CHAPTER 17

More Intelligent Models

The car-following models introduced up to this point share one thing in common: they are one-equation models, except for the Gipps model, which has two equations. This means that these models use a single equation to handle all driving situations, including start-up, speedup, free flow, approaching, following, and stopping. Hence, these models are referred to as single-regime models. The Gipps model is a two-regime model since it has an equation for free flow and another for car following. A model is called a multiregime model if it differentiates driving regimes and handles them using different equations. The car-following models introduced in this chapter fall into this category. In addition, car-following models can mimic the way of human thinking, e.g., using rules and reasoning based on neural networks.

17.1 PSYCHOPHYSICAL MODEL

A typical psychophysical model is the one proposed by Wiedemann [64] in 1974. The model considers two major factors influencing driver's operational control: relative position $\Delta x = x_{i-1} - x_i$ and relative speed $\Delta\dot{x} = \dot{x}_i - \dot{x}_{i-1}$. Hence, the working principle of the model can be illustrated by a diagram with $\Delta\dot{x}$ as the horizontal axis and Δx as the vertical axis (see Figure 17.1).

The operating condition of a vehicle i in relation to its leading vehicle $i - 1$ can be represented as a point $(\Delta\dot{x}, \Delta x)$ in the diagram. As vehicle i moves, its operating point changes accordingly, leaving a trajectory in the diagram. The relation of the two vehicles can be interpreted by examination of the location of the operating point. For example, if the point is on the negative side of $\Delta\dot{x}$, vehicle i is traveling more slowly than vehicle $i - 1$, while the relation is reversed if the point is on the positive side of $\Delta\dot{x}$. In addition, the point is always on the positive side of Δx since vehicle $i - 1$ is in front. The smaller Δx is, the closer the two vehicles are to each other. Hence, the two vehicles collide if Δx is less than one vehicle length l. This

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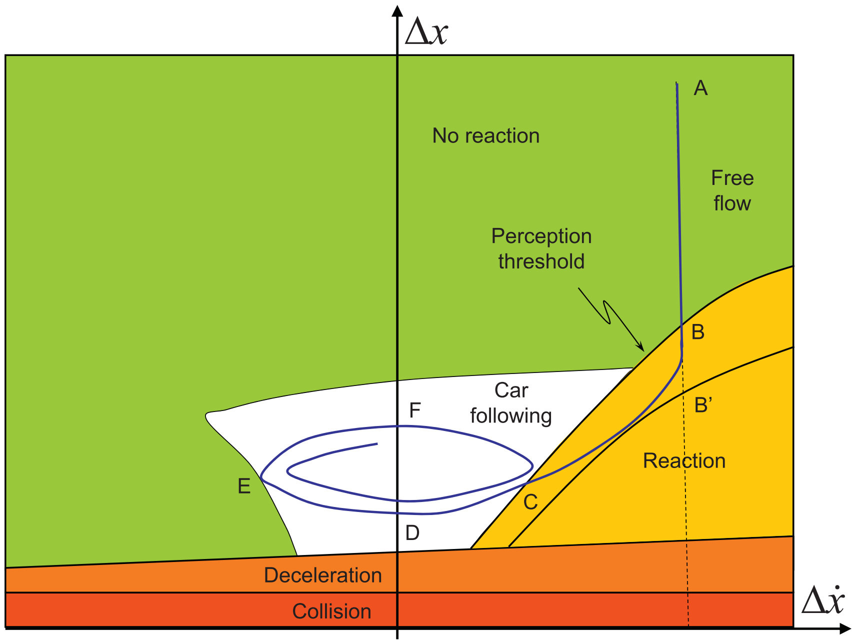


Figure 17.1 Illustration of a psychophysical model.

situation is depicted by the *collision* area in the diagram bounded by the horizontal axis and a horizontal line at $\Delta x = l$.

On top of this area is another area, denoted the *deceleration* area, where the two vehicles are so close that an imminent collision causes the following vehicle to back up for safety.

Now, suppose vehicle i is traveling on a highway with the leading vehicle $i - 1$ far ahead and vehicle i is faster than vehicle $i - 1$. The operating condition can be represented by point A, which has a large positive Δx and a positive $\Delta\dot{x}$. Since vehicle $i-1$ is far ahead, driver i does not have to respond to vehicle $i - 1$, an area of which is denoted as *no reaction* in the diagram.

