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Development and Validation of an Errorable Car-Following Driver Model

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Abstract — **an errorable car-following driver model was presented in this paper. This model was developed for evaluating and designing of active safety technology. Longitudinal driving was first characterized from a naturalistic driving database. The stochastic part of longitudinal driving behavior was then studied and modeled by a random process. The resulting stochastic car-following model can reproduce the normal driver behavior and occasional deviations without crash. To make this model errorable, three error-inducing behaviors were analyzed. Perceptual limitation was studied and implemented as a quantizer. Next, based on the statistic analysis of the experimental data, the distracted driving was identified and modeled by a stochastic process. Later on, time delay was estimated by recursive least square method and was modeled by a stochastic process as well. These two processes were introduced as random disturbance of the stochastic driver model. With certain combination of those three error-inducing behaviors, accident/incident could happen. Twenty-five crashes happened after eight million miles simulation (272/100M VMT). This simulation crash rate is higher by about twice with 2005 NHTSA data (120/100M VMT).**

I. Introduction

Driver behavior has long been an important topic for transportation and ground vehicle research. The way drivers respond to the surrounding traffic influences roadway designs, traffic rules and human-vehicle interface. Based on traffic flow analysis and vehicle testing results, car-following driver models have been developed to evaluate traffic capacity and congestion [1]–[6]. More recently, with the development of active safety technology (AST) [7]–[9], car-following driver models were used to evaluate the efficiency and accuracy of such systems [10], [11]. AST was designed to assist a human driver when he or she is not able to avoid or mitigate a crash; in other words, when the driver is either making a mistake or simply is not able to handle the situation. Therefore, for evaluating AST, models that achieve driving tasks perfectly and preciously seem to be less useful. On the contrary, a model that makes mistake like human drivers would be more suitable for the development of AST systems. To our best knowledge, such an "errorable" driver model is not available from the literature.

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II. Approach

An errorable car-following driver model is based on the concept that a model that normally achieves car-following tasks could be made to make mistakes, which could generate accidents or near-accidents that are of interest to AST developers. Driver errors can be viewed as a recurring event which, combines with events from surrounding vehicles, could result in an accident. For example, a driver may be distracted or engaging in alter-control tasks and thus fails to adjust vehicle speed at a regular pace. If the leading vehicle happens to decelerate at the wrong moment, a rear-end collision could happen. The human behavior (distraction) and lead vehicle deceleration can be described by stochastic processes. If proper human cognition/error mechanisms are included and proper probability functions are used to introduce human errors, it is possible to reproduce accident/incident behavior that is statistically similar to field testing results – which is the goal of this research.

The field testing database used was from Road-Departure Crash-Warning System Field Operational Test [12]. The RDCW system was designed to analyze road departure behavior. This system was implemented on 11 passenger vehicles with data acquisition system. Seventy-eight test drivers were participated and each of them drove a test vehicle for four weeks. Total data set accumulated 83,000 miles of driving and over 400 signals were captured at 10 Hz sampling rate. A massive set of numerical, video and audio data were collected, including longitudinal driving

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information, like vehicle velocity, acceleration, range, range rate…etc. Participates of this FOT received no instruction nor interfere about longitudinal driving. Hence, large quantity of naturalistic field-driving data can be used for car following analysis.

III. DRIVER MODEL TEMPLATE

As discussed in the previous section, the errorable model is derived from a model that normally achieves car-following tasks. Any existing car-following model can fulfill the need. However, majority of them assume driving as a deterministic process; the vehicle states can be calculated exactly by dynamic equations [1]–[6] or heuristic rules [13]–[16]. Precise prediction of vehicle states might be useful in traffic analysis, but has little interest for AST development. In actual driving, human would not perform deterministically and randomness is always observed. The stochastic behavior of driving has been studied in [17]–[20]. They modeled human randomness with a random noise. By adjusting the magnitude and parameters of this noise, models can be tuned to fit the test data. This modeling procedure can reproduces the stochastic behavior of the human driver. However, those tuning processes of noise magnitude are not convincing and have less reflection of actual driving behavior.

