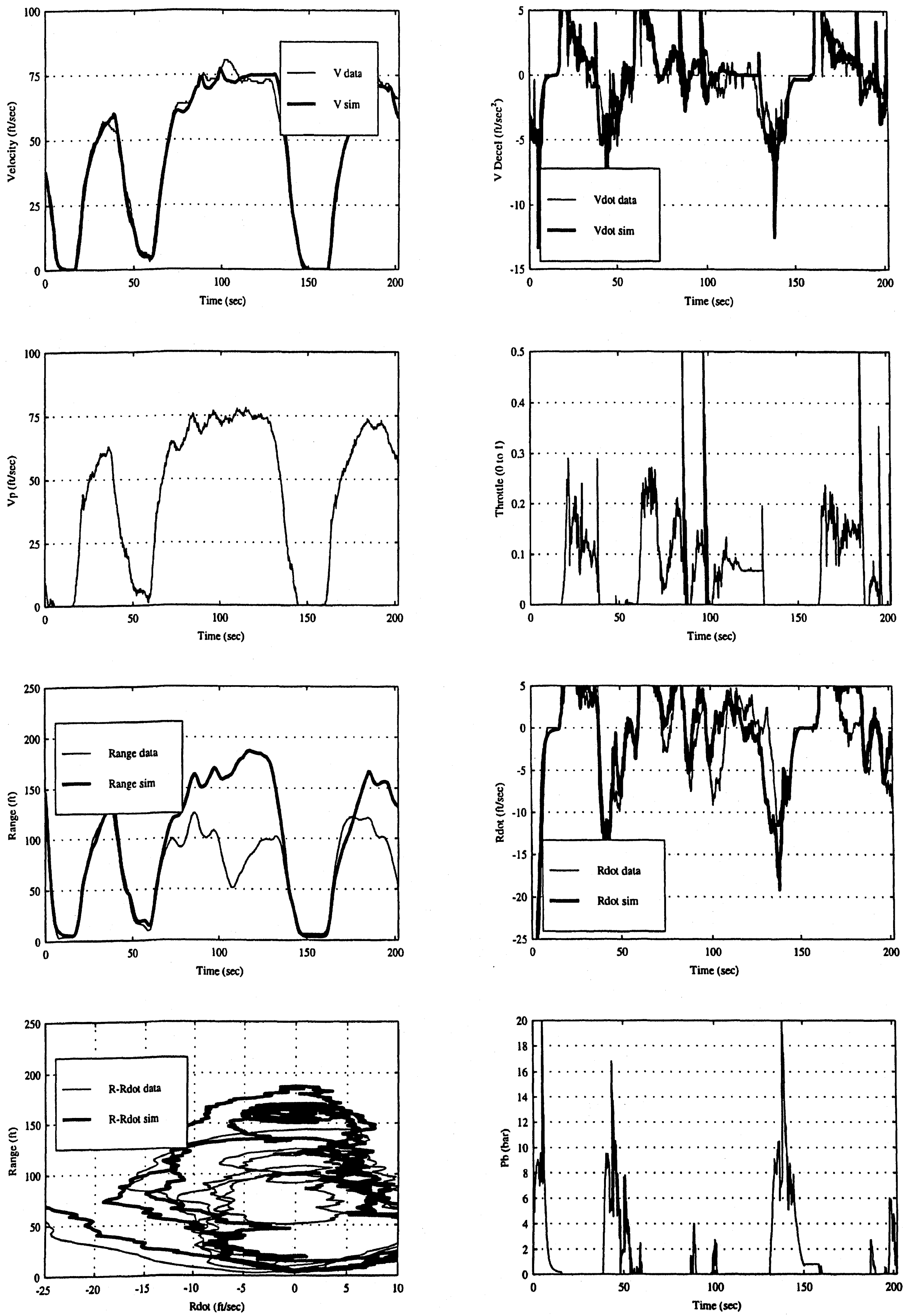
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.3, Tc = 2.8, T2 = 2.8, T3 = 2.3, rms = 19.39, meanRerr = 12.44
Driver: $z151_5 7$.txt



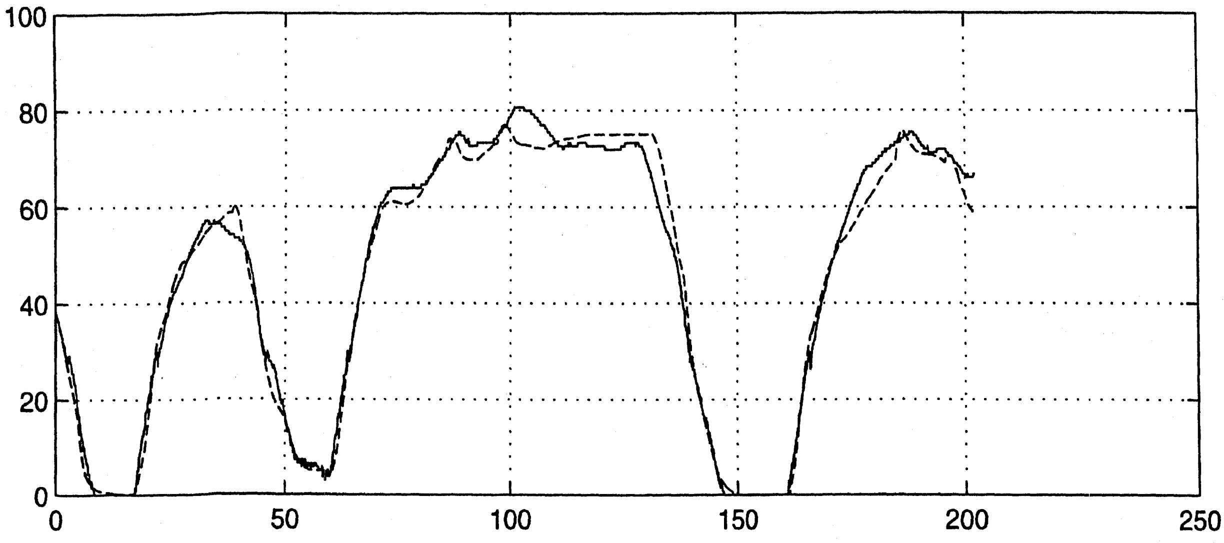


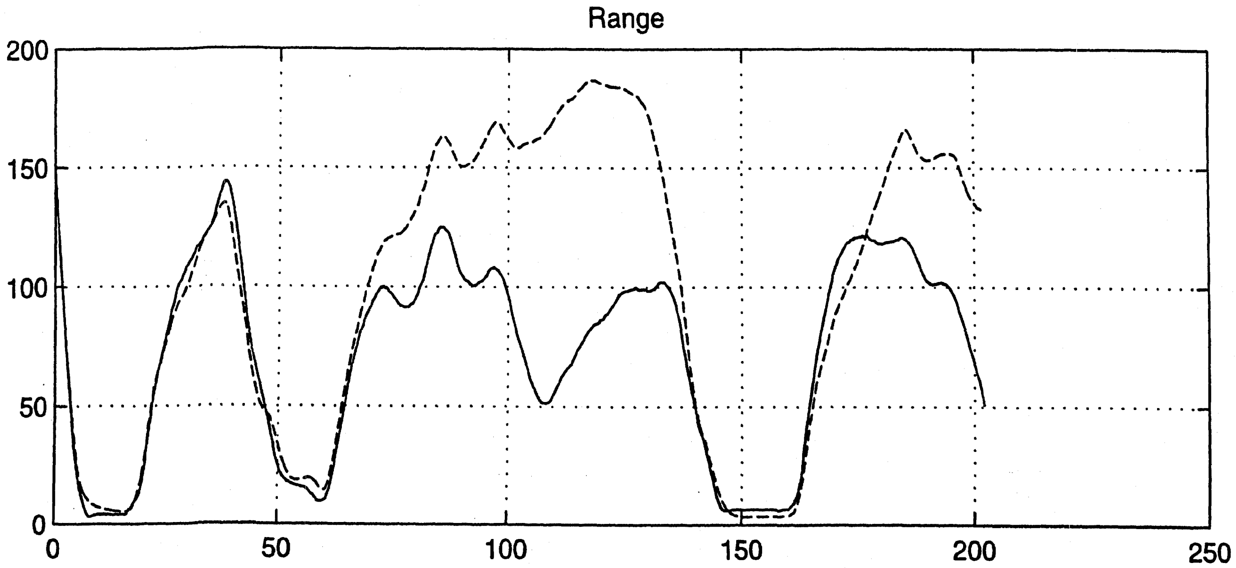


BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9
Driver: z151_5 9.txt

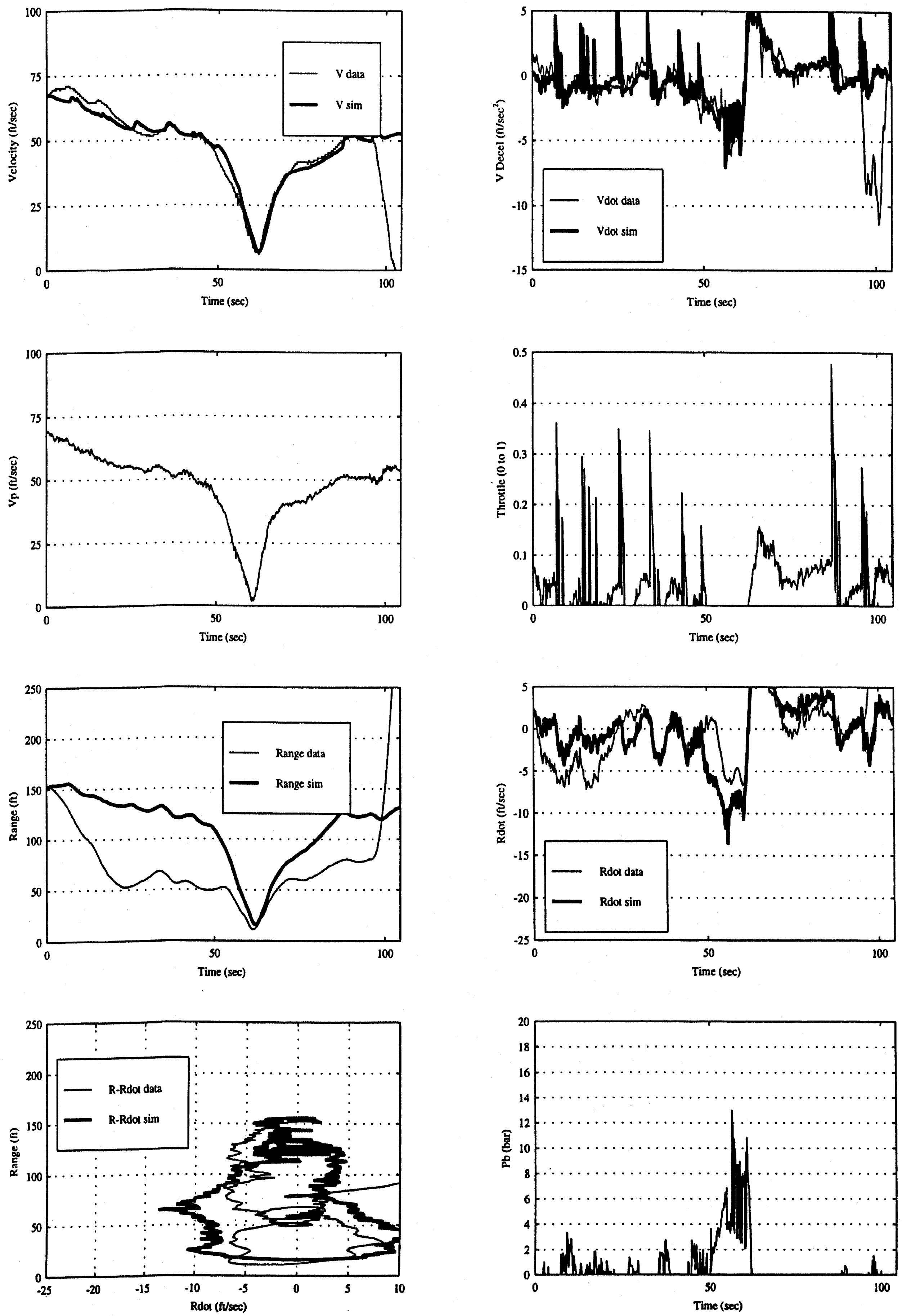


BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9, rms = 45.81, meanRerr = 30.44
Driver: $z151_5 9$.txt

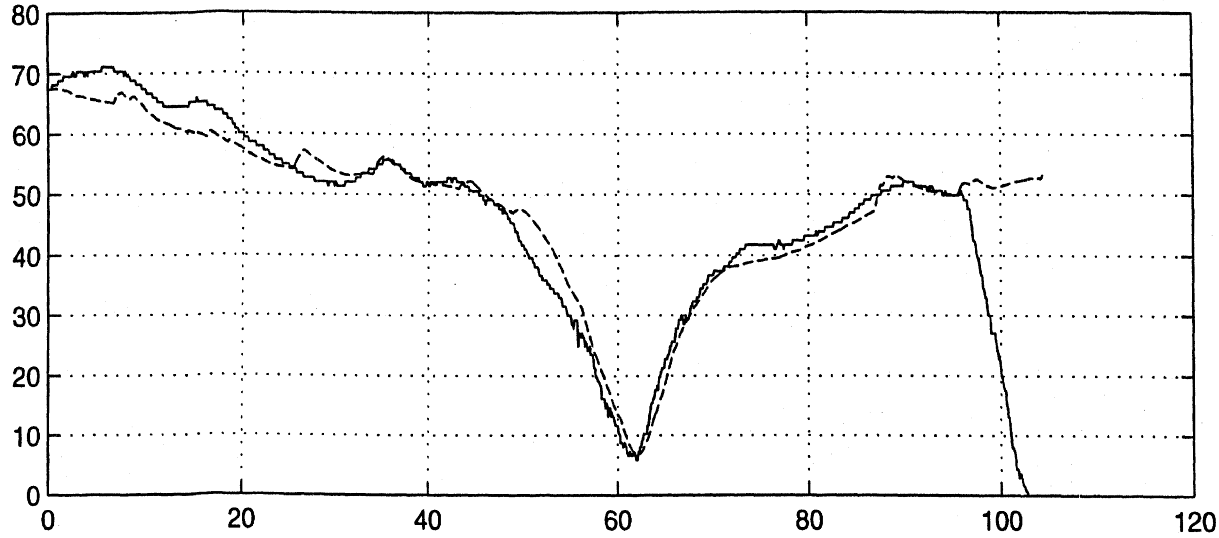


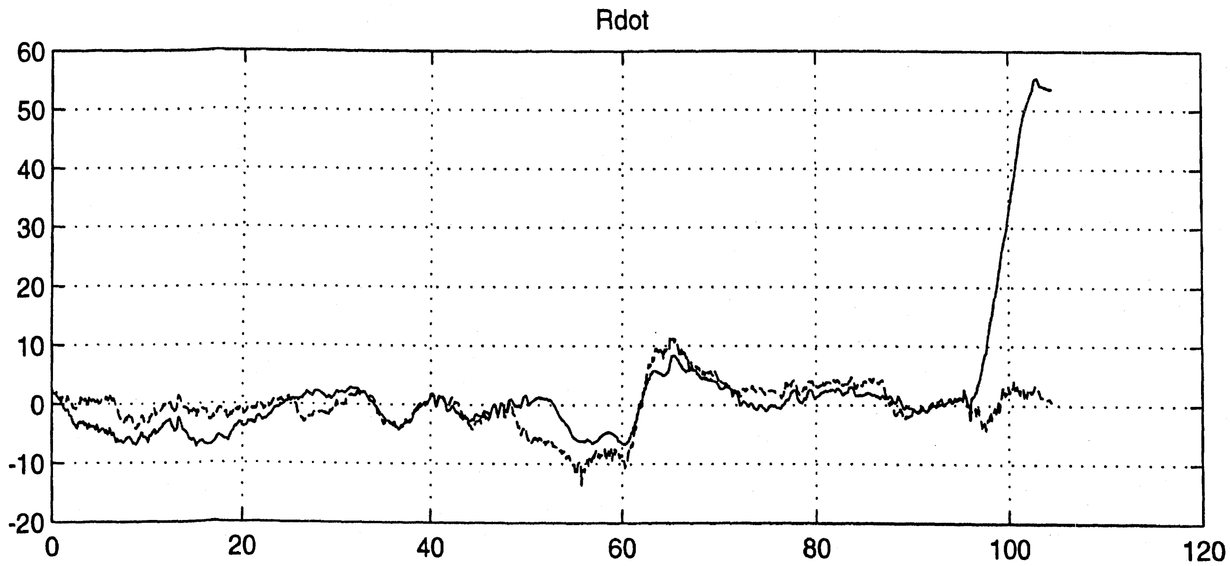


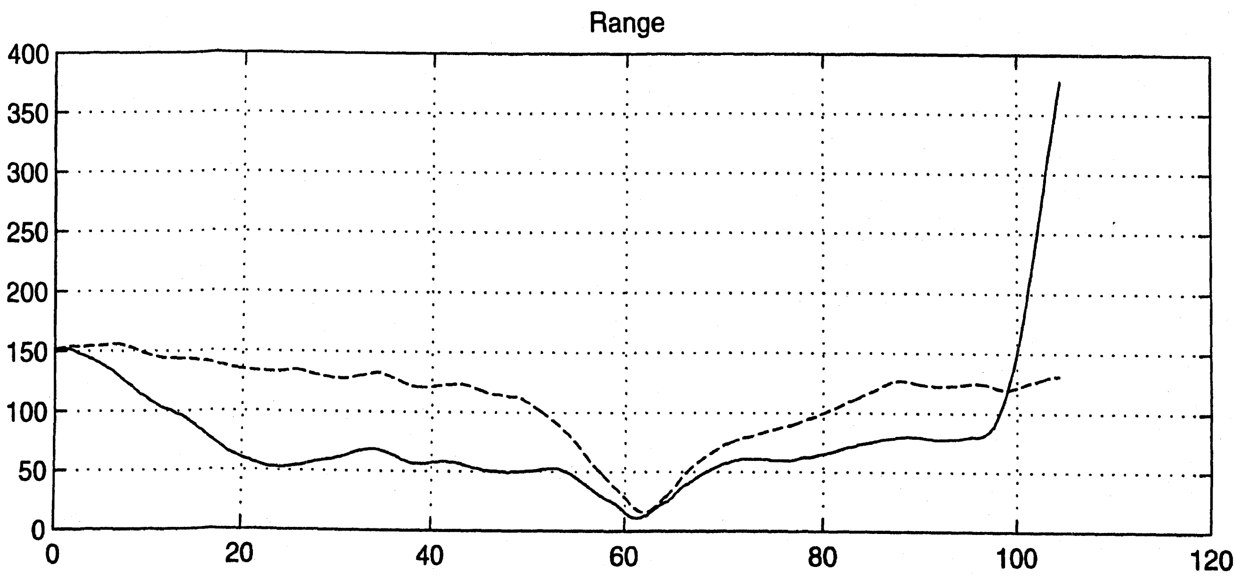
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0
Driver: z151$_6$3.txt