As vehicle i keeps moving, the relative speed $\Delta\dot{x}$ remains unchanged, but the relative separation Δx decreases. Hence, the operating point moves downward. Sooner or later, vehicle i will catch up and begin to respond to vehicle $i - 1$ as the gap is closing. However, the cutoff point is rather vague since this is a subjective matter. Perhaps a better way to draw the line is to set an upper limit such as point B, before which drivers are less likely to respond, and a lower limit such as point B′, after which drivers definitely need to respond. Note that points B and B′ vary as $\Delta\dot{x}$ changes.

The trajectory of point B or point B′ under different $\Delta\dot{x}$ separates the *reaction* area from the *no reaction* area.

Since driver i is most likely to respond to vehicle $i-1$ by slowing down (if lane change is not an option), the operating point moves downward and left toward to point C and finally to point D when the two vehicles are traveling at the same speed. Now the two vehicles are in the car-following regime, during which driver i tries to keep the same pace as vehicle $i-1$ separated by a comfortable distance. However, drivers are easily bored and distracted, especially during long trips. As a result, driver i might slow down unconsciously (e.g., when using a cell phone). Consequently, $\Delta\dot{x}$ becomes negative and keeps decreasing while Δx increases. As such, the operating point moves from D toward E, at which point the opening gap reminds driver i that he or she is falling behind. Hence, the driver begins to catch up, during which time $\Delta\dot{x}$ increases but is still negative, while Δx keeps increasing. This corresponds to a transition from E to F, when the two vehicles are again traveling at the same speed but with a large gap in between. Next, driver i may want to keep accelerating in order to shorten the gap to a comfortable level, which is denoted as a transition from F back to C. Therefore, as the driver oscillates back and forth around his or her comfortable car-following distance, the operating point drifts around within an area in the diagram denoted as *car following*.

The **psychophysical** model got its name because it involves both psychological activities (such as perception-reaction threshold and unconscious car following) and physical behavior (e.g., accelerating and decelerating efforts). Compared with the models introduced before, this model captures more driving regimes explicitly, such as free flow (*no reaction* area), approaching (*reaction* area), following (*car following* area), and decelerating (*deceleration* area).

17.2 CARSIM MODEL

The CARSIM model [65] is another multiregime model which consists of a set of acceleration algorithms:

A1: Vehicle i is moving but has not yet reached its desired speed v_i. Depending on vehicle i's initial speed and the urgency of the task, the acceleration rate is found by from Figures 17.2 and 17.3.

A2: Vehicle i has reached its desired speed v_i. No specific algorithm is provided except that the driver will try to reach v_i as fast as possible while satisfying all safety and operational constraints.

Speed, mph	Cars, ft/s^2	Trucks, ft/s^2	Speed, kph	Cars, m/s^2	Trucks, m/s^2
0-15	8.80	2.20	0-24	2.68	0.67
15-30	5.50	1.10	24-48	1.68	0.34
30-40	5.17	0.88	48-64	1.58	0.27
40-50	4.17	0.44	64-80	1.27	0.13
50-60	3.08	0.44	80-96	0.94	0.13
>60	2.09	0.44	>96	0.64	0.13

Figure 17.2 Typical acceleration rates on a level road.

Speed change, mph	Acceleration, ft/s^2	Deceleration, ft/s^2	Speed change, kph	Acceleration, m/s^2	Deceleration, m/s^2
0-15	4.84	7.77	0-24	1.48	2.37
15-30	4.84	6.74	24-48	1.48	2.05
30-40	4.84	4.84	48-64	1.48	1.48
40-50	3.81	4.84	64-80	1.16	1.48
50-60	2.93	4.84	80-96	0.89	1.48
60-70	1.91	4.84	96-112	0.58	1.48

Figure 17.3 Normal acceleration and deceleration rates for passenger cars.