An alternative approach of constructing a stochastic driver model (SDM) was proposed in this paper. Instead of modeling stochastic behavior as noises, this approach considers driving as a stochastic process. The SDM was based on the assumption that, the driver normally has intention to achieve a desired vehicle state (speed) and as long as this state was roughly achieved, some deviations would be acceptable. This deviation of control is due to various reasons like driver's imperfection in control, perception, or exogenous disturbances (powertrain dynamics, road gradient, etc…). This assumption was verified by the RDCW FOT data. In the test data, if the range is fixed, the vehicle accelerations are distributed along a linear function of range rate (Fig. 1.) and the distribution was showed in Fig. 2. This shows that the desired acceleration is proportional to the range rate and the gains are decreasing cubically with range. The stochastic deviation distributes around the desired acceleration and is a second order polynomial function of range (Fig. 2.). This result can be interpreted as: when the range is small, driver tends to use a higher control. Moreover, the less deviation under small range means driver has less freedom and has to perform the control more precisely.

In last section, the driver only responds to non-zero range-rate. In reality, human drivers also regulate range or time headway. Human driver would have a desired range and regulate the vehicle speed until the difference between the actual range and the desired range is small. The sliding mode control technique was applied to approximate this human's feedback action for regulating range or time headway. In the sliding mode control, a sliding surface (or manifold) was defined as a desired state space which the motion of the system was constrained in. In a car-following task, the sliding surface can be defined as zero range error, where the desired range is defined as vehicle speed multiplied by the desired time headway. This driver model can mimic human driver's range regulating behavior by constraining the vehicle states on this sliding surface. The sliding mode control law was derived in Appendix. The result is shown in (1) – (5). The time headway obtained from test data showed a stochastic behavior which can be modeled as a random walk. Therefore, a random number generator followed by a running average filter was used to generate time varying time headway signal. Another running average filter was implemented to smooth the random acceleration signal. The resulting model (Fig. 3.) can simulate the normal driver behavior and occasional deviations which were consisted with realistic driving data (Fig. 4.).

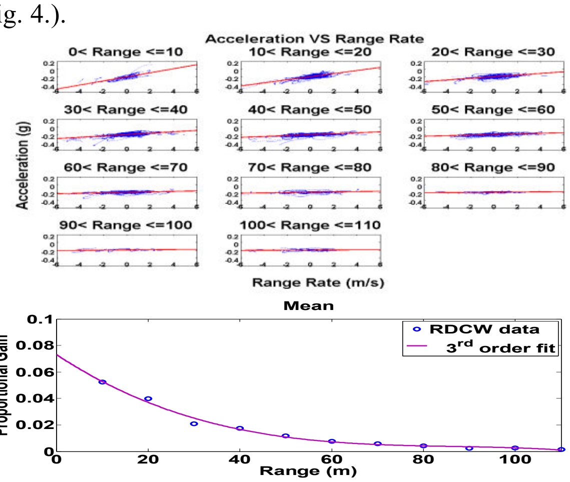

Fig. 1. RDCW data vehicle acceleration VS range rate with respect to different range

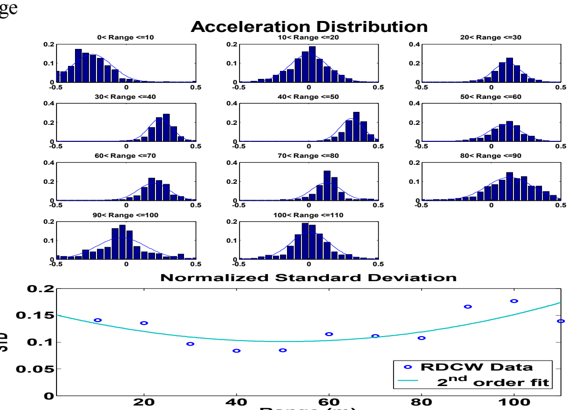

Fig. 2. RDCW data vehicle acceleration distribution with respect to different range