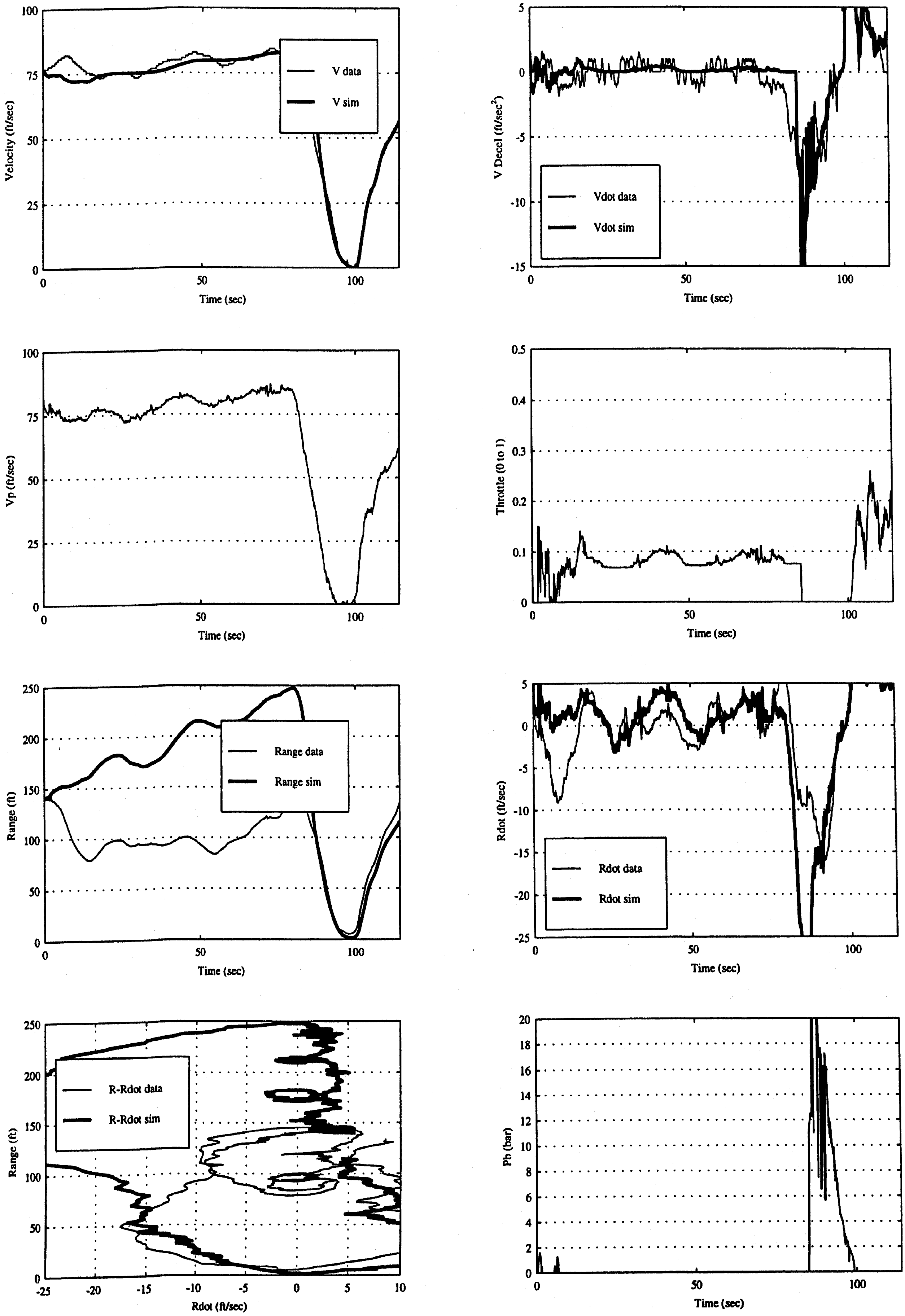
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0, rms = 55.73, meanRerr = 44.95
Driver: z151_6 3.txt



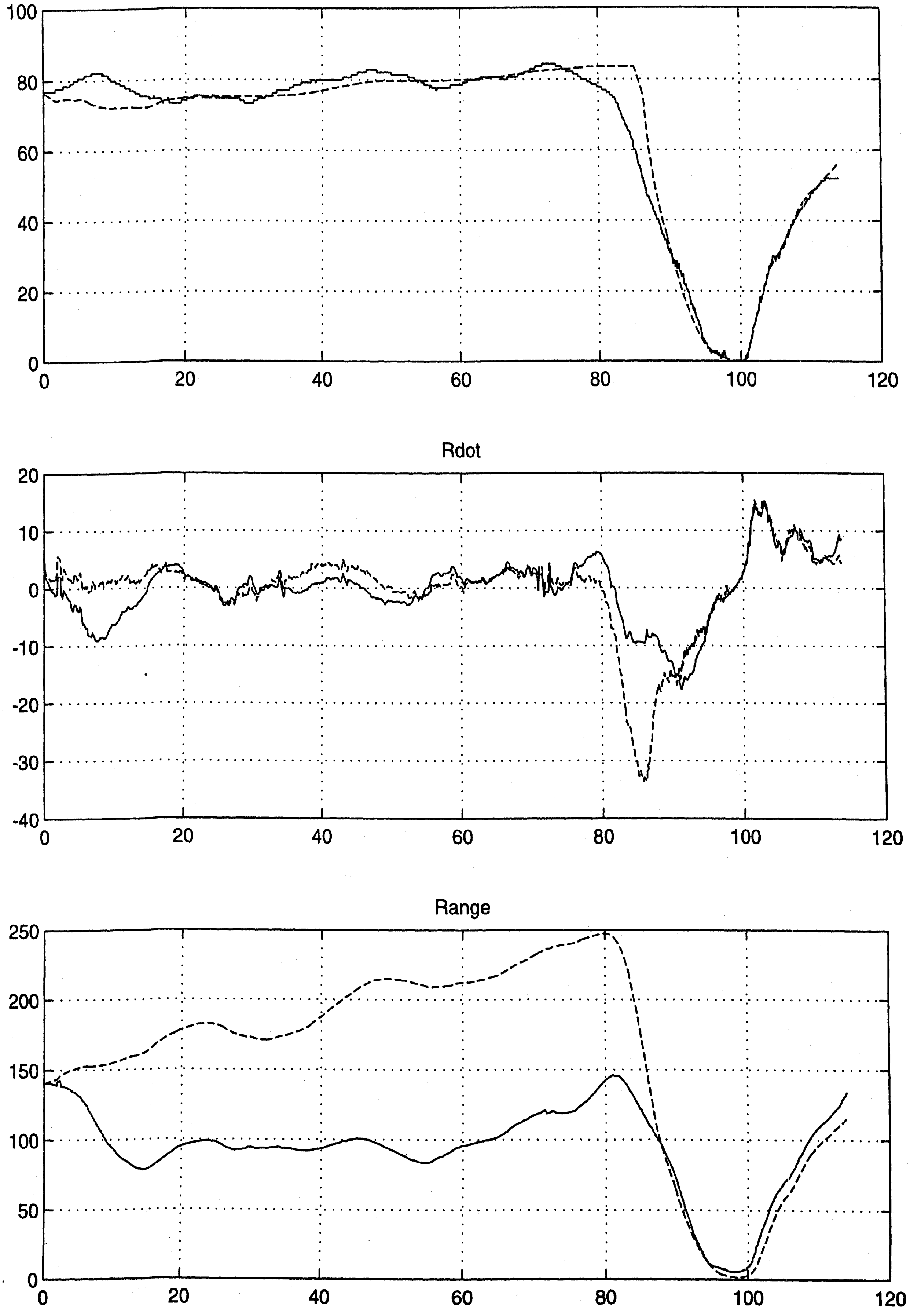




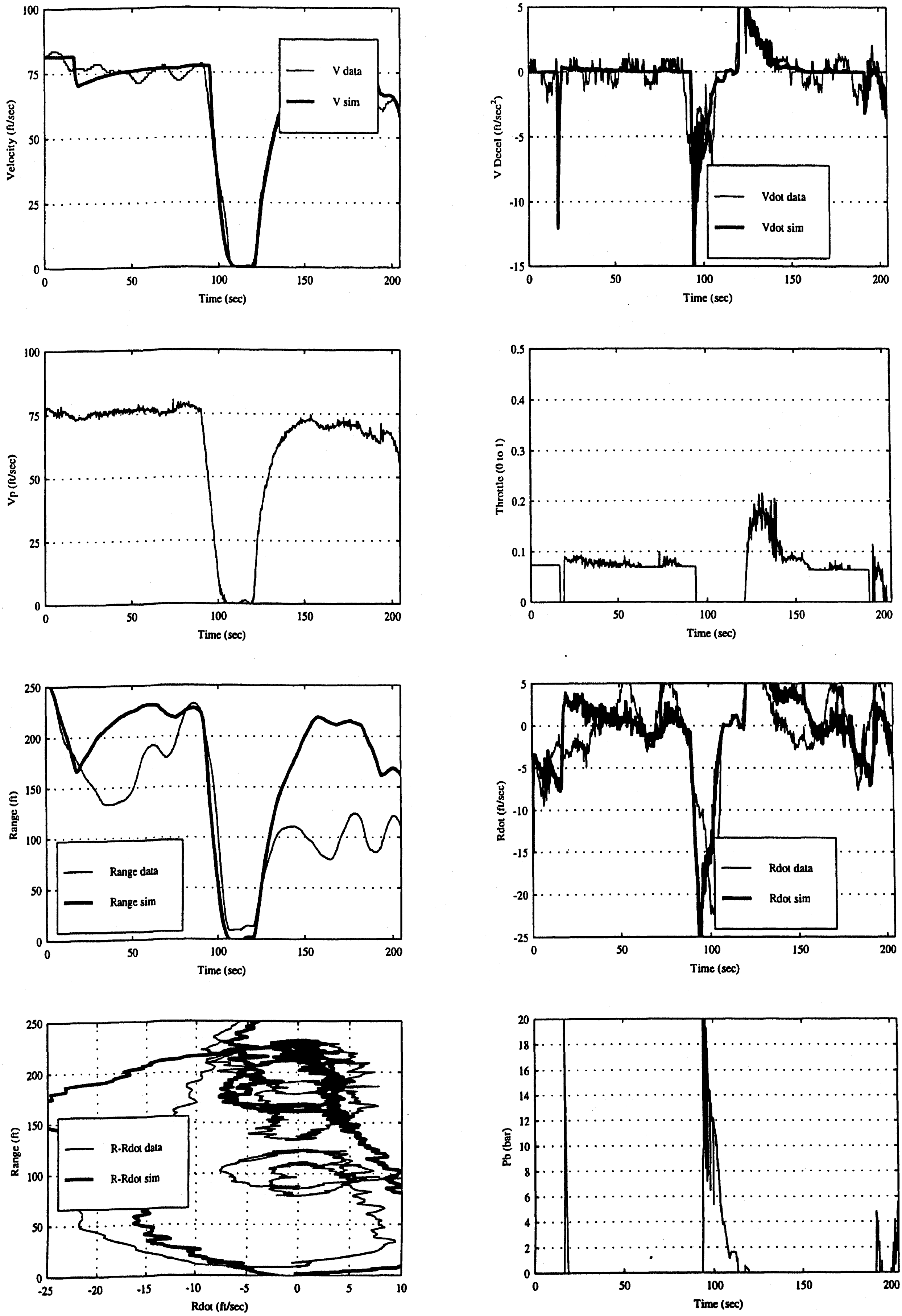
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0
Driver: z151$_7$0.txt



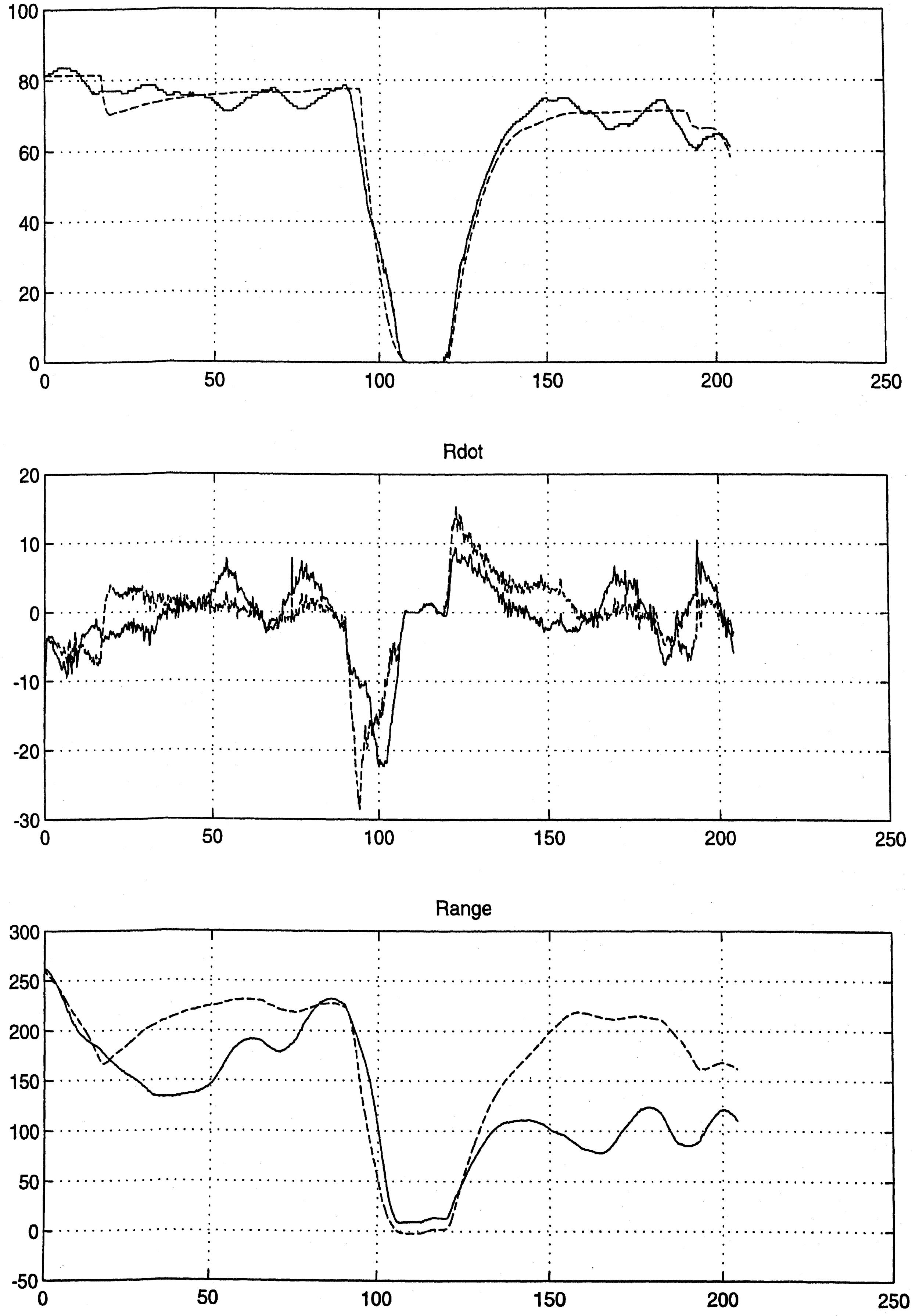
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0, rms = 83.13, meanRerr = 70.41
Driver: z151$_7$0.txt



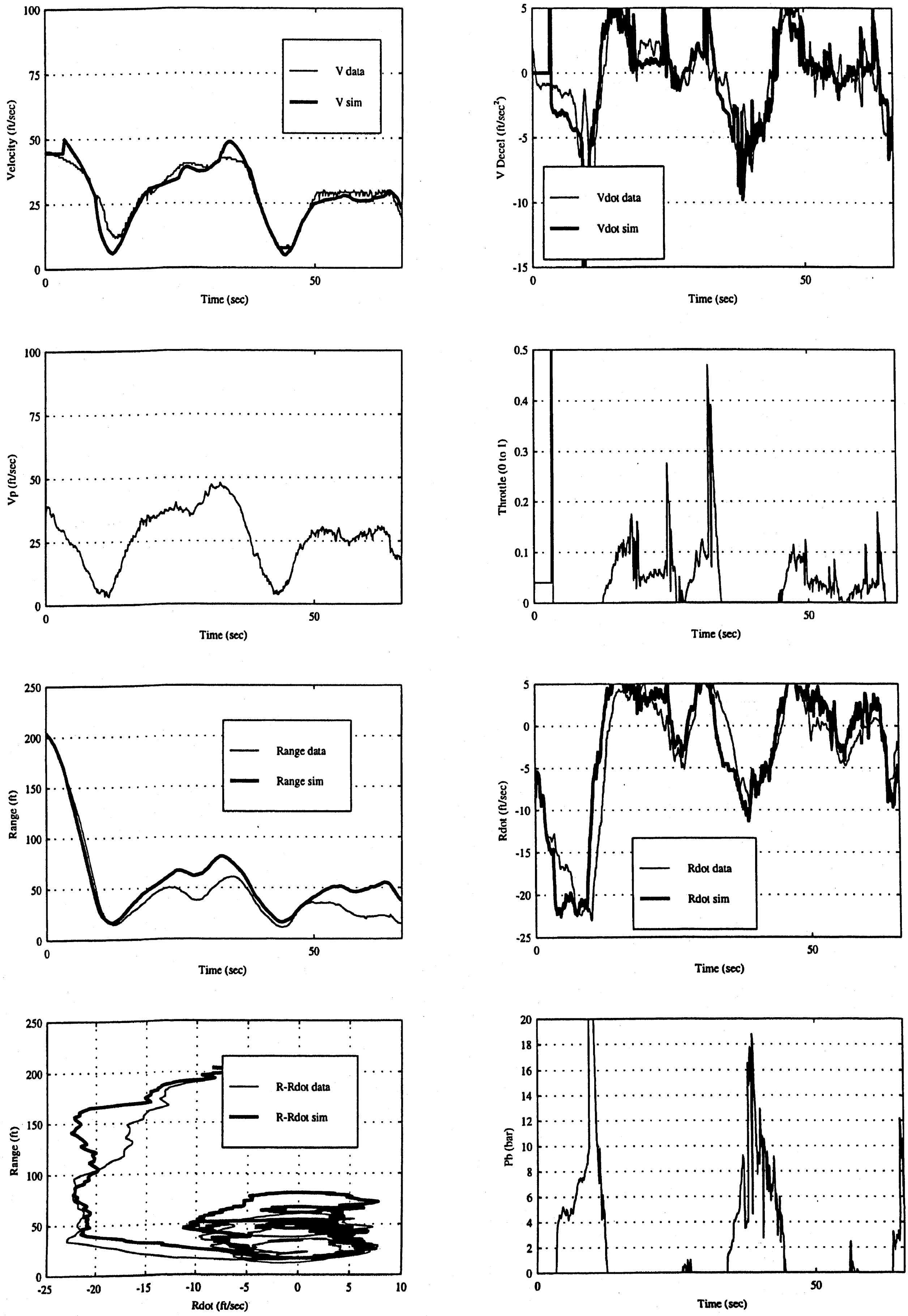
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.5, Tc = 2.8, T2 = 2.8, T3 = 2.5
Driver: z151$_8$0.txt



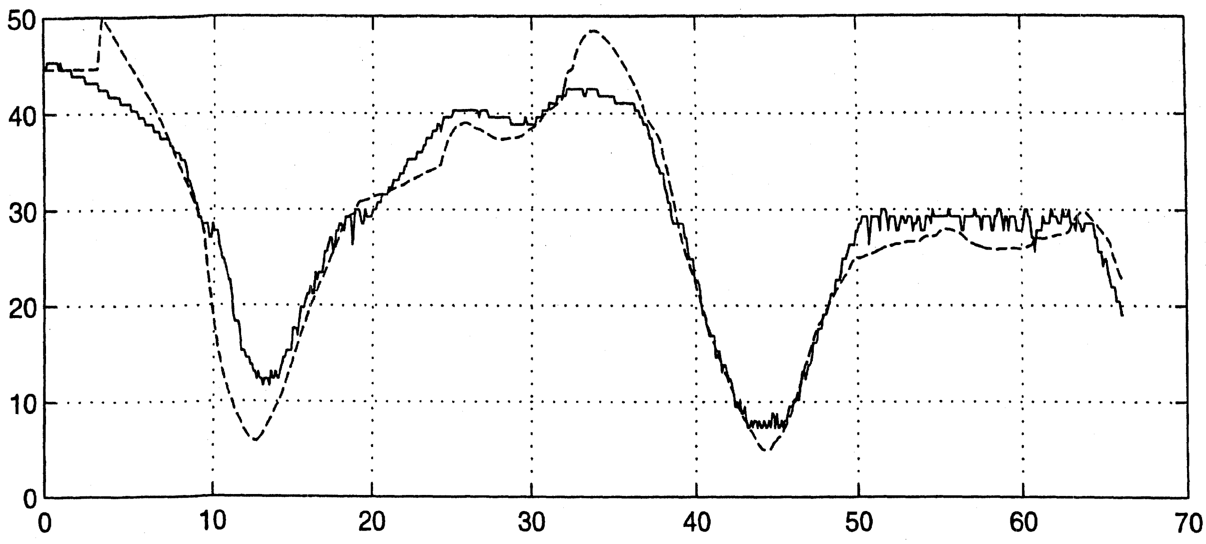
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.5, Tc = 2.8, T2 = 2.8, T3 = 2.5, rms = 64.55, meanRerr = 50.83
Driver: z151_8 0.txt