A3: Vehicle i was stopped and has to start from standstill. A maximum acceleration rate is applied constrained by a noncollision constraint after a response delay.
A4: Vehicle i is in car-following mode with its leader $i-1$. A4 is determined by the following safety rule being satisfied: vehicle i should leave a nonnegative gap $(s_i - l_{i-1} \geq 0)$ from vehicle $i-1$ should vehicle i be advanced one time step Δt: $s_i(t) = x_{i-1}(t) - x_i(t+\Delta t) \geq l_{i-1}$ where $x_i(t+\Delta t) = x_i(t) + \dot{x}_i \Delta t - 0.5 A_4 \Delta t^2$ and the other variables are as defined before.
A5: Vehicle i in car-following mode is subject to a noncollision constraint which is reinforced by considering the desired spacing:

$$s_i^*(t) = x_{i-1}(t) - x_i(t+\Delta t) \geq \max \begin{cases} \dot{x}_i(t+\Delta t)\tau_i + l_{i-1} \text{or} \\ \dot{x}_i(t+\Delta t)\tau_i + \frac{[\dot{x}_i(t+\Delta t)]^2}{2B_i} - \frac{[\dot{x}_{i-1}(t)]^2}{2B_{i-1}} + l_{i-1}, \end{cases}$$

where $\dot{x}_i(t+\Delta t) = \dot{x}_i(t) + A_5 \Delta t$, and B_i and B_{i-1} are the maximum deceleration rates of vehicle i and vehicle $i-1$, respectively. The astute reader immediately recognizes that the first choice of the right-hand side follows the rationale of the Forbes model [53, 54, 66] and the second choice is similar to that of the Gipps model [57] if driver i is willing to apply the emergency brake (i.e., $b_i = B_i$) as well.

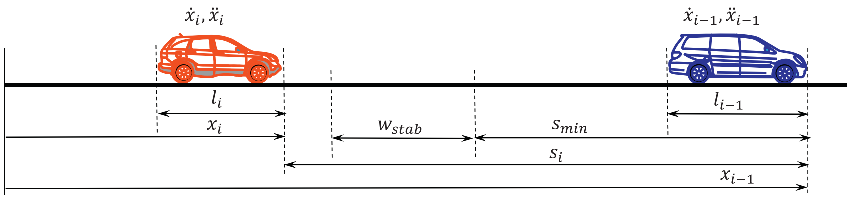


Figure 17.4 Illustration of a rule-based model.

17.3 RULE-BASED MODEL

The model developed by Kosonen [67] is a representative of rule-based models (see Figure 17.4), and is reproduced below:

1. NO SPEED CHANGE

   Keep the present speed level (default case).

2. ACCELERATE IF $[\dot{x}_i < v_i]$ and $[t - t_{\text{last}} > T_{\text{acc}}(\dot{x}_i)]$

   The current speed $\dot{x}_i$ is less than the desired speed v_i and the time elapsed from the last acceleration t_{last} is more than T_{acc}.

3. NO ACCELERATION IF $[s_{ij} < s_{\min}(\dot{x}_i, \dot{x}_j) + w_{\text{stab}}(\dot{x}_i, \dot{x}_j)]$

   The distance from obstacle s_{ij} is less than the minimum safe distance $s_{\min}$ plus the width of the stable area w_{stab}.

4. SLOW DOWN IF $[s_{ij} < s_{\min}(\dot{x}_i, \dot{x}_j)]$

   The distance from obstacle s_{ij} is less than the minimum safe distance $s_{\min}$.

5. DO NOT SLOW DOWN IF $[\dot{x}_i < \dot{x}_j]$ or $[t - t_{\text{last}} < T_{\text{maxdec}}]$

   Own speed is less than obstacle speed or maximum deceleration rate is exceeded.

6. GOTO ZERO IF $[s_{ij} < 0]$ and (Obstacle = physical)

   Distance to physical obstacle is below zero (= collision).

At each time step, the motion of vehicle i is checked against the above rules one by one. A later rule always supersedes earlier ones should there be a conflict. Compared with the models presented before, the rule-based model is closer to human intelligence with less mathematical tractability.