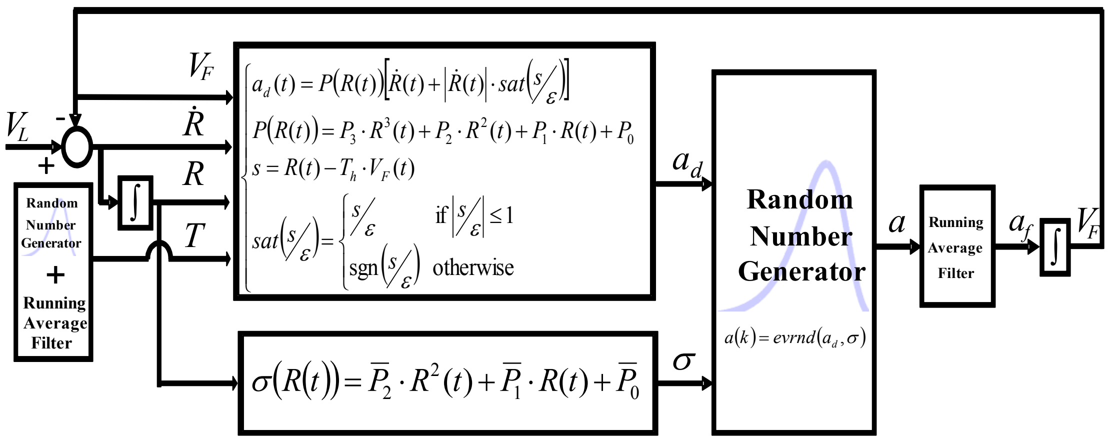

Fig. 3. Stochastic Driver Model Diagram

$$a_d(t) = P(R(t)) \cdot \left(\dot{R}(t) + |\dot{R}(t)| \cdot sat\left(s/\varepsilon\right)\right) \quad (1)$$

$$P(R(t)) = \left(P_3 \cdot R^3(t) + P_2 \cdot R^2(t) + P_1 \cdot R(t) + P_0\right) \quad (2)$$

$$s = R(t) - T_h \cdot V_F(t) \quad (3)$$

$$\sigma(R(t)) = \bar{P}_2 \cdot R^2(t) + \bar{P}_1 \cdot R(t) + \bar{P} \quad (4)$$

$$a(t) = f(a_d, \sigma) \quad (5)$$

, where R is range between two vehicles, P_i is polynomial coefficients, *sat*(.) is a saturation function, s is sliding surface, T_h is time headway, a is acceleration of vehicle, and f is a random number generator.

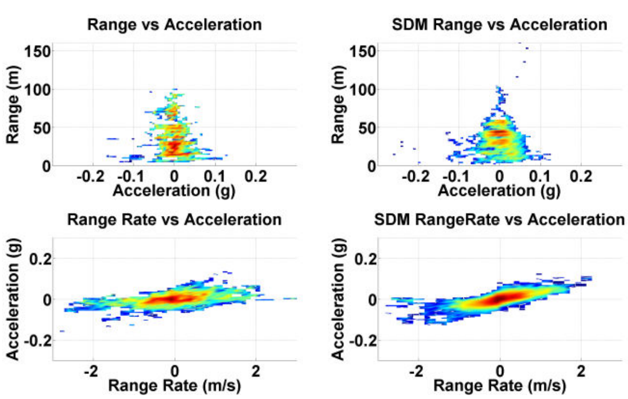

Fig. 4. Distribution of RDCW data and SDM simulation.

IV. ERROR-INDUCING BEHAVIORS

In this paper, three types of error-inducing behaviors were analyzed, perceptual limitation, distraction, and time delay. Each of them affects the normal driving and degrades the car-following performance. Individually, their effects might not be significant enough to induce a crash. However, combinations of those behaviors could cause crashes. To validate this hypothesis, the error-inducing behaviors were modeled as stochastic processes based on the frequency of their occurrences. Then, those stochastic processes of error were introduced into the longitudinal driver model (SDM) independently. The resulting errors or crashes would be similar to the human driving error, or at least in a statistical fashion.

Perceptual limitation is an important topic in psychology and psychophysics. In prior works, range and range rate are concluded as two important feedback cues used for car-following tasks. Therefore, the distance and velocity perceptual limitations are included as an error mechanism in our study. For range, a typical accepted localization threshold is 6 arc sec (0.5μ on the retina). Other than visual angle, people also utilize environmental information such as eye-height, relative position, and texture of the ground [21]. Therefore, with other additional information available, the perceptual limitation of distance or range perception can be neglected. The Just-Noticeable Difference of velocity discrimination is from 0.05-0.2 (ΔV/V) [22]–[25]. The perceptual limitation was imposed as a quantizer of range rate input. The disagreement of perceptual and real signals will be the cause of error.