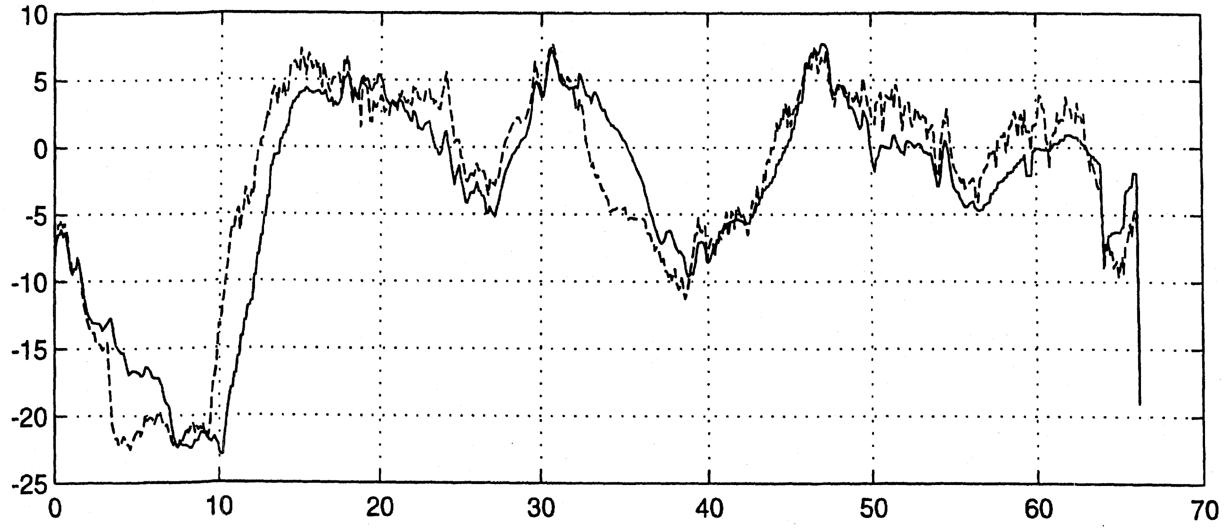
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3
Driver: z151$_8$9.txt



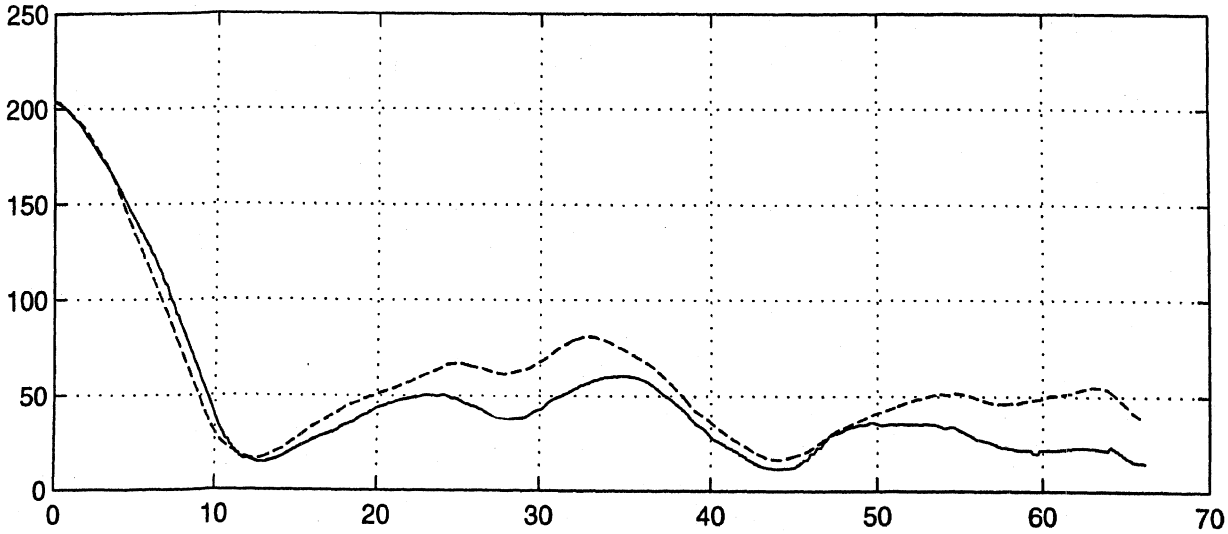
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.3, Tc = 2.8, T2 = 2.8, T3 = 1.3, rms = 15.86, meanRerr = 12.77
Driver: z151$_8$9.txt



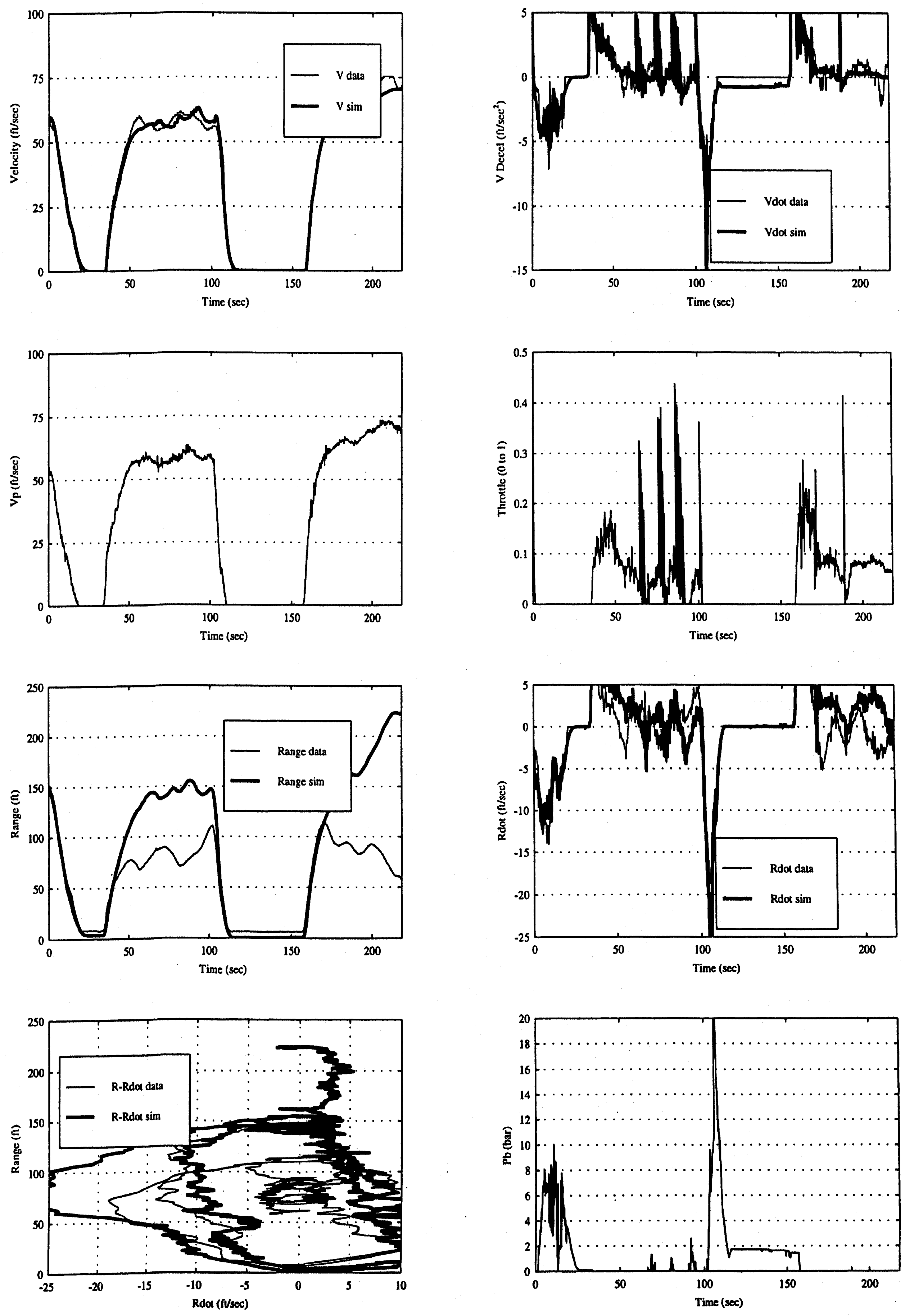
Rdot



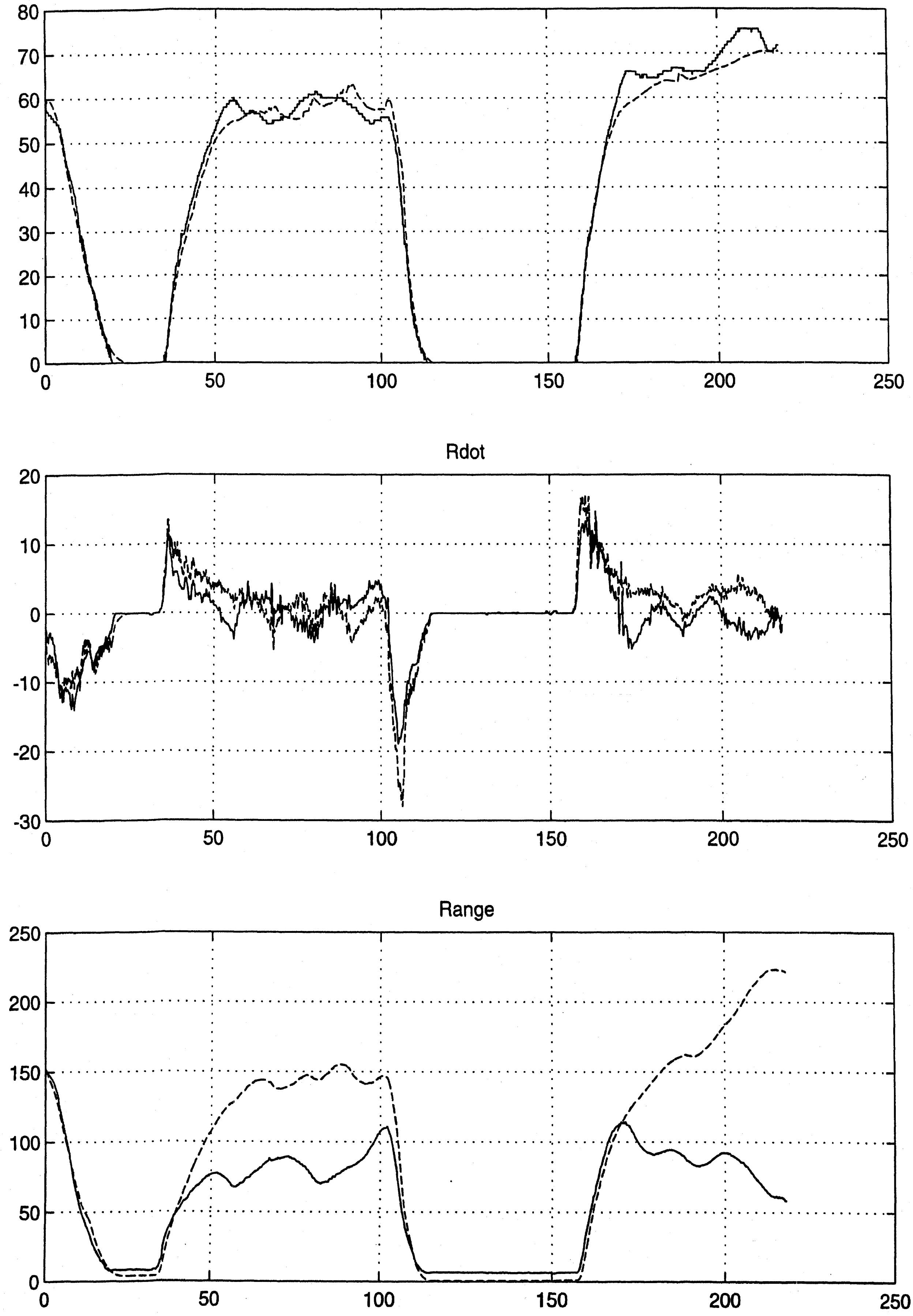
Range



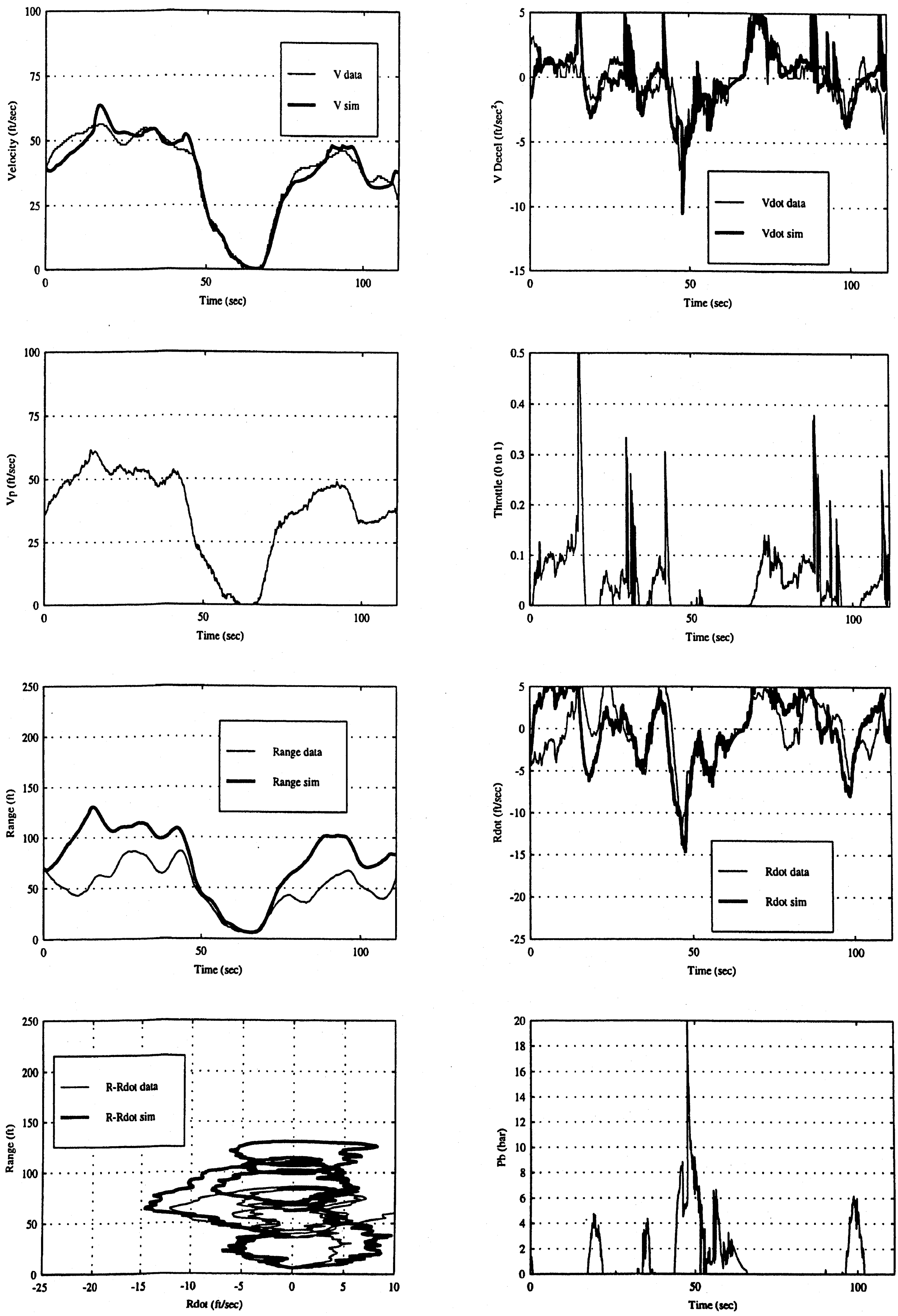
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.1, Tc = 2.8, T2 = 2.8, T3 = 2.1
Driver: z151$_9$1.txt



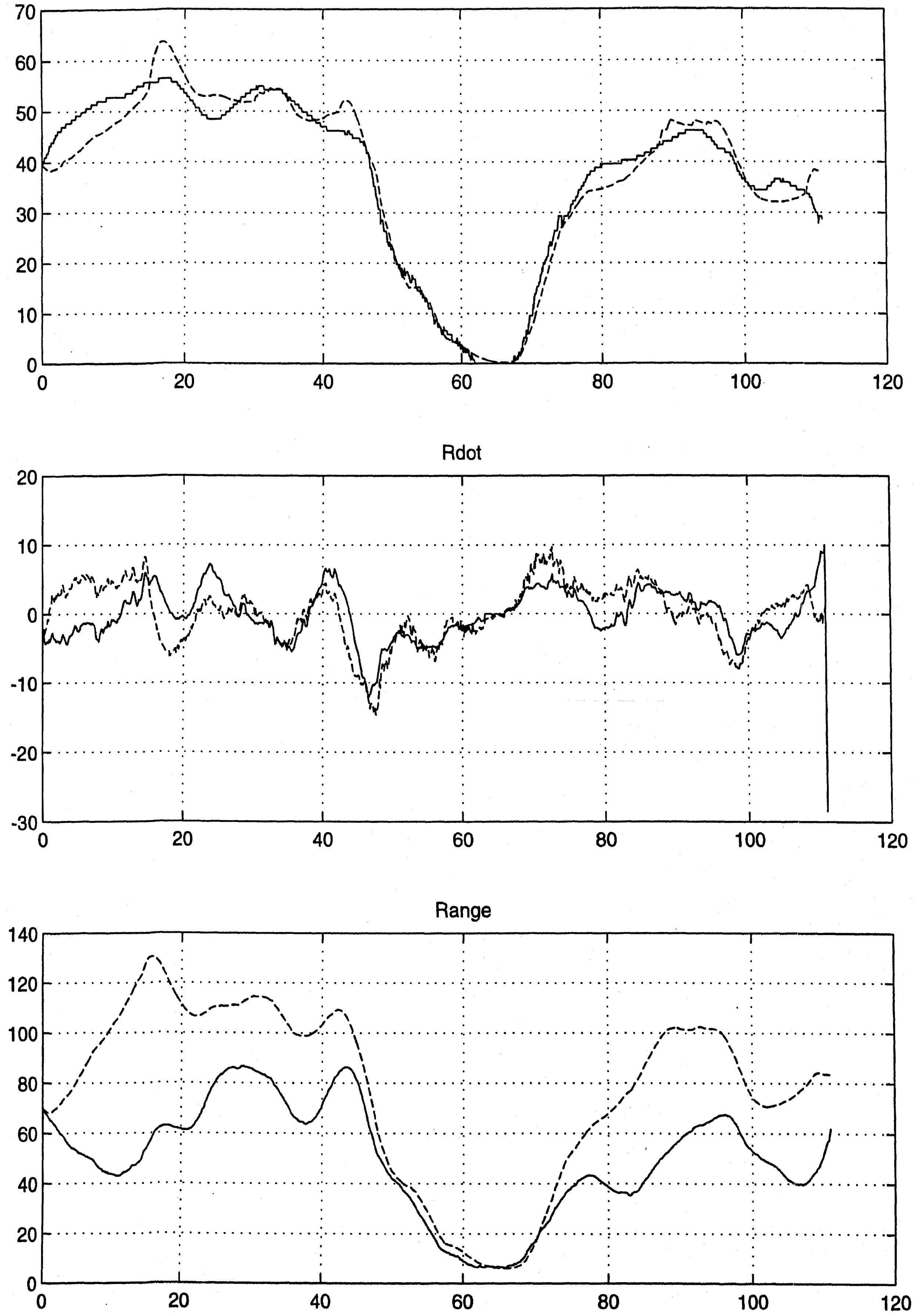
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.1, Tc = 2.8, T2 = 2.8, T3 = 2.1, rms = 54.78, meanRerr = 36.78
Driver: z151$_9$1.txt