17.4 NEURAL NETWORK MODEL

Perhaps the approach that best mimics driver behavior is artificial neural networks [68, 69]. This is because artificial neural networks are capable of

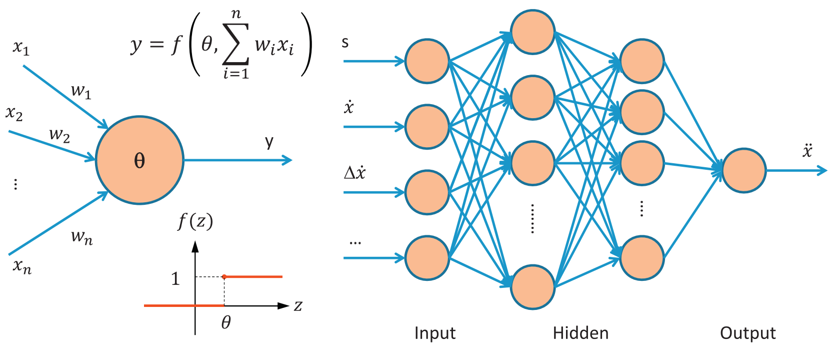


Figure 17.5 Illustration of a neural network model.

associating, recognizing, organizing, memorizing, learning, and adapting. A neural network typically consists of many interconnected working units called neurons; see Figure 17.5 for an example of a neural network in the right panel and a neuron in the left panel. A neuron receives inputs $x_1, x_2, \ldots, x_n$ which are weighted $w_1, w_2, \ldots, w_n$, respectively. The total input to the neuron is the weighted sum of individual inputs: $z = \sum_{i=1}^{n} w_i x_i$. The output of the neuron y depends not only on z but also on the threshold of the neuron θ. The neuron outputs 1 if $z \geq \theta$ and 0 otherwise.

Neurons with such a simple functionality can be organized into neural networks of varying complexity and topology. The right panel in Figure 17.5 illustrates an example of a back-propagation neural network. The network consists of one input layer (which in turn consists of a set of neurons), one output layer, and one or more hidden layers. Each neuron feeds its output only forward to neurons in the next layer, without backward feeding and cross-layer connection.

To apply neural networks to the modeling of car-following behavior, one first identifies a set of factors to be considered that influence the driver's operational control. For example, as discussed before, these influencing factors can be spacing s, speed $\dot{x}$, relative speed $\Delta\dot{x}$, etc. It is also possible to include other factors not considered before, such as a tailgating vehicle behind, weather, and intervehicular communication. These factors are represented by neurons in the input layer. The output layer in this example consists of only one neuron—acceleration/deceleration or speed choice. If one needs to model not only longitudinal but also lateral motion, a second neuron is necessary to represent steering effort. Between input and output layers lie one or more hidden layers. The more hidden layers the network has, the more flexible it is, but the more complex it becomes. After the neural network has been constructed, it needs to be trained before it can be useful.

The training process starts with data collection. For example, from field experiments, one observes that, at time t_1, a vector of input $[s(1), \dot{x}(1), \Delta\dot{x}(1), \ldots]$ results in driver operational control $[\ddot{x}(1)]$, and more patterns are observed at $t_2, t_3, \ldots, t_m$:

$$\begin{bmatrix} s(1), \dot{x}(1), \Delta\dot{x}(1), \ldots \\ s(2), \dot{x}(2), \Delta\dot{x}(2), \ldots \\ \ldots \\ s(m), \dot{x}(m), \Delta\dot{x}(m), \ldots \end{bmatrix} \Rightarrow \begin{bmatrix} \ddot{x}(1) \\ \ddot{x}(2) \\ \ldots \\ \ddot{x}(m) \end{bmatrix}. \tag{17.1}$$

After initializing the neural network (i.e., assigning initial values to connection weights and neuron thresholds), one imposes observations at t_1 (i.e., the first row of input data) at the input layer, which feeds forward to hidden layers and eventually to the output layer. If the computed output is different from the observed output, the error is propagated backward layer by layer to adjust their connection weights and neuron thresholds. This is why networks of this kind are called back-propagation networks. After the error has been propagated backward, the same input is imposed again at the input layer and the network computes a new output. This time, the output error, if any, should be smaller than in the previous round. Again, the error needs to be propagated back, and all the weights and thresholds are adjusted for a new round of learning. The process continues until the computed output becomes sufficiently close or equal to the observed output. This completes the learning of the first input-output pattern (i.e., the first row of data set 17.1). Next, one continues with the training of the second row, the third row, and so on. The training is completed after all data in the set have been trained and the neural network is able to associate the correct output with the corresponding input.