Driver distractions can occur from several sources: in-vehicle tasks, cell phone, or even “look but didn’t see” [26]. When distraction happened, the driver will stop updating the feedback cues and/or control actions. The perceived range, range rate, and speed would remain unchanged from the previous step. Drivers are also assumed to freeze their control actions previous level. Once the distraction ends, the driver will resume updating the information and perform proper control adjustment. The above statement can be realized by using a switch and a register. However, the real difficulty is how to define the duration (how long) and the frequency (how often) of the distraction which consistent with human driver behavior. To quantify the driver’s distraction behavior, a large amount of real longitudinal driving data was collected from RDCW database. Then, the stochastic driver model (SDM) was used to identify the driver’s normal or distracted behavior.

The SDM contains two elements, desired accelerations and possible deviations. Based on the actual test data, the SDM can use desired acceleration to predict the next vehicle states and calculate their possible deviations respectively. If the test data landed outside one standard deviation of the prediction, we defined it as a deviated behavior (Fig. 5.). In this paper, the deviated behavior was assumed to be a consequence of distraction. This analysis was applied to the RDCW data and the result is shown in Fig. 6. Therefore, the duration and frequency of deviated behavior was directly used to reproduce distraction. After sixty thousand data points per driver (10 drivers total) was analyzed, a random distraction generator was constructed. It can generate distraction with random duration and frequency that represent real driving situations (Fig. 7.).

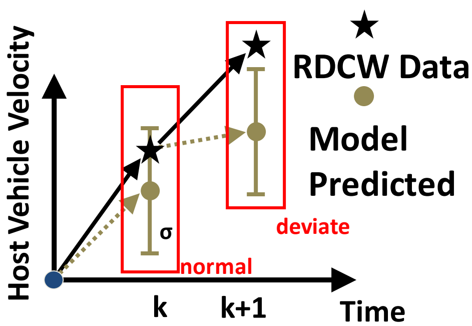

Fig. 5. Normal and Deviated Behavior Definition

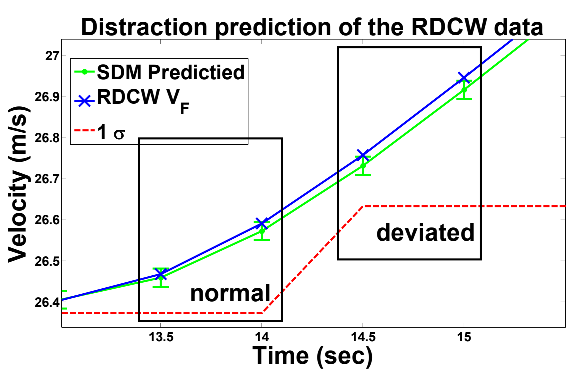

Fig. 6. Normal and Deviated Behavior of RDCW Data

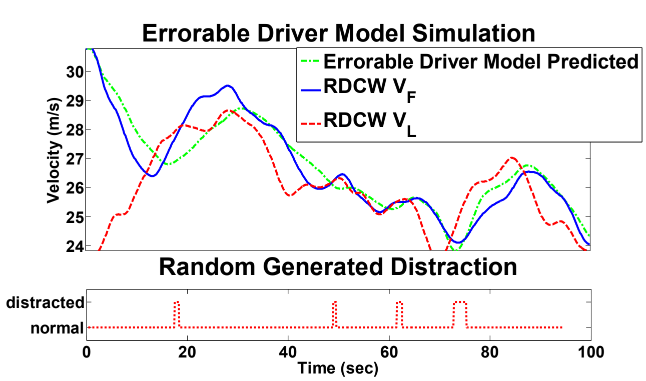

Fig. 7. Random Distraction Simulation

Time delay is another source for driver error. Neuromuscular delay and brain processing time are two major sources of time delay. Neuromuscular delay may be a constant for each driver [27], but the brain processing time is not. Therefore, the total time delay will be a time varying variables. A recursive least square (RLS) method was used to estimate the total time delay. Several ARMA models with different delay step were used to fit the test data simultaneously by the RLS algorithm. For every single data point, the delay step of the most accurate ARMA model was chosen as driver's time delay and the time delay sequence was constructed. This sequence shows a significant character that the delay step increases with time and, then dropped or reset to zero (Fig. 8.). To duplicate this characteristic, a probability distribution of time delay was first obtained from the time delay sequence. The inverse Gaussian distribution was selected to describe this probability distribution and a random value generator was derived. Next, the delay step was increased from zero to a random number then reset. The resulting time delay sequence can represent the real sequence obtained by RLS and be used for simulation.