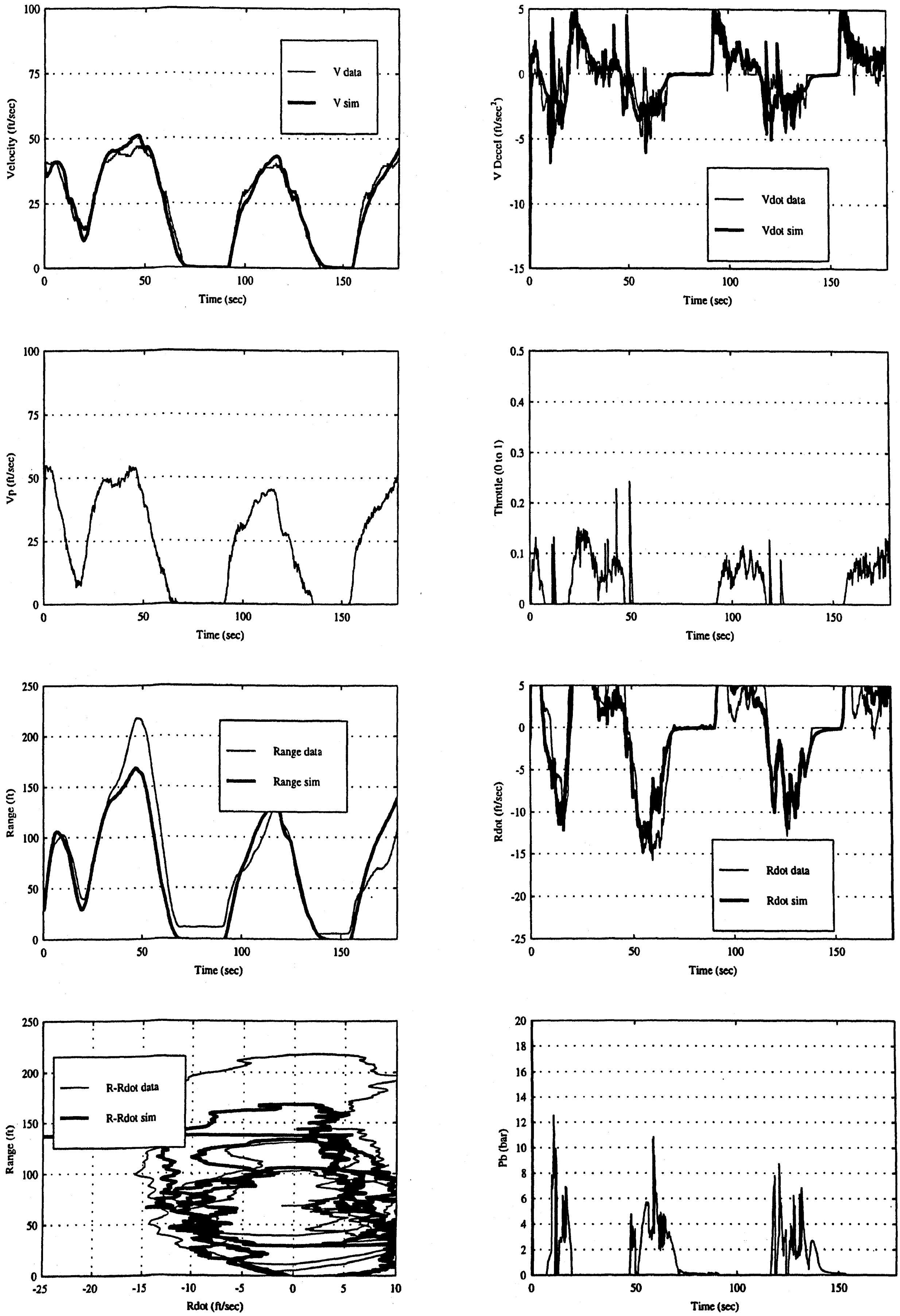
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.7, Tc = 2.8, T2 = 2.8, T3 = 1.7
Driver: z151$_9$5.txt



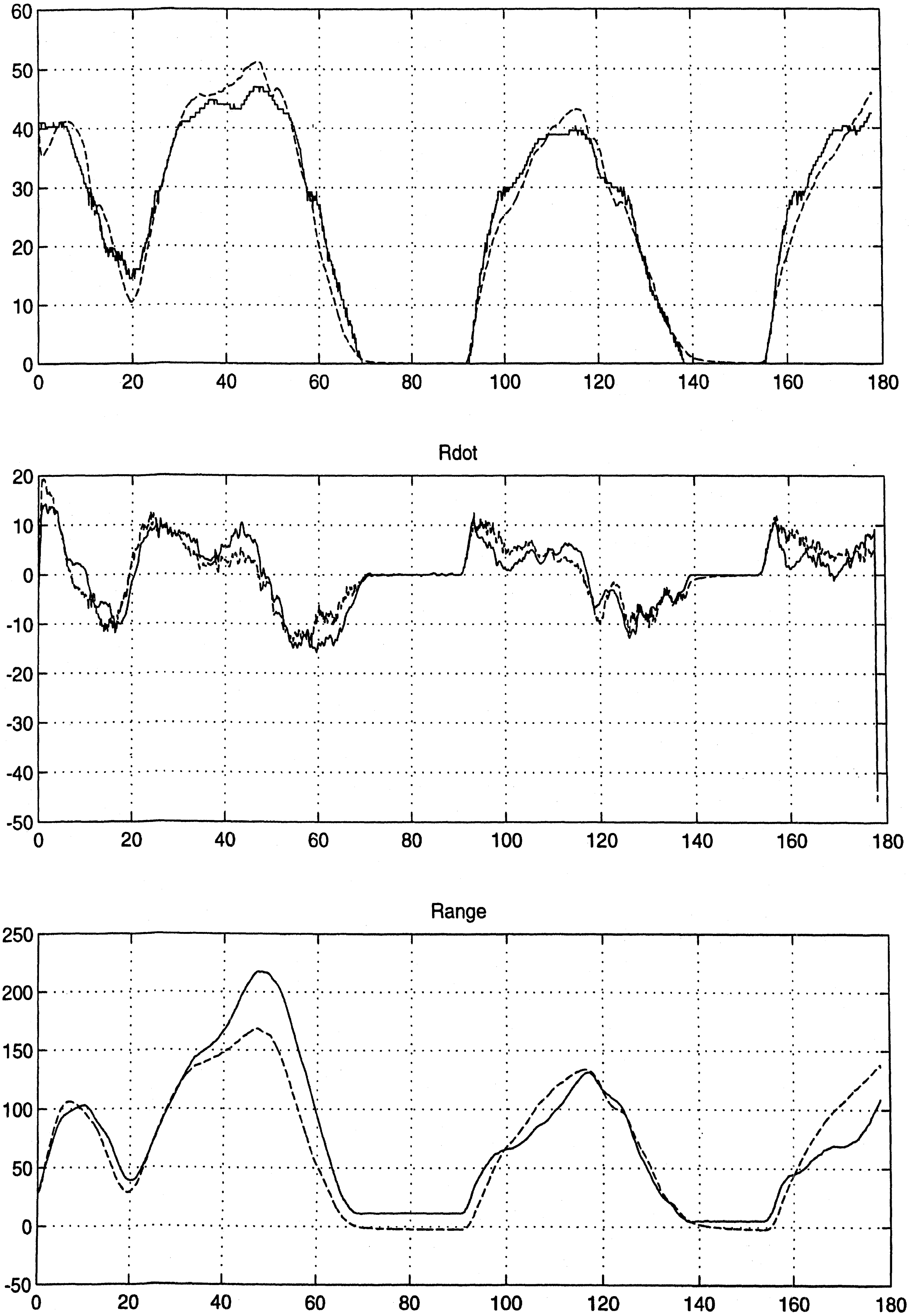
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.7, Tc = 2.8, T2 = 2.8, T3 = 1.7, rms = 33.32, meanRerr = 27.28
Driver: $z151_95$.txt



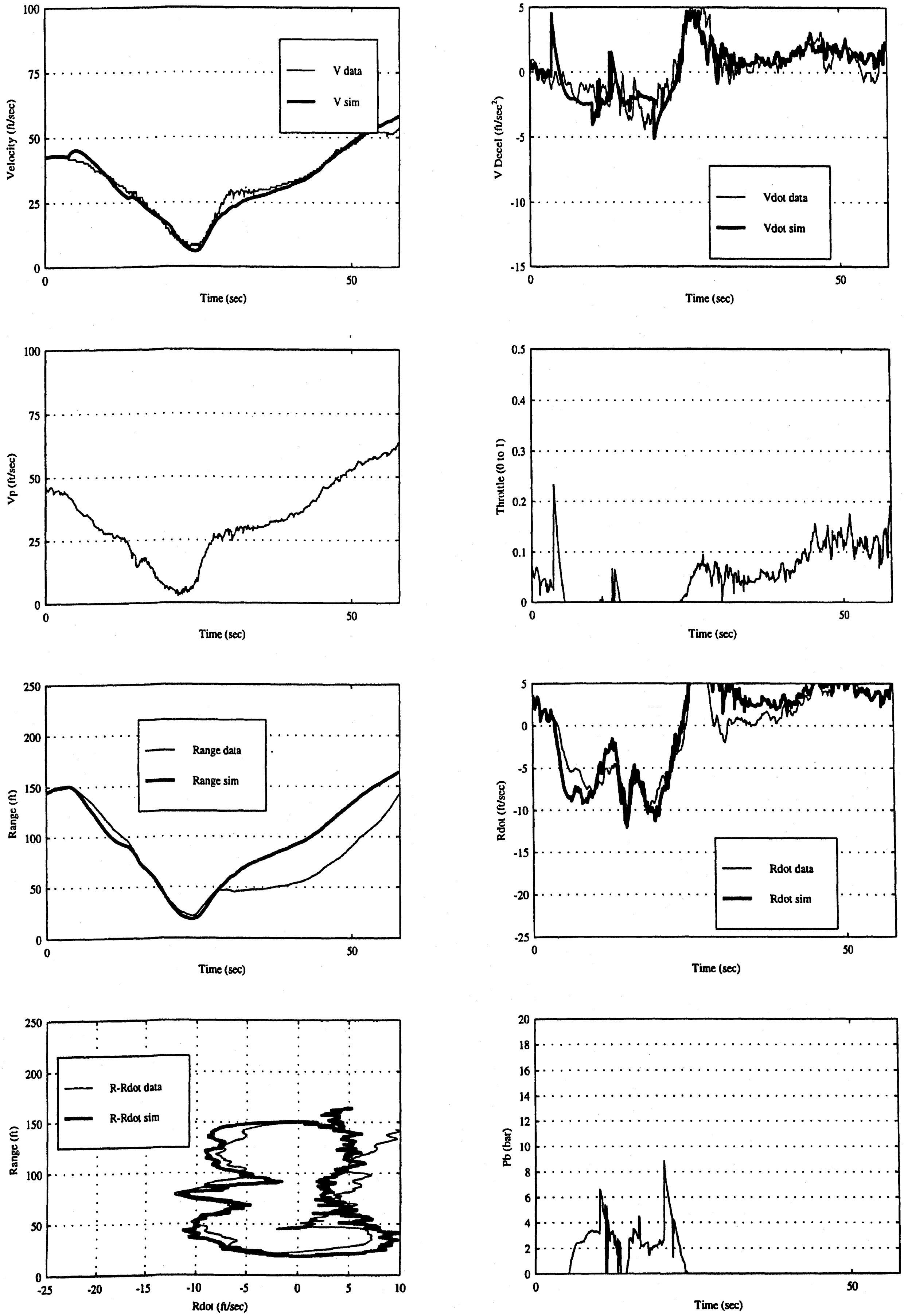
BMW Model, data vs. simulation (RunB).
Model 151, Th = 3.2, Tc = 2.8, T2 = 2.8, T3 = 3.2
Driver: z153$_1$05.txt

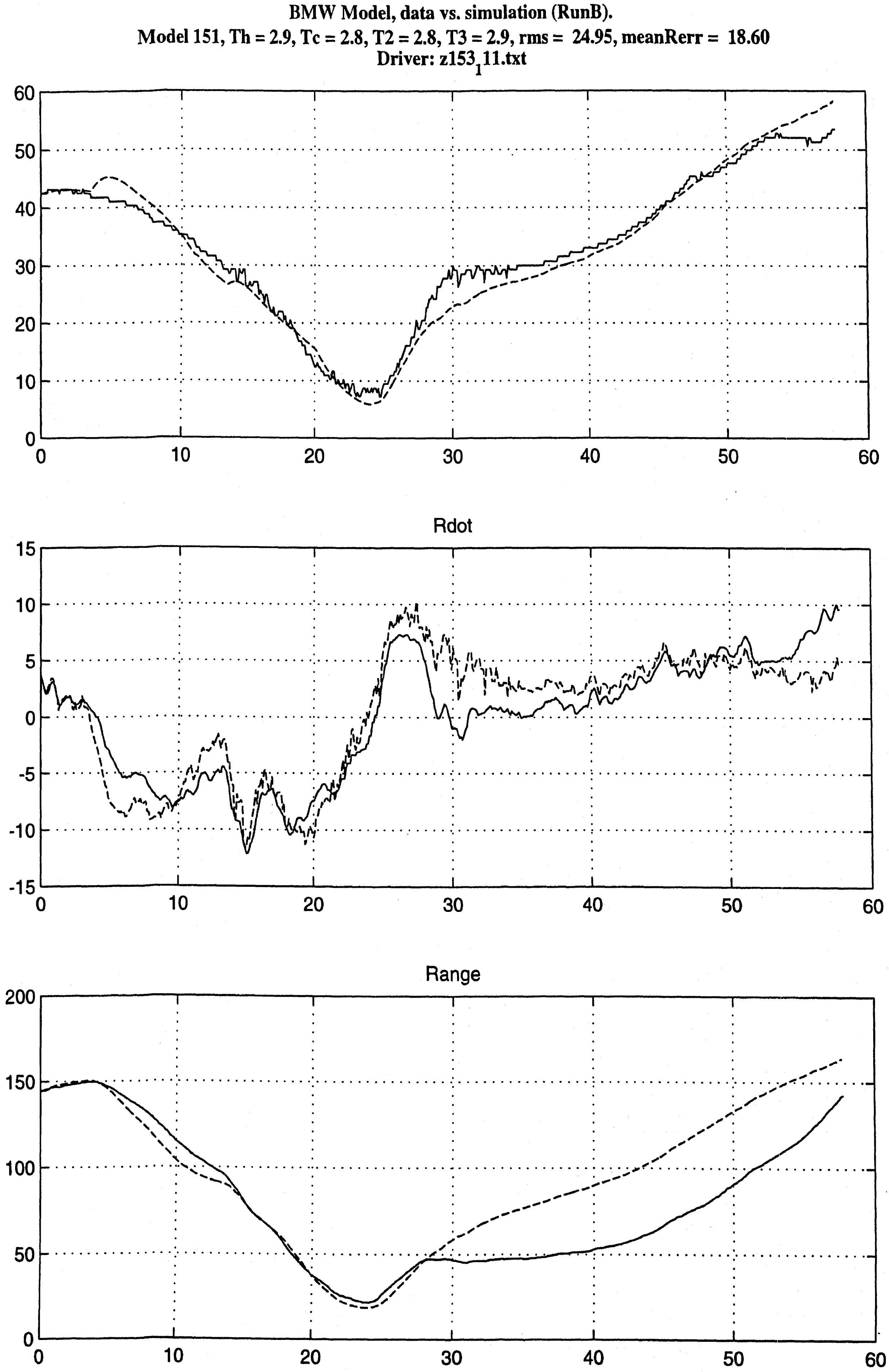


BMW Model, data vs. simulation (RunB).
Model 151, Th = 3.2, Tc = 2.8, T2 = 2.8, T3 = 3.2, rms = 21.36, meanRerr = 15.65
Driver: z153_1 05.txt

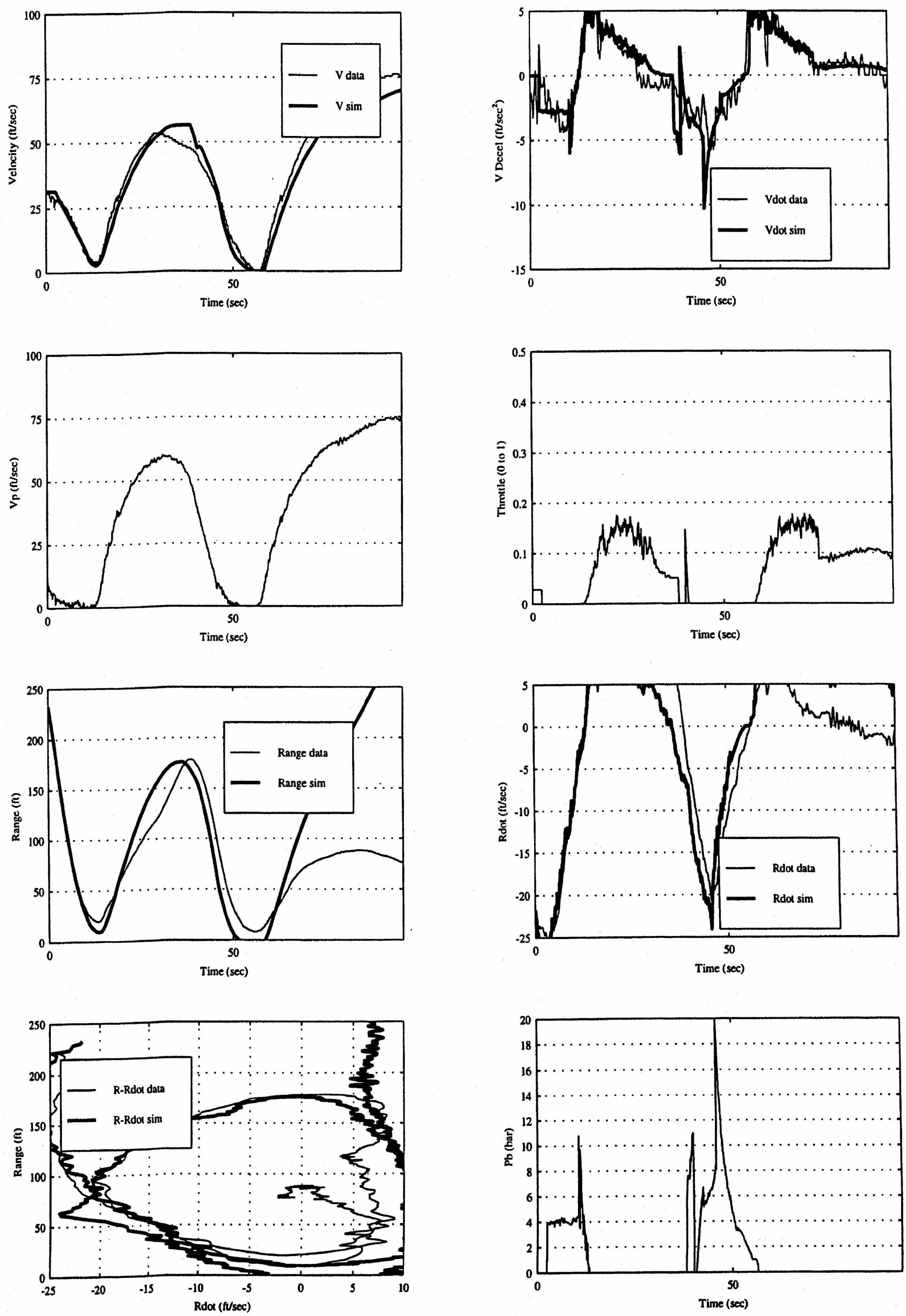


BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.9, Tc = 2.8, T2 = 2.8, T3 = 2.9
Driver: z153_1 11.txt

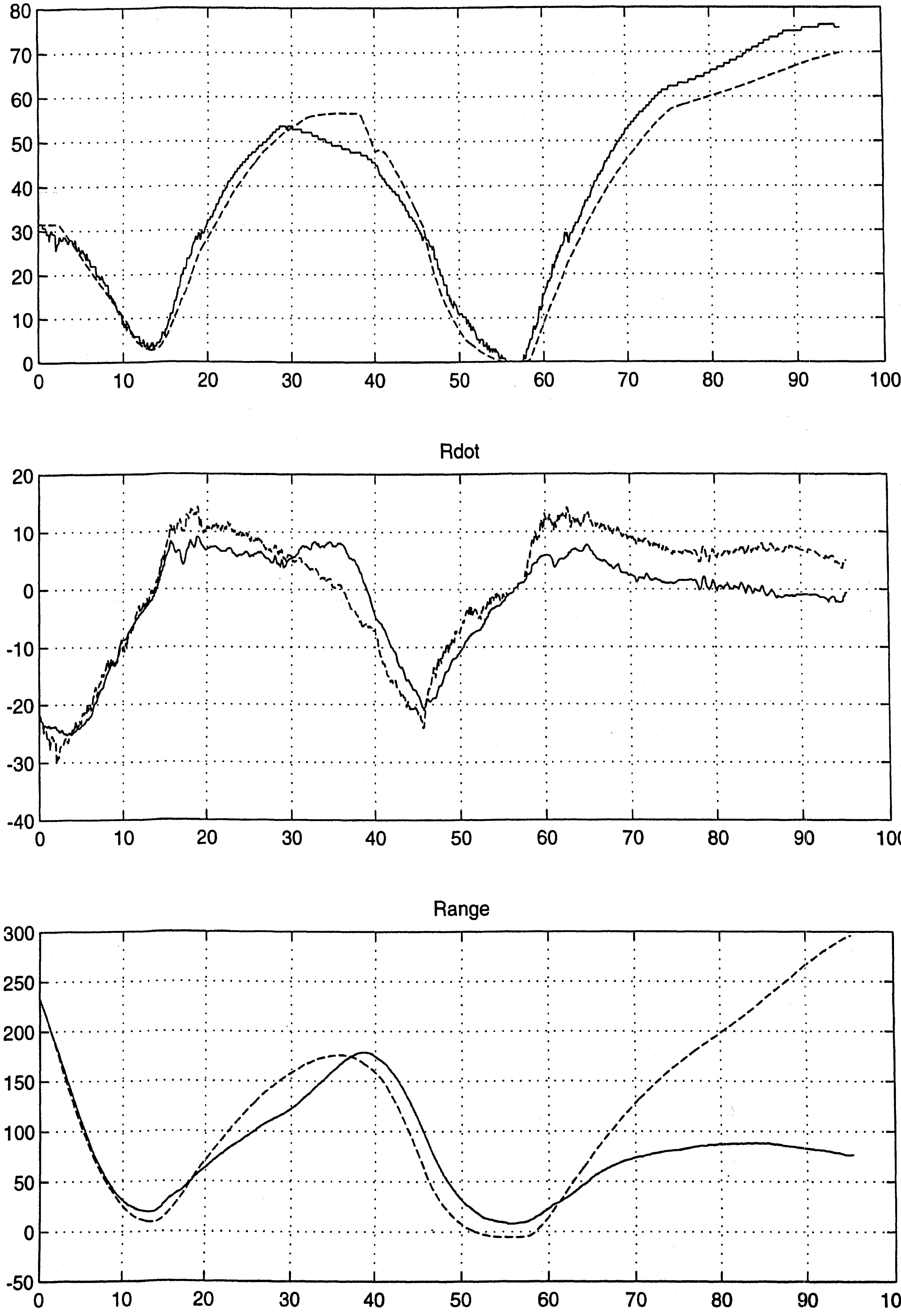



BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.9, Tc = 2.8, T2 = 2.8, T3 = 2.9, rms = 24.95, meanRerr = 18.60
Driver: z153_1 11.txt
60
50
40
30
20
10
0
0
10
20
30
40
50
60
Rdot
15
10
5
0
-5
-10
-15
Range
200
150
100
50