The trained neural network is now ready to be applied to vehicle operational control. At any moment, the neural network is able to search for an output (i.e., acceleration/deceleration or speed in the next step) on the basis of the input it receives (i.e., current spacing s, speed $\dot{x}$, relative speed $\Delta\dot{x}$, etc.). In addition, the neural network may continue learning while working, and hence adapt to a new environment which it has never encountered before.

17.5 SUMMARY OF CAR-FOLLOWING MODELS

It is time to summarize the car-following models introduced so far. One way to classify these models is to look at the model output. *Dynamic models* employ acceleration/deceleration $\ddot{x}_i(t)$ as the model output and the modeling philosophy behind these models is that, at any time, the driver tries to answer the following questions: Should I speed up or slow down next? By how much? Example models for this category are General Motors models (GM models), the IDM, the CARSIM model, the rule-based model, the psychophysical model, and the longitudinal control model, which will be introduced in Chapter 22. *Steady-state models* use speed $\dot{x}_i(t)$ as the model output, and the modeling philosophy behind these models is that, at any time, the driver tries to answer the following question: What is my target speed next? Example models for this category are the Pipes model, the Forbes model, the Gipps model, the Newell nonlinear model, and the Van Aerde model. *Static models* employ displacement $x_i(t)$ as the model output, and the modeling philosophy behind these models is that, at any time, the driver tries to answer the following question: Where should I be next? An example model for this category is the Newell simplified car-following model.

Another way to classify these models is to examine model intelligence. For example, the Pipes model is a one-equation model, and this equation handles all driving situations—that is, they are treated as a single regime. Hence, the Pipes model is a single-regime model. Also in this category are the Forbes model, GM models, Newell models, the IDM, and the Van Aerde model. The Gipps model consists of two equations, one for free flow and the other for car following, and hence is a two-regime model. Both the CARSIM model and the psychophysical model differentiate more driving regimes, and hence are multiregime models. Further, the rule-based model incorporates driving strategies for various driving regimes into a set of simple IF-THEN rules. Better yet, the neural network model applies artificial intelligence to organize, learn, and adapt to driving experiences. Illustrated in Figure 17.6, car-following models become more and more intelligent as one moves from left to right.

On the other hand, since there is only one equation in a single-regime model, it is easy to track the effect of an input on the output. In addition, it is tractable to aggregate/integrate such a microscopic model in order to understand its macroscopic properties. Therefore, single-regime models are mathematically attractive. Two-regime or multiregime models, however, are inevitably piecewise and involve discontinuity, which makes them less mathematically attractive. Though computationally simple, the rule-based model consists of a set of IF-THEN rules rather than a clearly defined mathematical formulation. Hence, it is very difficult to analyze macroscopic properties of this kind of model. The neural network model, in the extreme, is very intractable because there is no clear mathematical formulation that defines the relation between input variables and the output variable. If a model with a clear mathematical formulation is analogous to a transparent box through which one can trace an input all the way to the output, a neural network is like a black box in which what is happening is a mystery.

A more rigorous effort with regard to the taxonomy of microscopic models was made by the Next-Generation Simulation program[1] (see Figure 17.7). The diagram consists of four modules/rows from top to bottom: *route-choice* models, *lane-changing* models, *gap-acceptance* models, and *car-following* models. In the car-following module, there are a few lines representing different modeling approaches. For example, one approach is called *stimulus-response*, which starts with with a few papers published around 1960 serving as the basis of GM models. Labeled along this line are further models that have been proposed or existing models that have been revised, showing the historical evolution of this modeling approach. One line up is the *desired measure* approach, along which are the Pipes model, the Newell nonlinear model, the Gipps model, and the CARSIM model. The next line is the *psychophysical* approach, where one finds the Wiedeman model. This is followed by the *rule-based* approach, an example of which is the Kosonen model. The IDM is on its own at the top. Note that the neural network model a potential addition to this module. The other modules and models shown can be interpreted in a similar way.

Figure 17.6 Summary of car-following models.