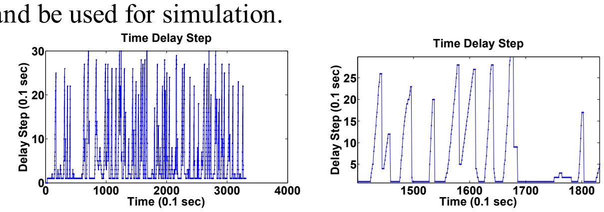

Fig. 8. Estimated Time Delay Sequence

V. ERRORABLE DRIVER MODEL

All the three error-inducing behaviors discussed above were implemented into the SDM (Fig. 8.) and leading vehicle velocity profiles from actual driving were used as simulation input. The simulation result was compared with actual crash data obtained from NHTSA report [28]. In year 2005, the average rate for all type of crash is 206 per 100M Vehicle Mileage Travel (VMT). For passenger and light truck, about 60% of the crashes are front or rear crashes. Thus, the actual crash rate for rear-end collision is approximately 120/100M VMT. Eight million miles of driving was simulated and twenty-five crashes happened (272/100M VMT). The higher simulation crash rate is possibly due to the fact no feedback is implemented under near-crash situations – while in actual driving a driver is likely to be prompted for action by passengers, brake light, etc. In the errorable driver model simulation, there was no such mechanism embedded. Therefore, a higher crash rate can be expected. This problem can be alleviated by cooperating with proper warning or adjusting algorithm. This process is just like human driver or AST. AST is designed to assist a human driver that is lack of crash avoidance or mitigation mechanism. With the existence of errorable driver model that create human mistake and lack of such mechanism, the role of human driver can be replaced in the evaluation and development of AST.

VI. Conclusion

An errorable car-following driver model was presented in this paper. Longitudinal driving behavior was characterized based on realistic driving data extracted from RDCW database. The stochastic part of longitudinal driver behavior was studied and modeled by a random process. The resulting car-following model can reproduce the normal driver behavior and occasional deviations similar to the realistic driving data. To make the model errorable, three error-inducing behaviors were analyzed. Perceptual limitation was studied and implemented as a quantizer. Then, based on the statistic analysis of the experimental data, the distracted driving was identified and modeled by a stochastic process. Later on, time delay was estimated by recursive least square method and was modeled by a stochastic process as well. These two processes were introduced as random disturbance of the SDM. With certain combination of those three error-inducing behaviors, accident/incident could happen. Twenty-five crashes happened after eight million miles simulation (272/100M VMT). This simulation crash rate is about twice higher with 2005 NHTSA data (120/100M VMT).

The higher crash rate can be expected because of the lack of feedback mechanism under near crash situation. In actual driving, a driver is likely to be prompted for action by passengers, brake light, etc and performance a proper correction. However, cooperating with proper crash avoidance or mitigation algorithm, this crash rate can be alleviated. For the future study, the effects of each error-inducing behavior need to be understood in detail. Furthermore, a systematic way of "controlling" the crash rate would be helpful for the future application.