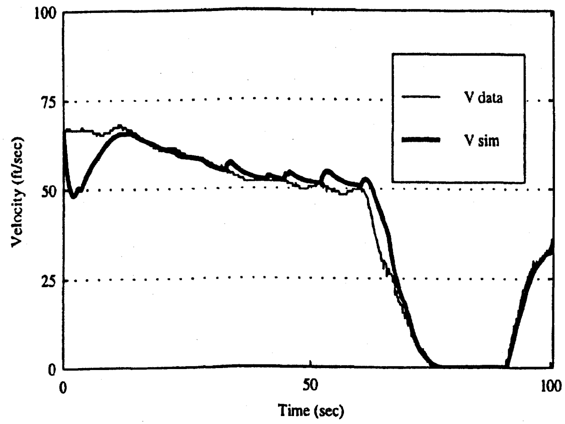
BMW Model, data vs. simulation (RunB).
Model 151, Th = 3.2, Tc = 2.8, T2 = 2.8, T3 = 3.2
Driver: z153_1 14.txt

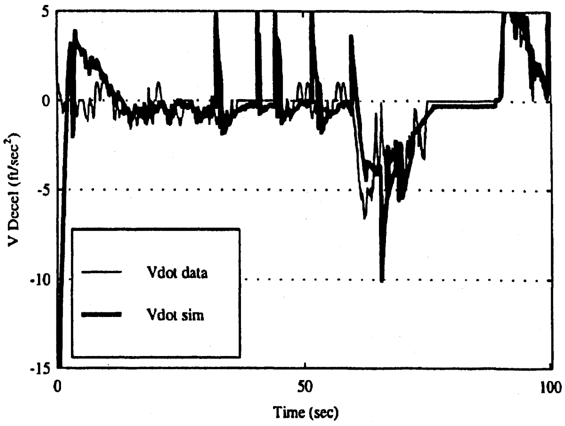


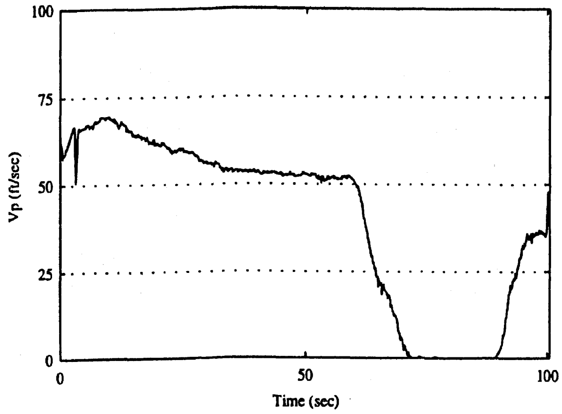
BMW Model, data vs. simulation (RunB).
Model 151, Th = 3.2, Tc = 2.8, T2 = 2.8, T3 = 3.2, rms = 75.07, meanRerr = 47.15
Driver: z153_1 14.txt

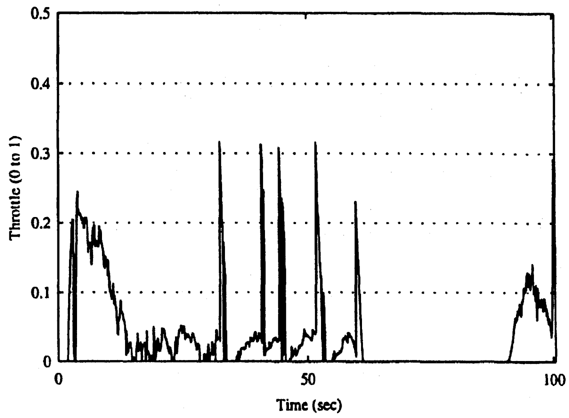


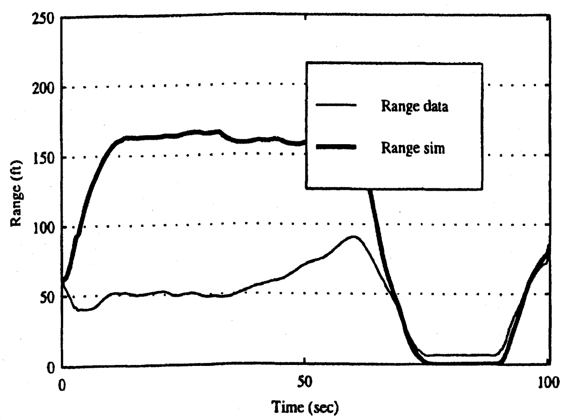
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.5, Tc = 2.8, T2 = 2.8, T3 = 2.5
Driver: z153$_1$16.txt

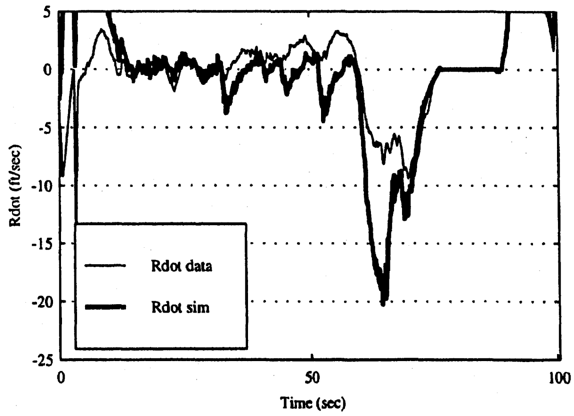


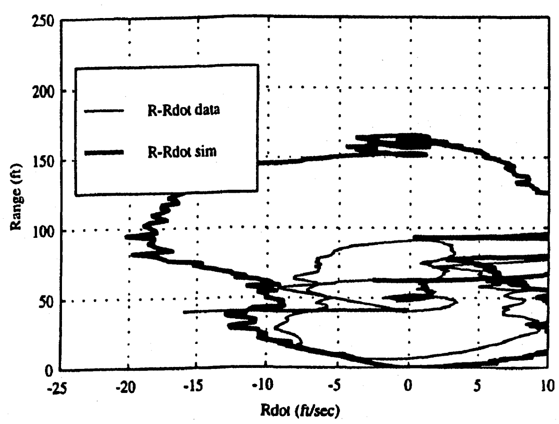


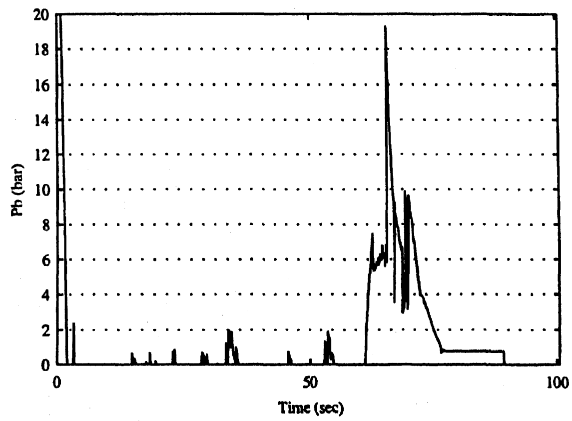




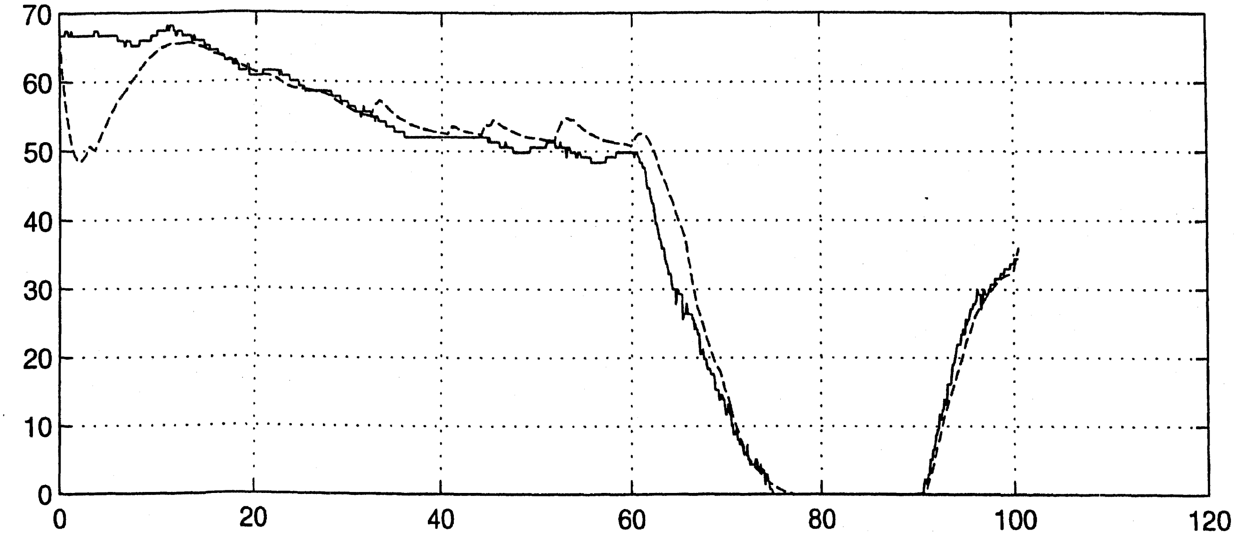




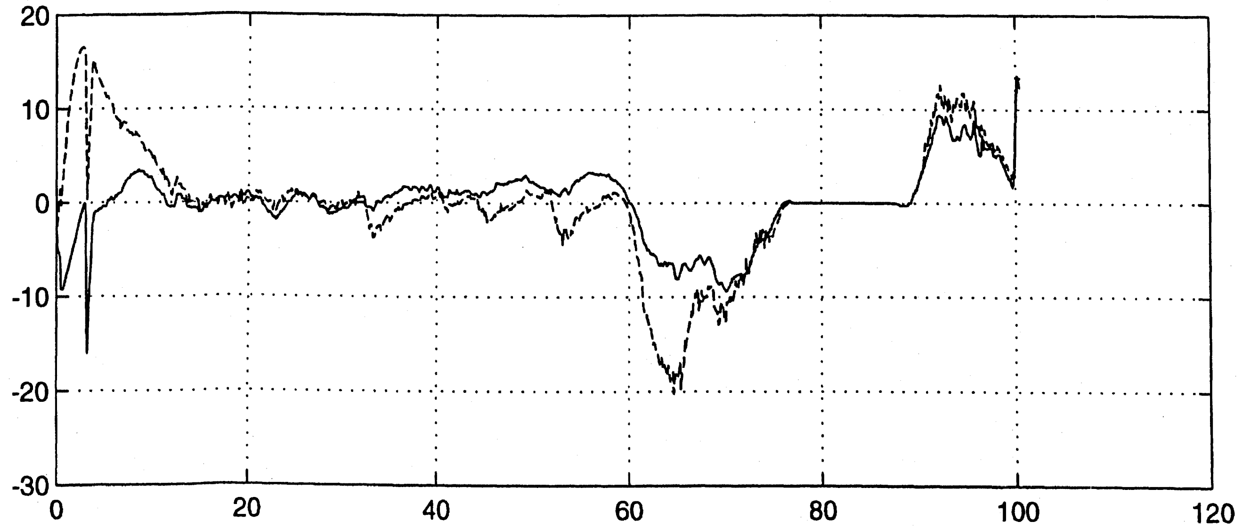




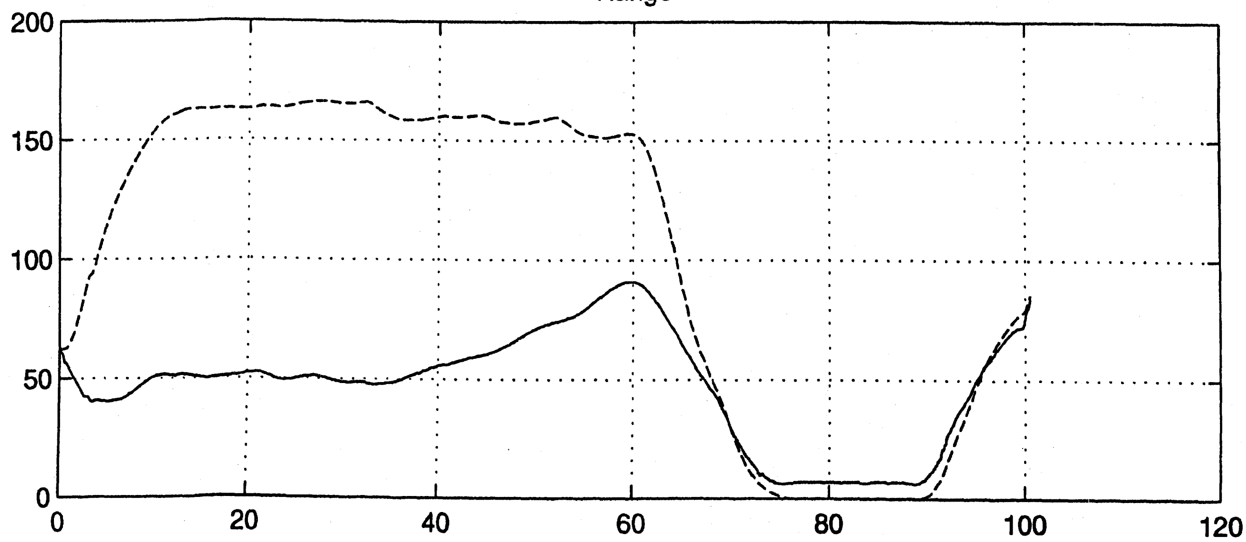
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.5, Tc = 2.8, T2 = 2.8, T3 = 2.5, rms = 76.95, meanRerr = 61.49
Driver: $z153_1 16$.txt



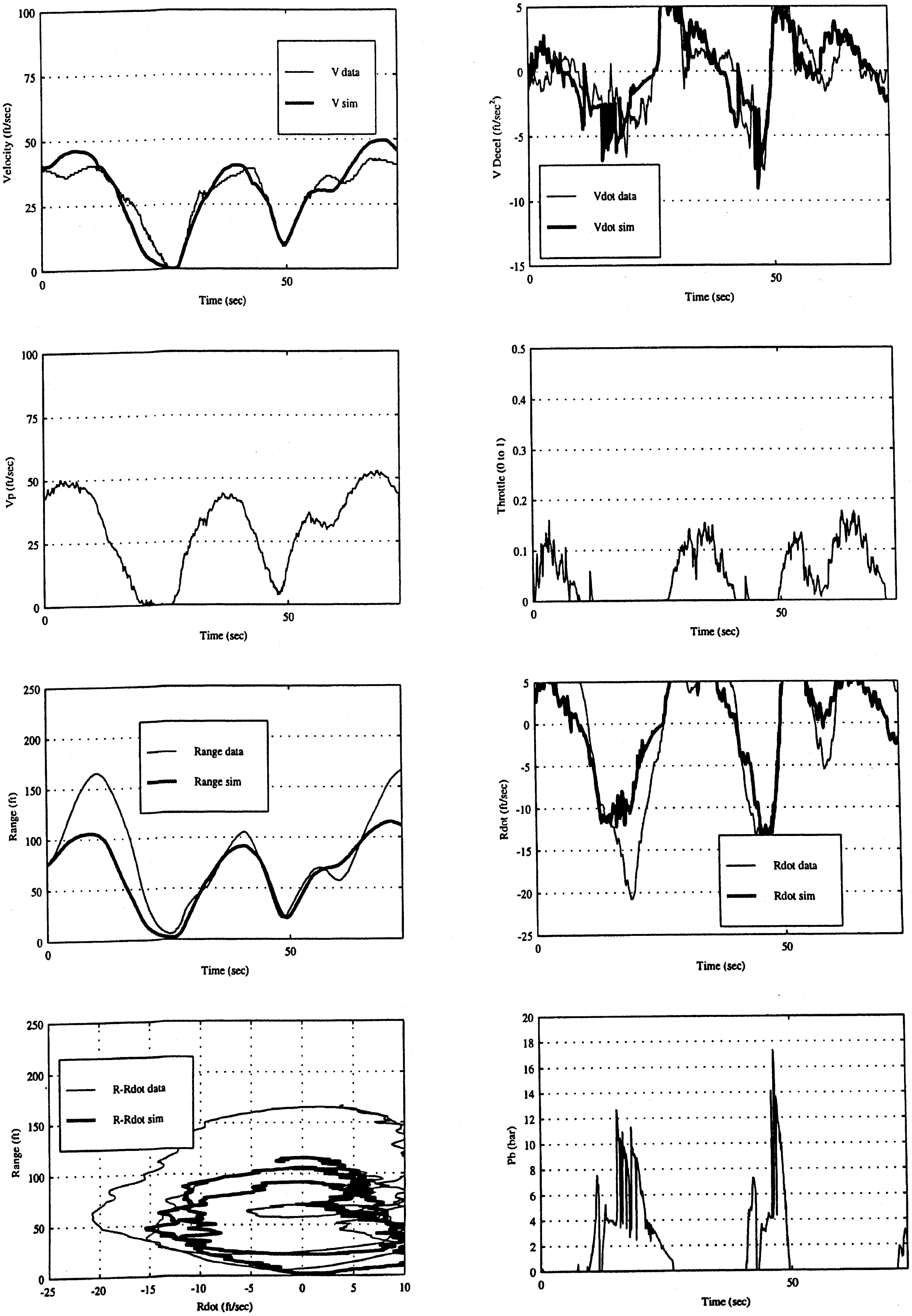
Rdot



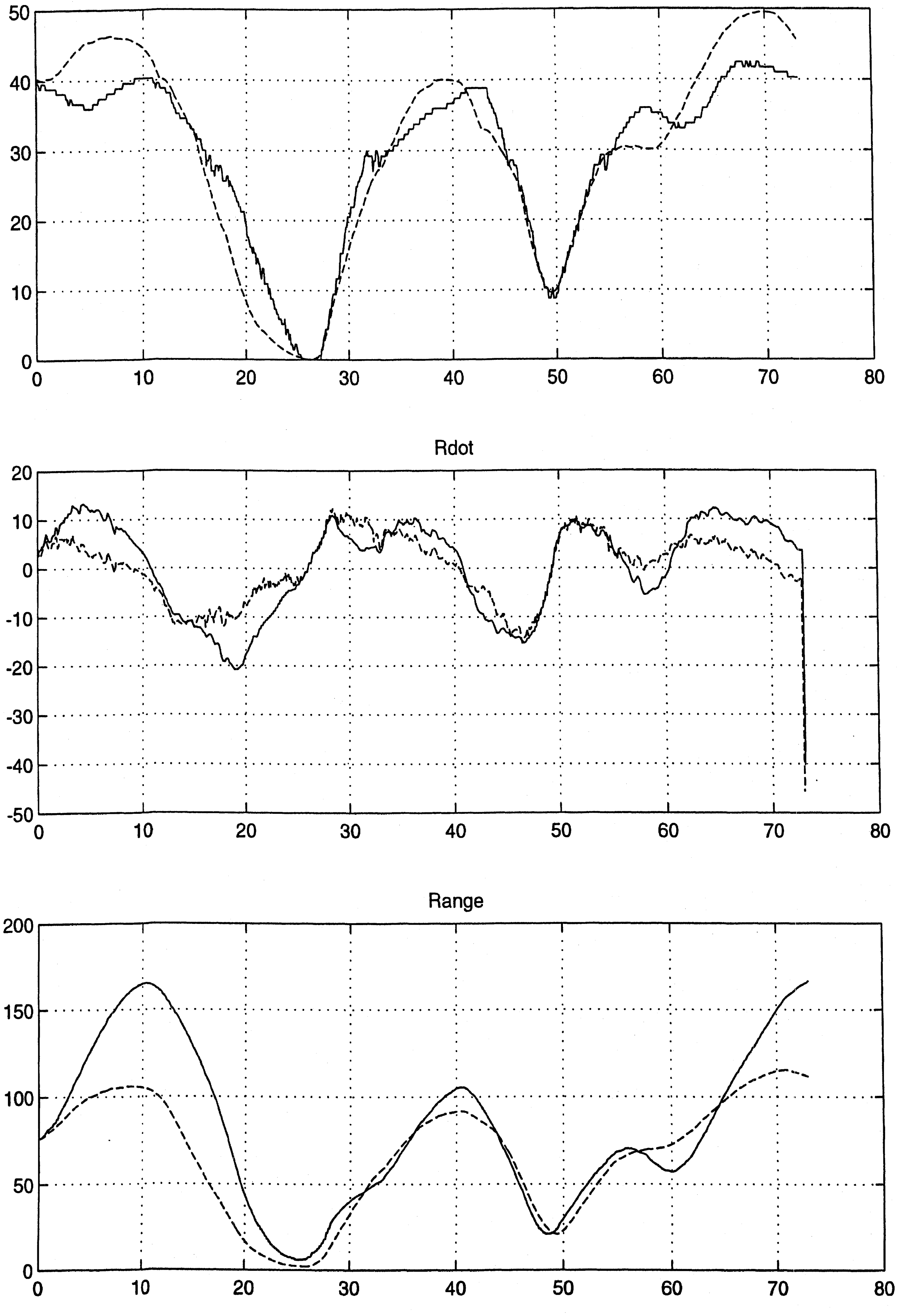
Range



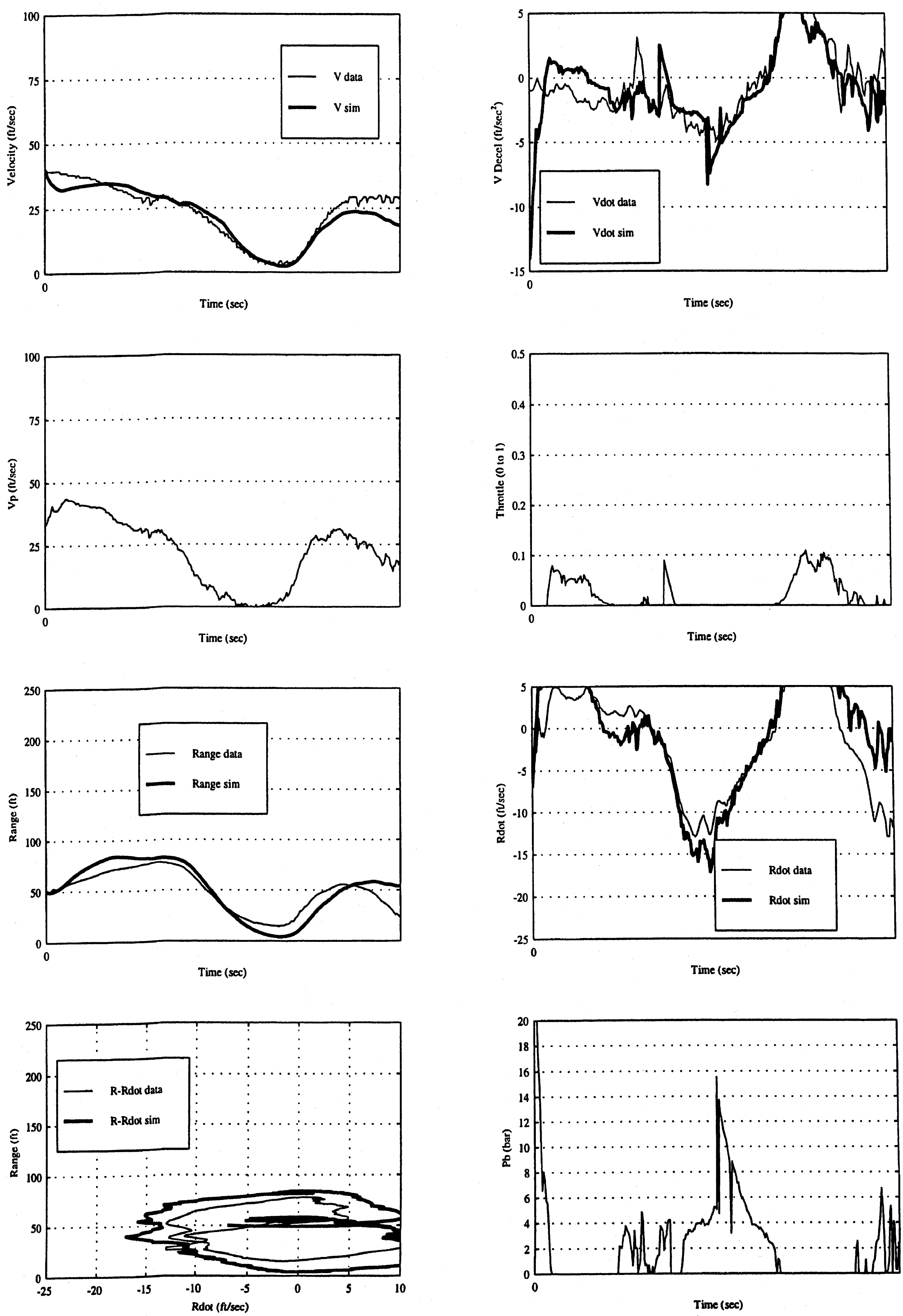
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.2, Tc = 2.8, T2 = 2.8, T3 = 2.2
Driver: z153$_1$52.txt



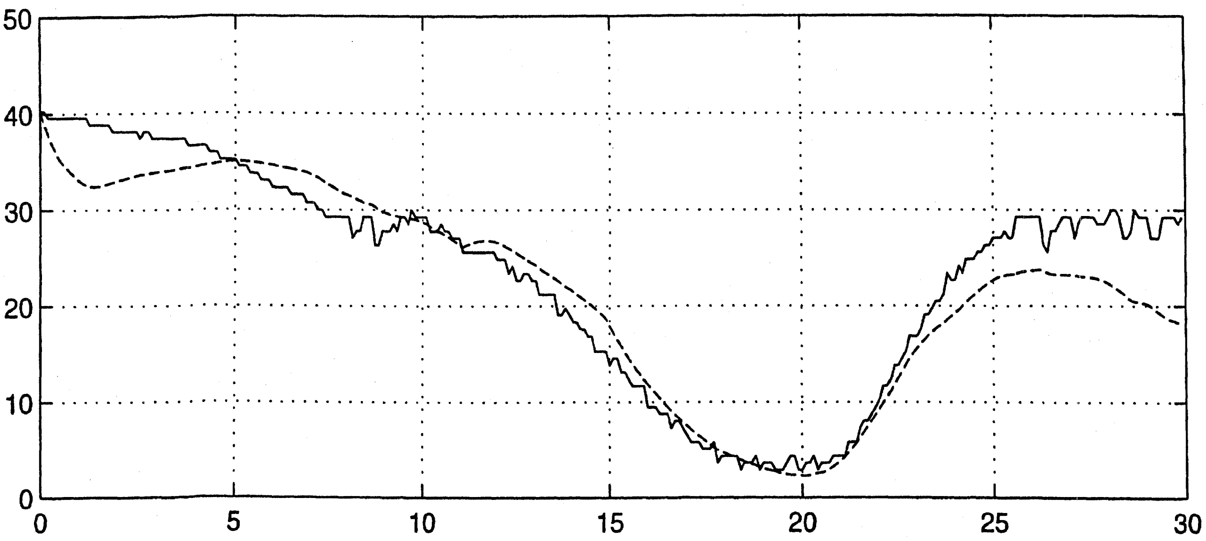
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.2, Tc = 2.8, T2 = 2.8, T3 = 2.2, rms = 27.52, meanRerr = 18.64
Driver: z153_1 52.txt

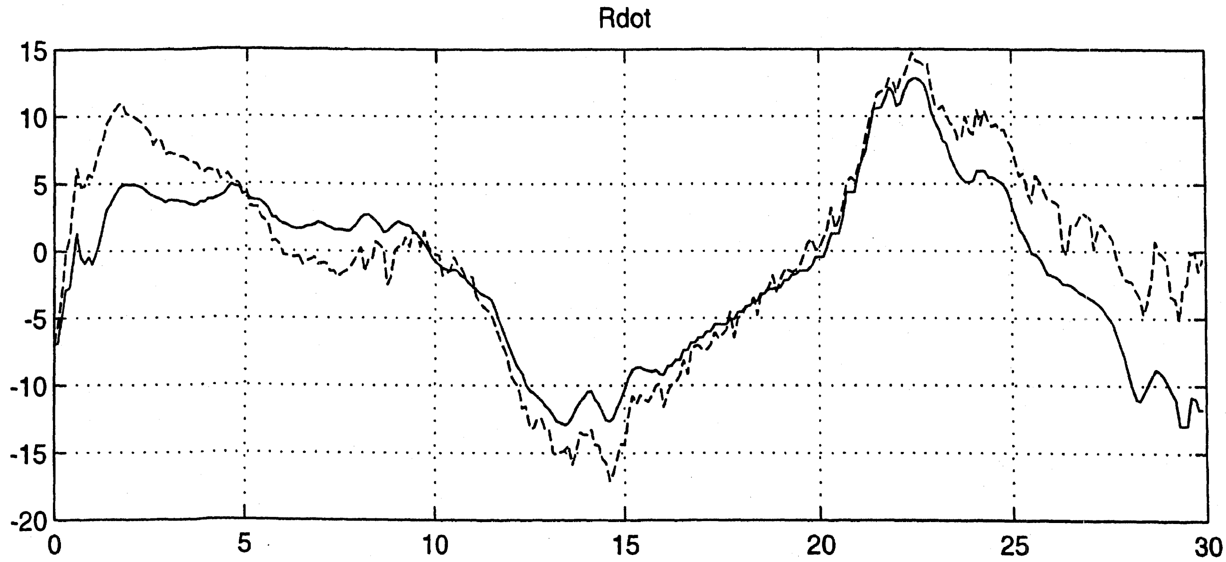


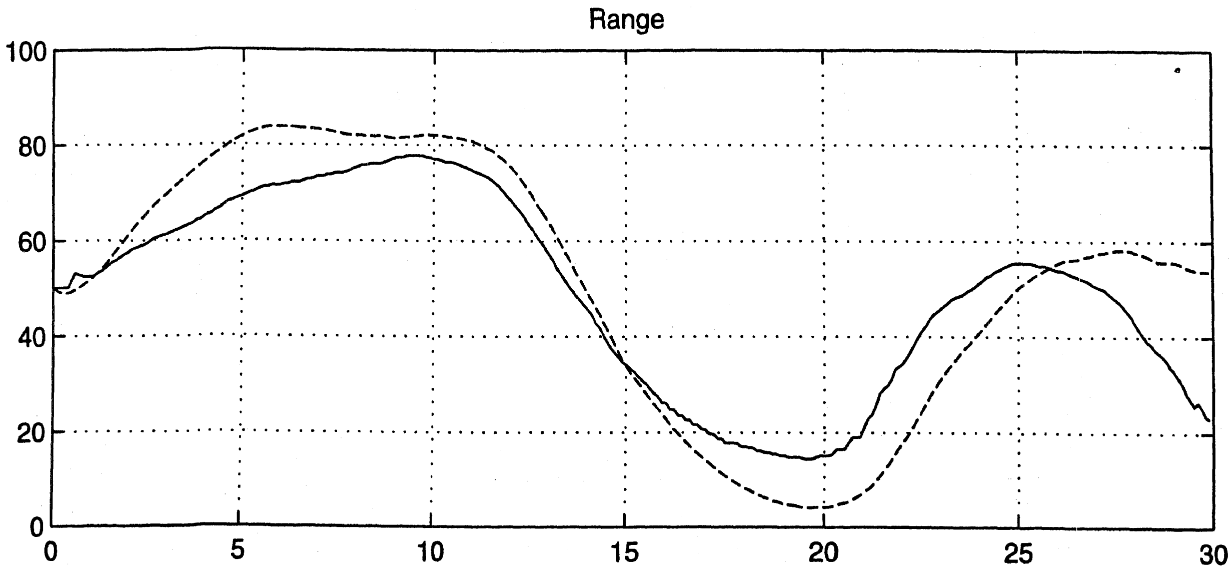
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.6, Tc = 2.8, T2 = 2.8, T3 = 2.6
Driver: z153$_1$56.txt



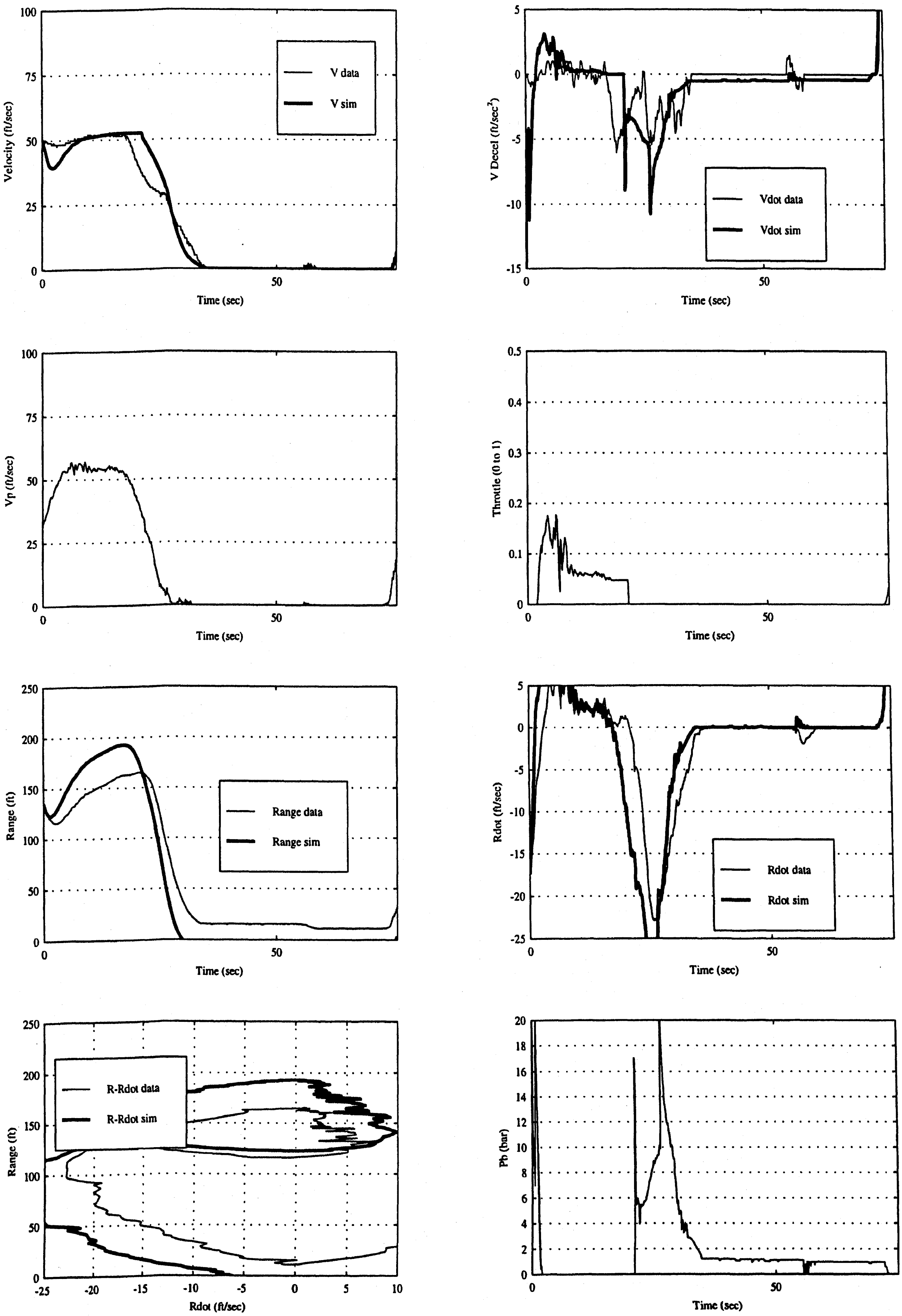
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.6, Tc = 2.8, T2 = 2.8, T3 = 2.6, rms = 10.39, meanRerr = 8.21
Driver: z153_1 56.txt



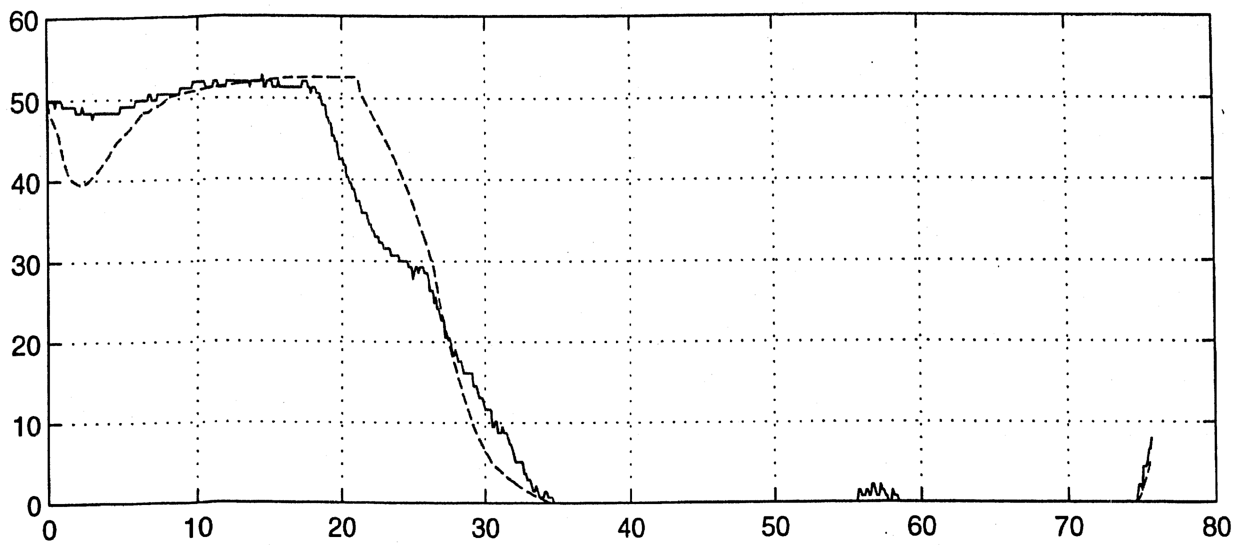


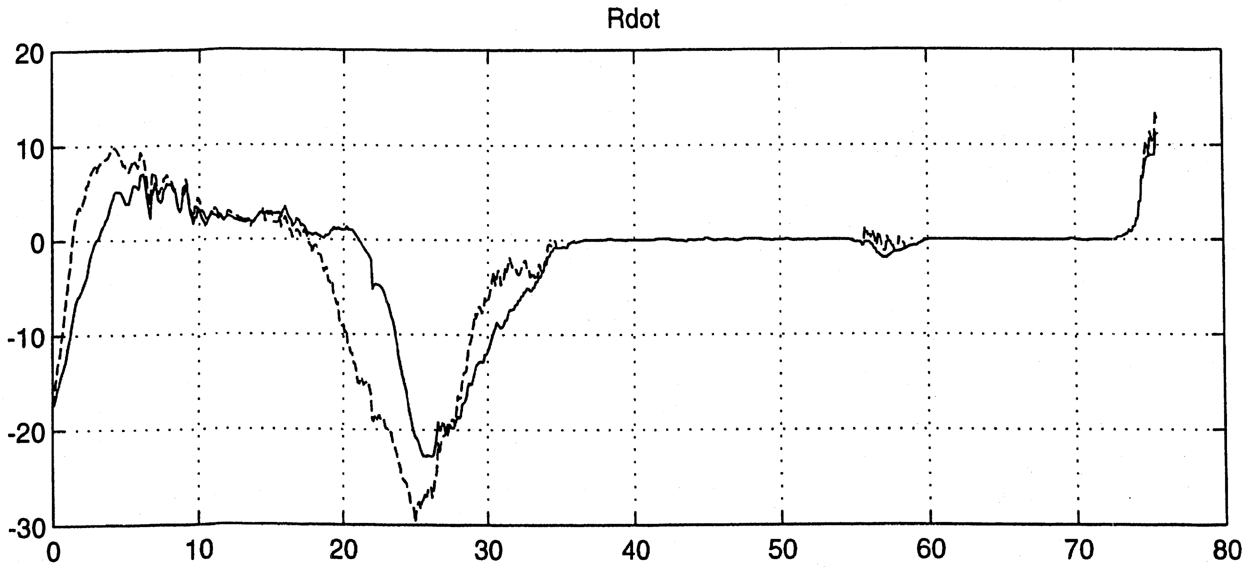


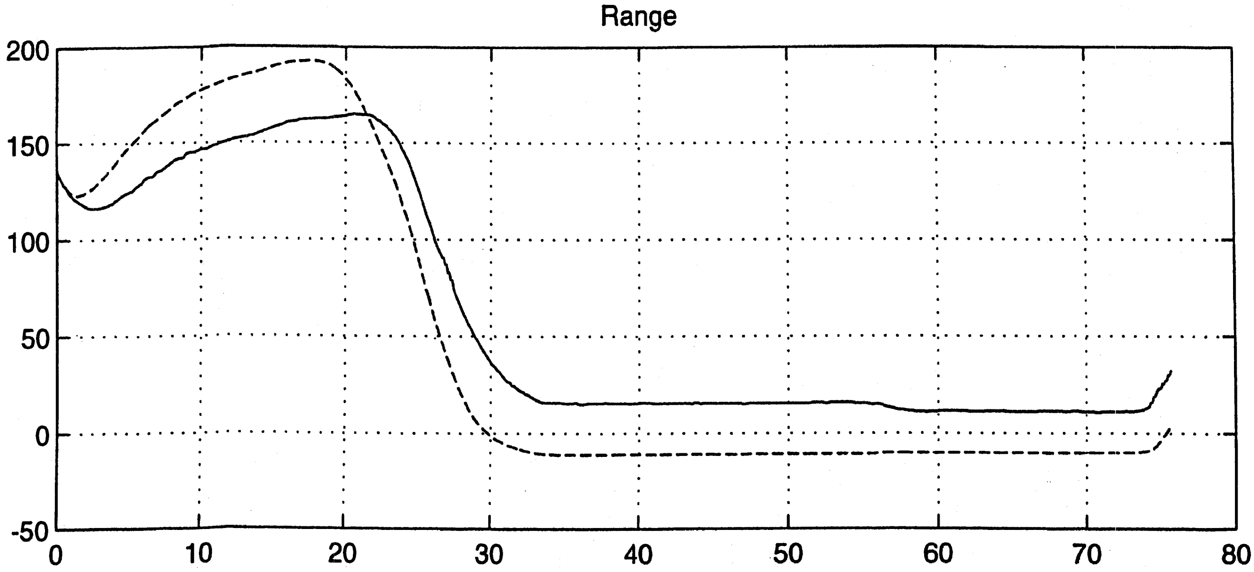
BMW Model, data vs. simulation (RunB).
Model 151, Th = 3.8, Tc = 2.8, T2 = 2.8, T3 = 3.8
Driver: $z153_1 60.txt$