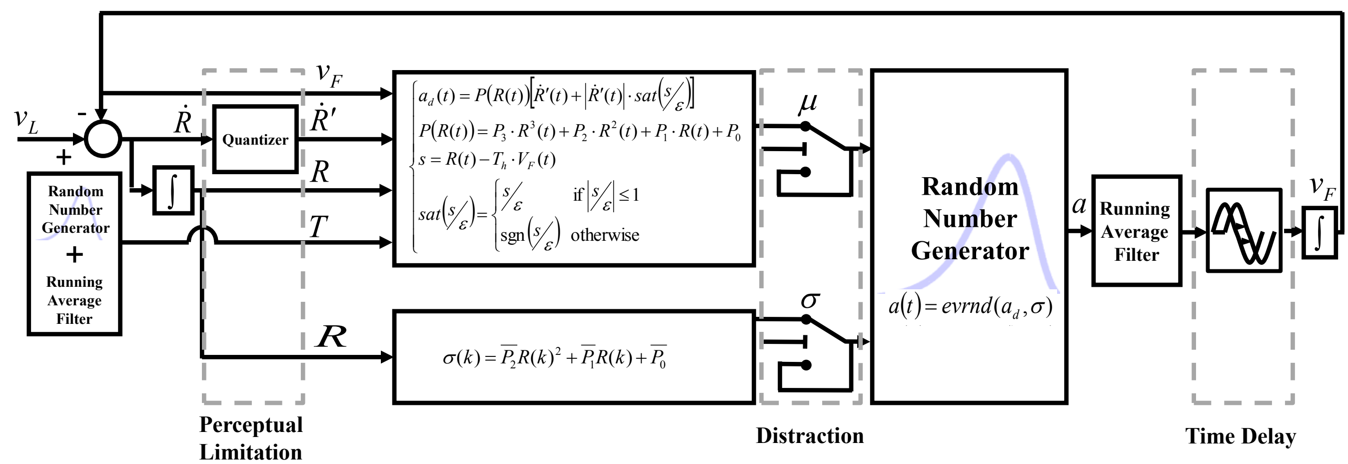

Fig. 9. Errorable Driver Model Diagram

Appendix

A sliding mode control law will derived for the stochastic driver model to model the human driver feedback action for regulating time headway.

We take the original stochastic driver model as our system

$\dot{X}_F = V_F$

$a_F = P(V_F, V_L)(V_L - V_F) + u$

And the sliding mode surface was defined as

$$s = \left[\int V_L dt - X_F\right] - T_h V_F = 0$$

Our control objective is to use input u for regulating vehicle state so that sliding mode surface can always be satisfied.

To present this model in terms of range and range-rate, we can modify it as

$\dot{R} = V_L - V_F$

$\ddot{R} = a_L - a_F = a_L - (P(V_F,V_L)(V_L - V_F) + u) = -P(V_F,V_L)\dot{R} - u + a_L$

The sliding mode surface would become

$$s = \left[\int V_L dt - X_F\right] - T_h \cdot V_F = \left[\int V_L dt - X_F\right] - T_h(V_L - \dot{R}) = 0$$

$$\dot{s} = [V_L - \dot{X}_F] - T_h(\dot{V}_L - \ddot{R}) = [V_L - V_F] - T_h(a_L - \ddot{R})$$

$$= [V_L - (V_L - \dot{R})] - T_h(a_L - (-P(V_F,V_L)\dot{R} - u + a_L))$$

$$= \dot{R} - T_h \cdot P(V_F,V_L)\dot{R} - T_h \cdot u$$

To satisfied the Lyapunov condition

$$\dot{V} = s \cdot \dot{s} = s[\dot{R} - T_h \cdot P(V_F,V_L)\dot{R} - T_h \cdot u]$$

$$= s[\dot{R} - T_h \cdot P(V_F,V_L)\dot{R}] - s \cdot T_h \cdot u \le 0$$

$$\left|\frac{\dot{R} - T_h \cdot P(V_F,V_L)\dot{R}}{-T_h}\right| = \frac{\left|(-1 + T_h \cdot P(V_F,V_L))\dot{R}\right|}{T_h}$$

$$= \frac{\left|-1+T_h \cdot P(V_F,V_L)\right| \cdot \left|\dot{R}\right|}{T_h} < \frac{\left|\dot{R}\right|}{T_h}\left|T_h \cdot P(V_F,V_L)\right| = \frac{\left|\dot{R}\right|}{T_h}(T_h \cdot P(V_F,V_L))$$

Therefore, we can choose our input u as

$$u = \frac{\left|\dot{R}\right|}{T_h}(T_h \cdot P(V_F,V_L)) \cdot \operatorname{sgn}(s)$$

The resulting model would be

$$\dot{X}_F = V_F$$

$$\begin{aligned} a_F &= P(V_F,V_L)(V_L - V_F) + u \\ &= P(V_F,V_L)(V_L - V_F) + (\left|\dot{R}\right|/T_h)(T_h \cdot P(V_F,V_L)) \cdot \operatorname{sgn}(s) \\ &= P(V_F,V_L)(V_L - V_F) + P(V_F,V_L) \cdot \left|\dot{R}\right| \cdot \operatorname{sgn}(s) \\ &= P(V_F,V_L)[(V_L - V_F) + \left|\dot{R}\right| \cdot \operatorname{sgn}(s)] \end{aligned}$$

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