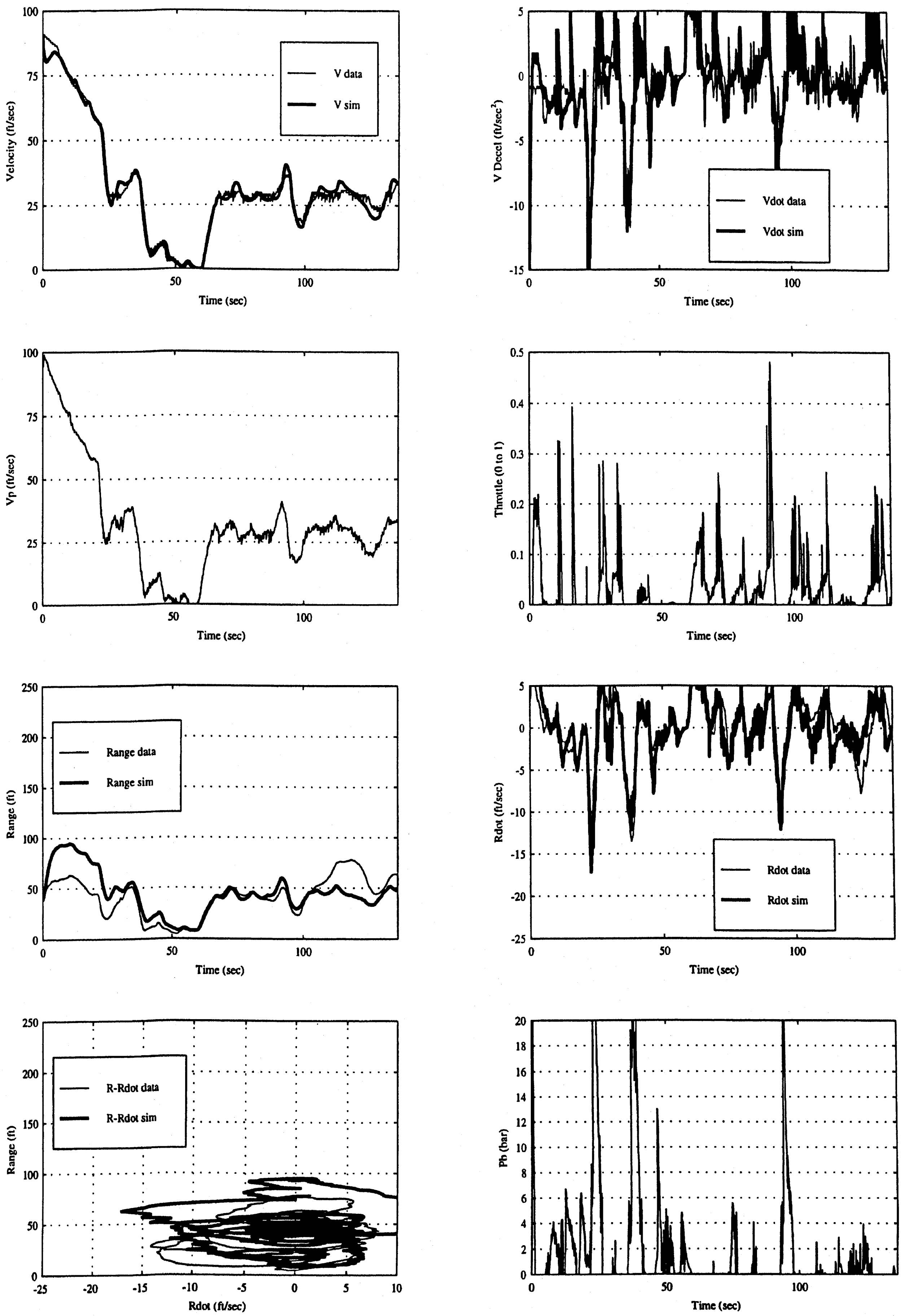
BMW Model, data vs. simulation (RunB).
Model 151, Th = 3.8, Tc = 2.8, T2 = 2.8, T3 = 3.8, rms = 26.83, meanRerr = 25.52
Driver: z153_1 60.txt



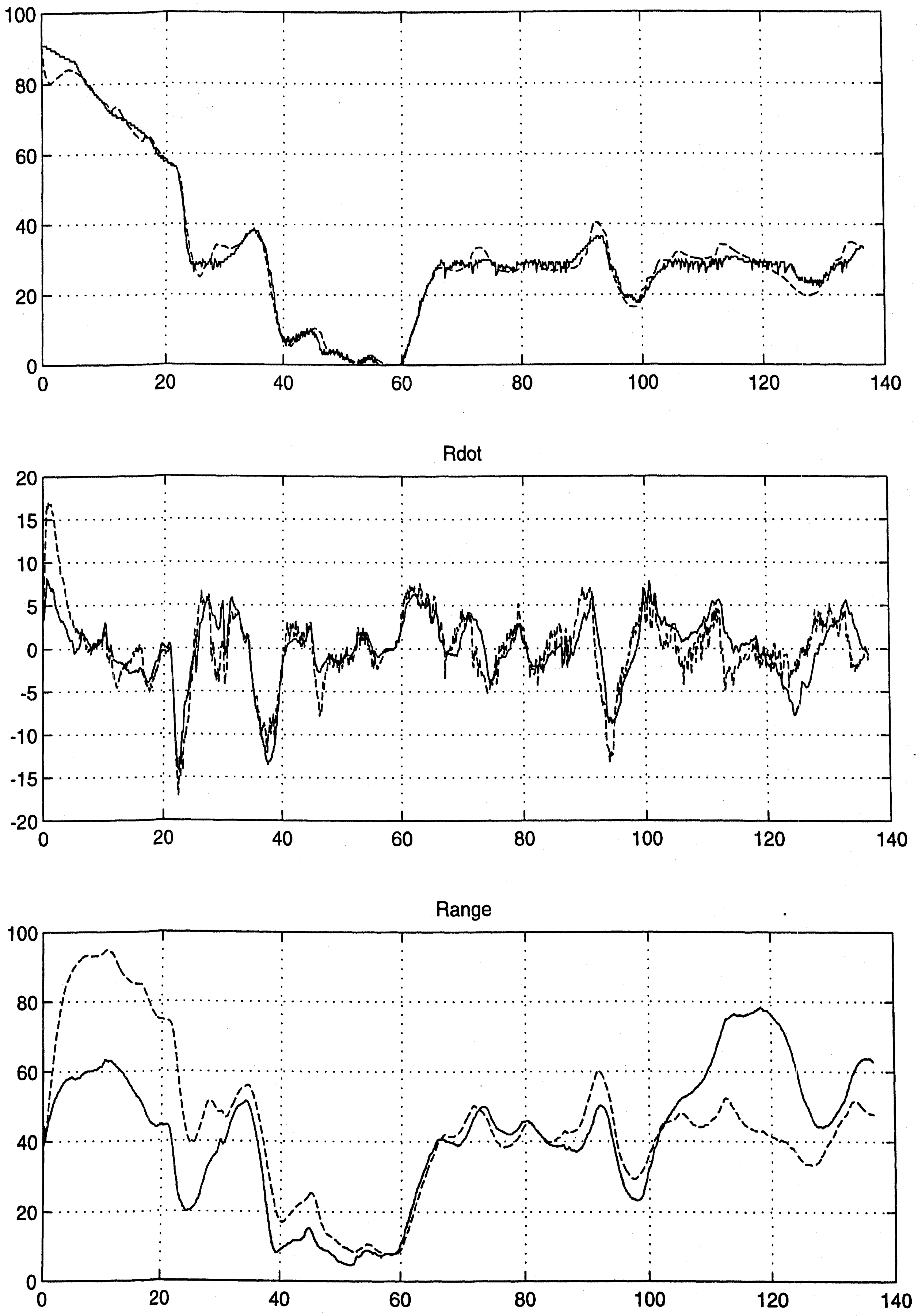




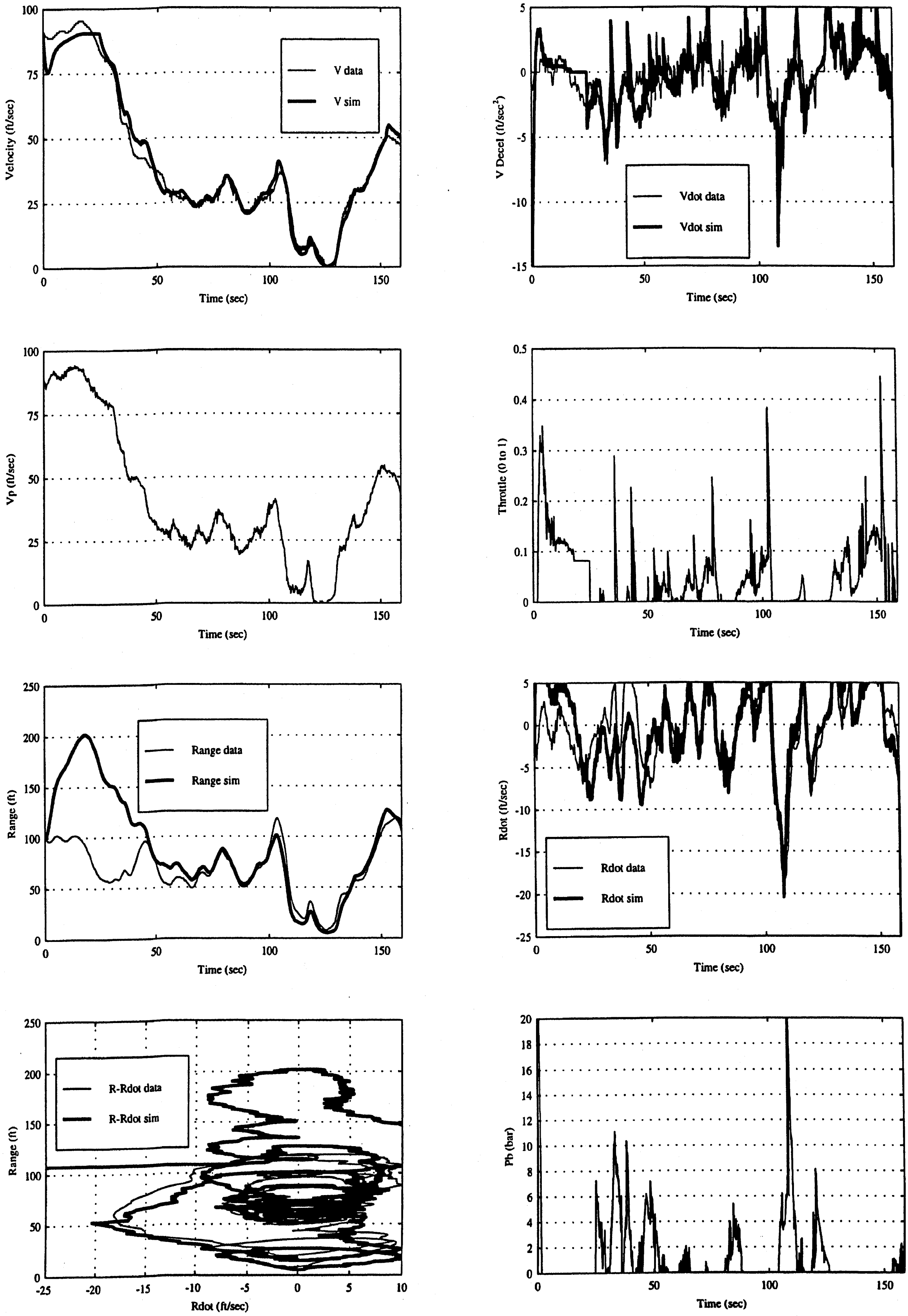
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.0, Tc = 2.8, T2 = 2.8, T3 = 1.0
Driver: $z153_2 1.txt$



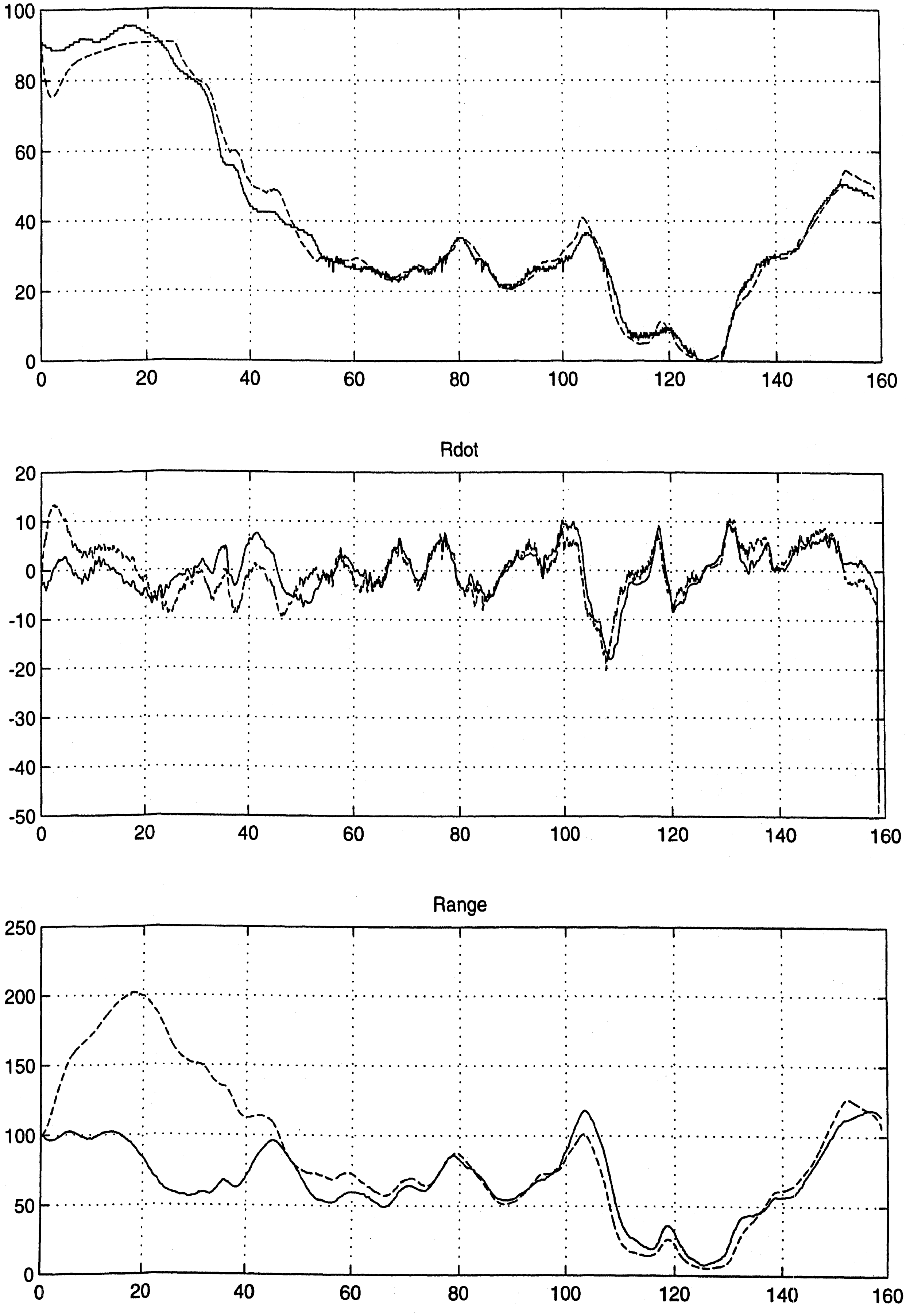
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.0, Tc = 2.8, T2 = 2.8, T3 = 1.0, rms = 17.06, meanRerr = 12.57
Driver: z153$_2$1.txt



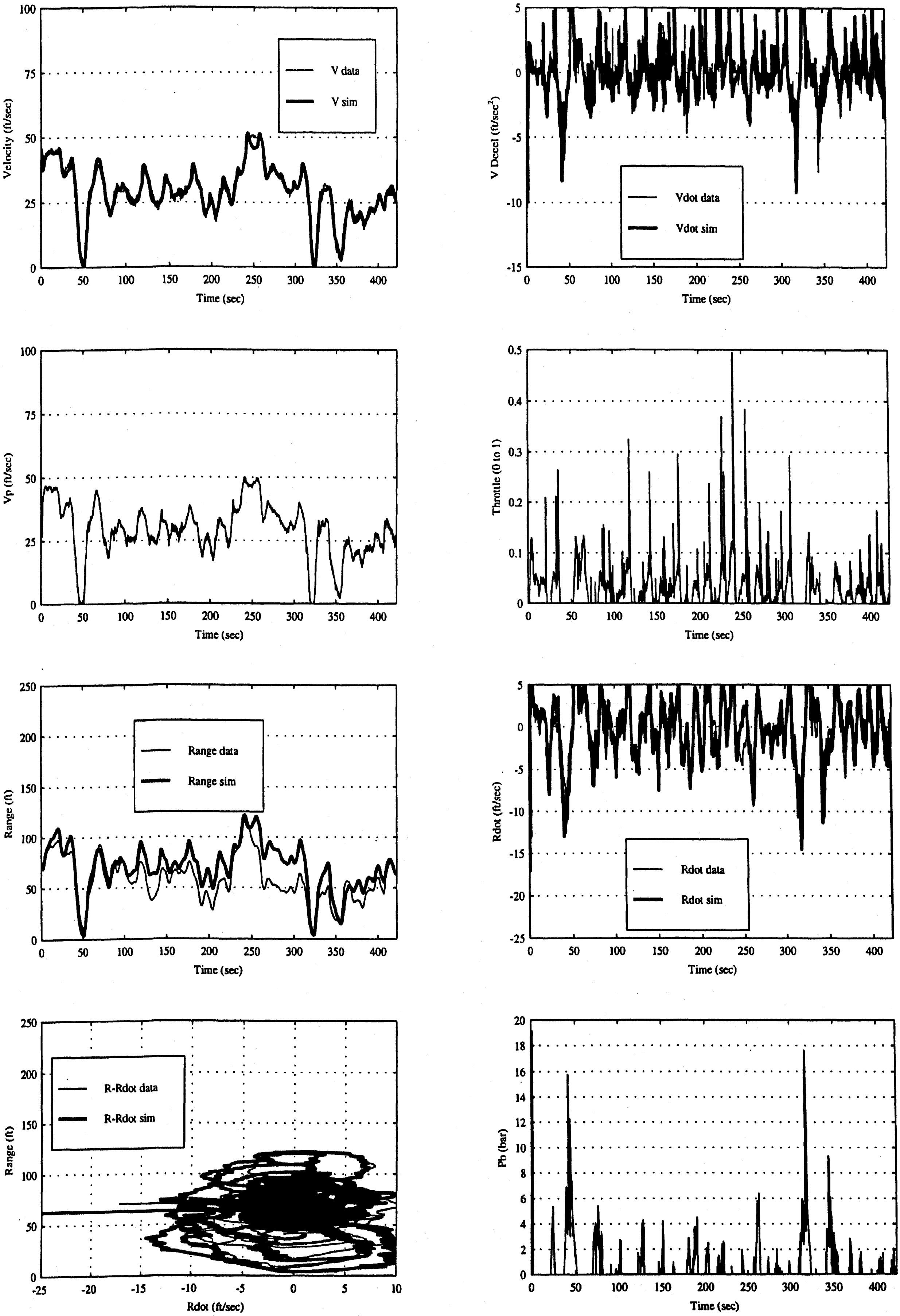
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9
Driver: z153_6 7.txt



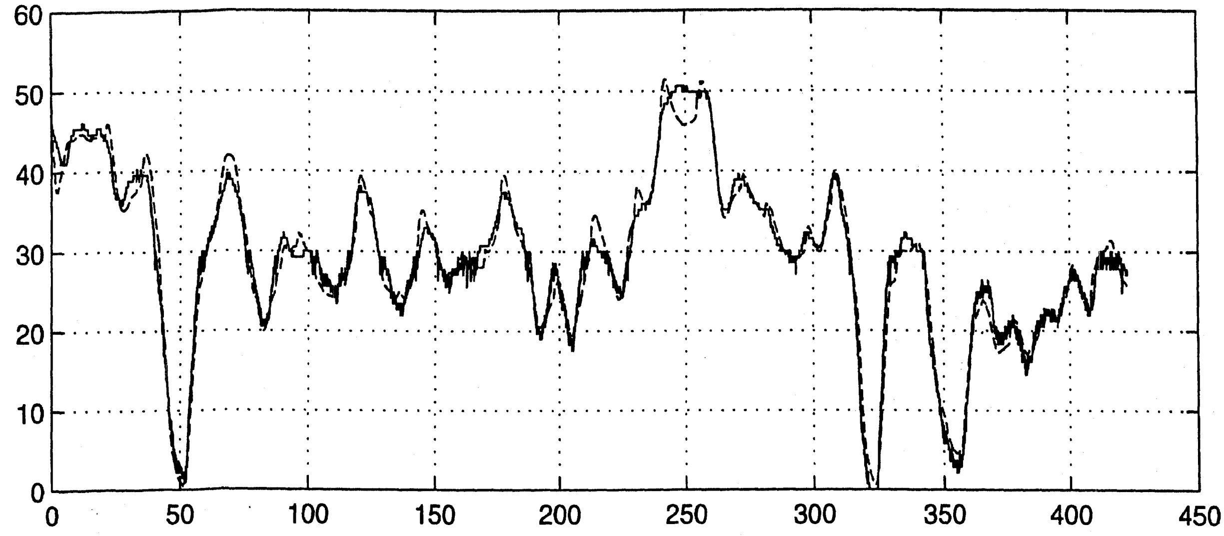
BMW Model, data vs. simulation (RunB).
Model 151, Th = 1.9, Tc = 2.8, T2 = 2.8, T3 = 1.9, rms = 43.42, meanRerr = 25.90
Driver: z153$_6$7.txt



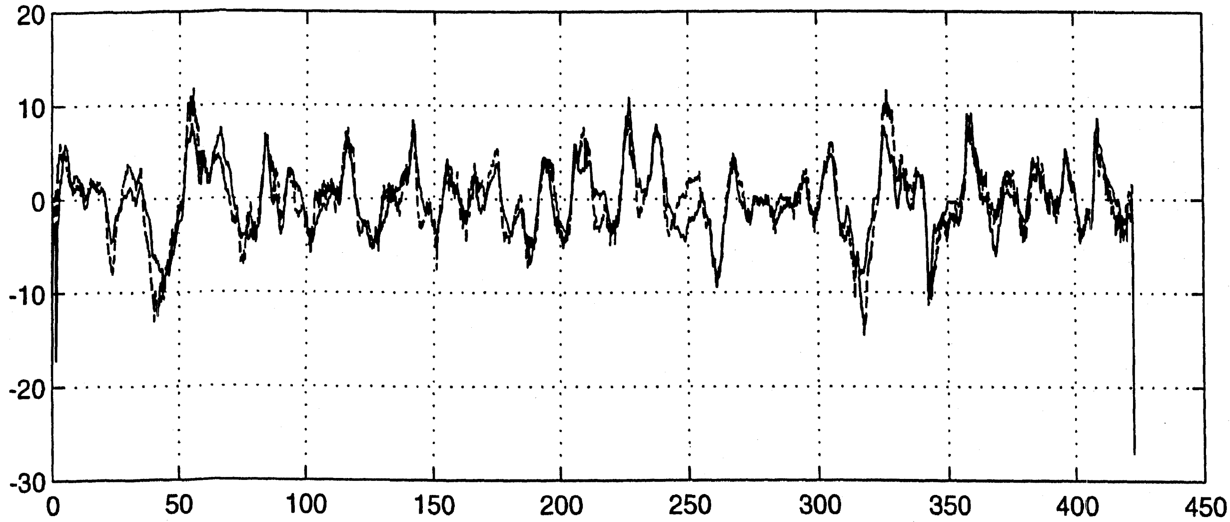
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0
Driver: z153_7_8.txt



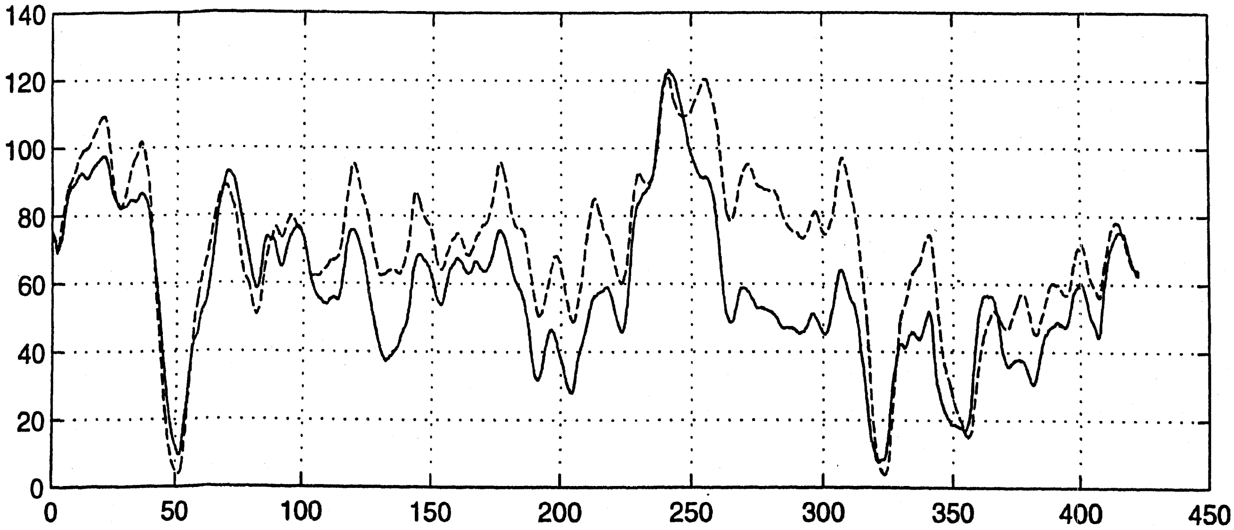
BMW Model, data vs. simulation (RunB).
Model 151, Th = 2.0, Tc = 2.8, T2 = 2.8, T3 = 2.0, rms = 16.97, meanRerr = 13.94
Driver: z153_7_8.txt



Rdot



Range



APPENDIX D

The observation that drivers tend to use short headway times appears to be puzzling, although a clue to this preference can be gained by noting the characteristic human threshold on detection of the rate of change of visual angle. The visual angle subtended by an object at range R with maximum edge boundaries separated by a distance W is illustrated in Figure 33. The following relationship between the visual angle θ and range R represents the connection between the longitudinal world represented by R and the vertical-plane world view that is projected on the driver's eye:

$$W = R\theta \qquad (1)$$

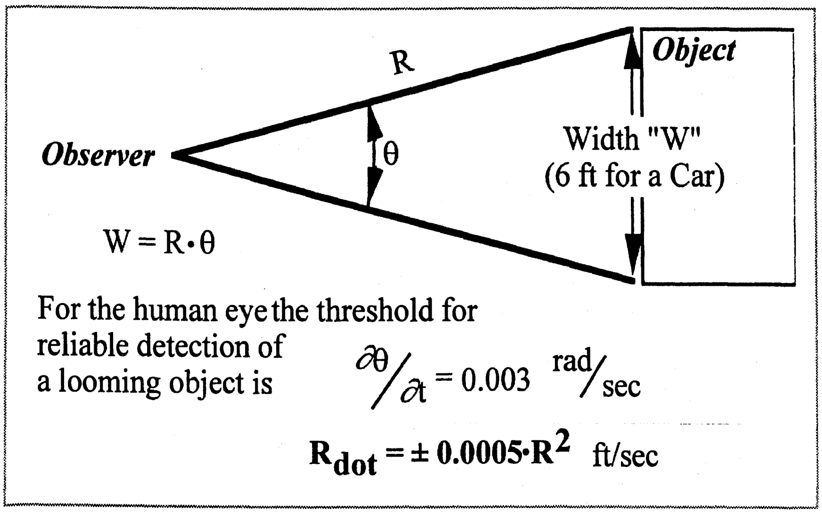


Figure 33. The visual angle, θ

There is an interesting type of symmetry associated with this relationship, as shown here:

$$R = W/\theta \quad \text{and} \quad \theta = W/R \qquad (2)$$

Differentiating the expressions for R and θ yields:

$$\text{Rdot} = -\,\theta\text{dot}/\,\theta^2 \text{ and } \theta\text{dot} = -\,\text{Rdot}/R^2 \qquad (3)$$

Considerations pertaining to headway control have centered mainly on the range-versus-range-rate space, however the above equations can be used to transform from the vehicle dynamics perspective expressed in terms of range and range rate to the driver's perspective defined by visual angle θ and its time rate of change θdot. The phase space defined by θ versus θdot is considered to be a mind's eye representation of the headway situation as the driver sees it.

As a direct result of this transformation, a threshold on θdot can be transformed from the mind's eye to a perception boundary in the range versus range rate diagram. The following expression, which is also listed in Figure 33, is a direct result of transforming the perceptual threshold given by θdot = ±0.003 radians/sec as suggested in reference [11] into the range-versus-range-rate phase space:

Rdot = ± 0.0005 R^2 (where R and Rdot are in ft and ft/sec) (4)

This expression has been used in a driver model to aid in developing bounds on the vehicle following capability of a driver [14]. The idea is that, if the driver's perceptual ability is limited, the driver's ability to develop useful commands is correspondingly limited. Observations of driver following behavior show that driver performance is characterized by a type of hunting behavior about a point defined by the apparent desired range at Rdot = 0. The hypothesized theory is that the driver has only a limited ability to determine range as well as a threshold limiting the ability to measure range rate. In a sense, the driver is not able to do perfect following because the driver does not have the resolution capability needed to follow perfectly.

Even though the relationships discussed here is non-linear, we have used a linear approximation to represent this effect in Figures 18 through 21.

APPENDIX E

Primary and Derived Channels Collected with the FOT Vehicle DAS

The numerical data flow starts with the collection of 38 primary signals at a rate of 10Hz from various sources on-board each FOT vehicle. These sources include ADC's infrared sensors, the vehicle's engine control unit, the video camera, the GPS, and the driver/vehicle interface. A list of the 38 primary signals is given in table 1. This table shows the name, type, description, and units of each signal. It also has a column called Logged. This column indicates if the signal is permanently stored on disk. Some of the logical signals are stored in a more compact format than that used for time histories. This format is explained later in this section under Transition Files. The following nomenclature is used in the column "Logged" to indicate which file the data is logged into: "H" – time history; "G" – GPS history, "T" – transition table.

The numerical data processing begins as these primary channels are read into the memory of the DAS. The computer then calculates what are called *derived channels*. These channels are combinations and manipulations of the primary signals. Examples of derived channels include: V_p (velocity of the preceding vehicle), road grade, distance, near, following, etc. There are 67 derived channels. The 31 floating-point derived channels are given in table 2. The remaining 36 are logical channels and are listed in table 3. Both tables show the name of the derived signal, a description (which includes its derivation), units, and whether it is logged to disk.

Table 1. Primary channels

Name	Type	Description	Units	Logged
AccMode	Integer	0=off, 1=standby, 2=Not Operating On a Target (NOOT), 3= Operating On a Target (OOT)		H
Accel	Logical	True if accel button is pressed		T
AccEnable	Logical	True after 1st week		
Altitude	Float	Altitude	m	G
Backscatter	Float	Backscatter (0 to 1023)		H
Blinded	Logical	True if ODIN 4 blinded bit is on		
Brake	Logical	True if brake pedal is pressed		H
Cancel	Logical	True if cancel button is pressed		T
AccOn	Logical	True if cruise or ACC switch is on		
Cleaning	Logical	True if ODIN 4 cleaning bit is on		
Coast	Logical	True if coast button is pressed		T
Concern	Logical	True if concern button is pressed		T
CurveRadius	Float	Curve radius	ft	
Date/Time	Double	UTC Days since 12/30/1899 + fraction of day	days	H
Downshift	Logical	True if controller requests downshift		T
EastVelocity	Float	East velocity, + for east	m/sec	
EcuError	Logical	True when a VAC to ECU communication error occurs		
HeadwayTime	Float	Selected headway time	sec	
HeadwaySwitch	Integer	headway switches , 1,2, or 4		
Latitude	Float	Latitude, + for north	radians	G
Longitude	Float	Longitude, + for east	radians	G
NetworkError	Logical	True when a DAS to Video communication error occurs		
NewTarget	Logical	True for .3 sec with new target		H
NorthVelocity	Float	North velocity, + for north	m/sec	
Range	Float	Distance to target	ft	H
RDot	Float	Rate of change of range	ft/sec	H
ReducedRange	Logical	True if ODIN 4 reduced range bit is on		
Resume	Logical	True if resume button is pressed		T
Set	Logical	True if set button is pressed		T
Throttle	Float	Throttle percent		H
Tracking	Logical	True when tracking a target		H
UpVelocity	Float	Up velocity, + for up	m/sec	
VacError	Logical	True when a VAC to DAS communication error occurs		
VacTime	Float	Time since ignition switch was turned on (based on VAC system clock)	min	H
ValidTarget	Logical	Tracking AND Velocity > 25mph		H
VCommand	Float	Velocity commanded by controller	ft/sec	H
Velocity	Float	Vehicle velocity	ft/sec	H
VSet	Float	Cruise speed set by driver	ft/sec	H

Table 2. Floating point derived channels

Name	Description	Units	Logged
AverageBackscatter	0 second moving average of Backscatter		
AverageDNearEncounter	second moving average of DNearEncounter	g's	H
AverageVDot	second moving average of -VDot	g's	H
CDot	erivative of DegreeOfCurvature	deg/sec	H
D	Dot^2 / (2•(Range- 0.7 • Vp)•32.2)	g's	
DecelAvoid	Dot^2 / (2•Range•32.2)	g's	H
DegreeOfCurvature	728.996 / CurveRadius	deg	H
Distance	ntegral of velocity	miles	H
DistanceEngaged	ntegral of velocity while engaged	miles	
DNearEncounter	Dot^2 / (2•(Range - 0.3•Vp)•32.2)	g's	H
DScore	f DScoreRegion then DScore = (D-0.03) / 0.47; if ScoreRegion then DScore = 1		H
EngMaxAvgDNear	aximum value of AverageDNearEncounter while EngNearEncounter is true	g's	
EngMaxAvgVDot	aximum value of AverageVDot while EngBrakeIntervention is true	g's	
Flow	elocity / (Range + L)	veh/sec	
Grade(GPS)	pVelocity / sqrt($NorthVelocity^2$ + $EastVelocity^2$)		G
Heading	eading angle calculated from NorthVelocity and EastVelocity	deg	G
HeadwayTimeMargin	ange / Velocity	sec	H
Hinderance	elocity / Vset		
ManMaxAvgDNear	aximum value of AverageDNearEncounter while ManNearEncounter is true	g's	
ManMaxAvgVDot	aximum value of AverageVDot while ManBrakeIntervention is true	g's	
RangeCheck	0.7 • Vp + $RDot^2$ / (2•0.5•32.2)	ft	
RangeNear	0.5 • Vp +$RDot^2$ / (2•0.1•32.2)	ft	
Rpt03	ange - $RDot^2$ / (2•0.03•32.2)	ft	
Thpt03	pt03/Vp if RDot < 0 or Range/Vp if RDot >= 0	sec	H
TimeToImpact	Range / Rdot	sec	H
TrackingError	imeConstant • Rdot + Range – Th • Vp	ft	
TScore	f TScoreRegion then TScore = (0.7-Th0) / 0.7		H
VDot	erivative of Velocity / 32.2	g's	H
VehicleResp	Command - Velocity	fps	
Vp	elocity + RDot	fps	H
VpDot	erivative of Vp / 32.2	g's	H

Table 3. Logical derived channels

Name	Description	Logged
AccBi	15-sec oneshot - AccEnable AND EngBrakeIntervention	T
AccFollowing	Following AND 0.9Rh < Range <1.1Rh	H
AccNe	15-sec oneshot - AccEnable AND EngNearEncounter	T
AccTracking	AccMode > 2	
AlwaysTrue	Always True	
BackscatterWarn	Backscatter > 50	H
CccBi	15-sec oneshot - NOT(AccEnable) AND EngBrakeIntervention	T
CccNe	15-sec oneshot - NOT(AccEnable) AND EngNearEncounter	T
Closing	NOT(Near) AND RDot <-5	H
Cutin	Range < RangeNear AND RDot >0	H
DScoreRegion	ValidTargetVgt35 AND RDot <= 0 AND Range > RangeCheck	
Engaged	AccMode > 1	T
EngBrakeIntervention	15-sec oneshot - Brake AND Vgt40 AND AverageVDot > 0.05 AND WasEngaged	
EngNearEncounter	15-sec oneshot – ValidTargetVgt40 AND AverageBackscatter <10 AND AverageDNearEncounter > 0.05 AND WasEngaged	
Following	NOT(Near OR Cutin) AND -5 <= RDot <= 5	H
HeadwayLong	True if long headway switch is pressed	T
HeadwayMedium	True if medium headway switch is pressed	T
HeadwayShort	True if short headway switch is pressed	T
LDegOfCurvature	| DegreeOfCurvature | > 3 AND V>50	
LVpDot	VpDot < -0.05g's AND V>35	
Man1Bi	15-sec oneshot - NOT(AccEnable) AND ManBrakeIntervention	T
Man1Ne	15-sec oneshot - NOT(AccEnable) AND ManNearEncounter	T
Man2Bi	15-sec oneshot - AccEnable AND ManBrakeIntervention	T
Man2Ne	15-sec oneshot - AccEnable AND ManNearEncounter	T
ManBrakeIntervention	15-sec oneshot - Brake AND Vgt40 AND AverageVDot > 0.05 AND NOT WasEngaged	
ManNearEncounter	15-sec oneshot – ValidTargetVgt40 AND AverageBackscatter <10 AND AverageDNearEncounter > 0.05 AND NOT WasEngaged	
Near	Range < RangeNear AND RDot <0	H
Separating	NOT(Cutin) AND RDot > 5	H
Stopped	Velocity <3	
TScoreRegion	ValidTargetVgt35 AND RDot <= 0 AND Range <= RangeCheck	
ValidTargetVgt35	ValidTarget AND V>35	
ValidTargetVgt50	ValidTarget AND V>50	
Vgt35	Velocity > 35	
Vgt40	Velocity > 40	
Vgt50	Velocity > 50	
WasEngaged	True if engaged within the last 15 seconds	