[1] http://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm

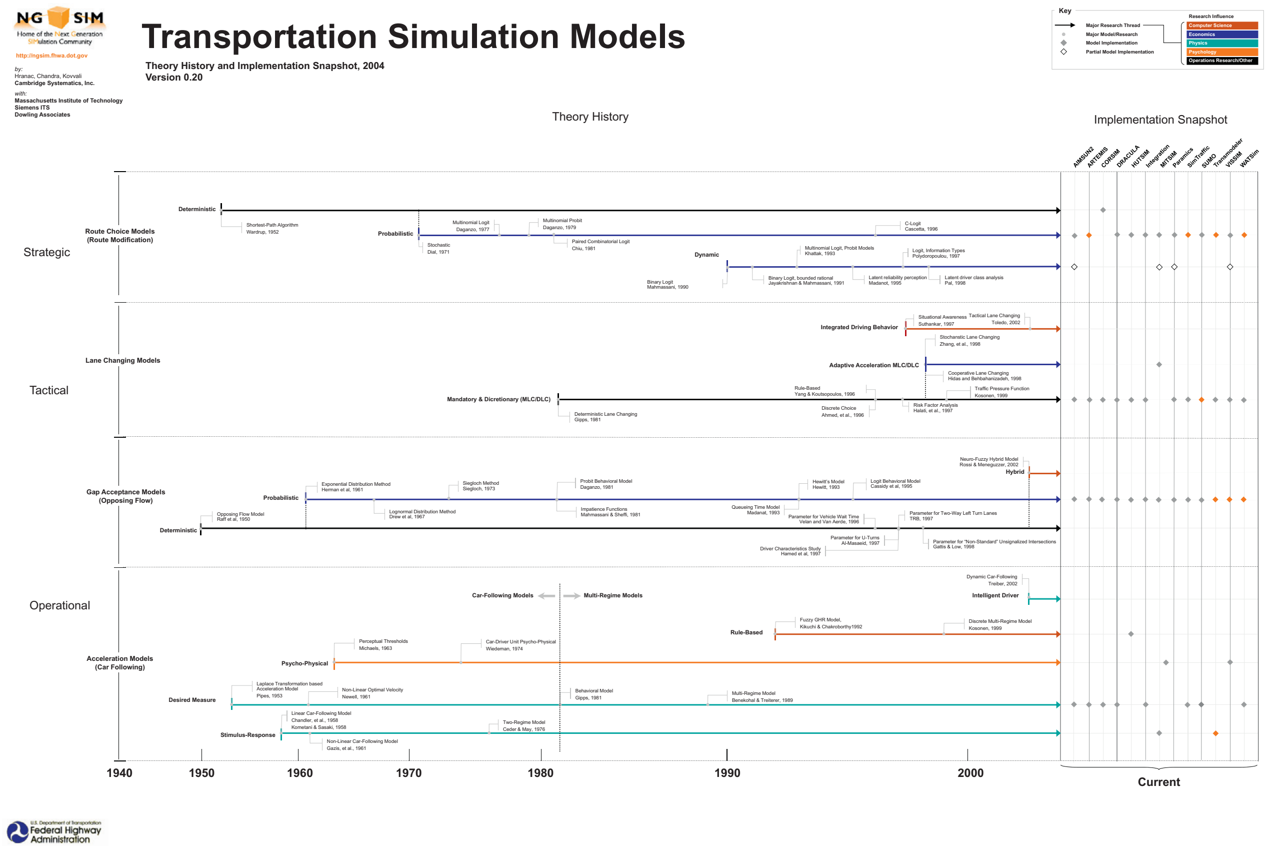
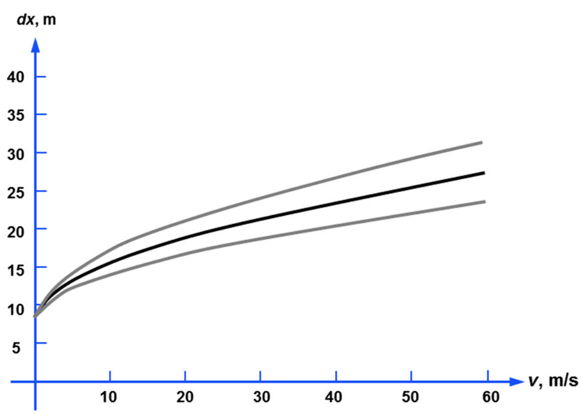


Figure 17.7 Taxonomy of microscopic models.

On the right-hand side of Figure 17.7 there are a set of vertical lines. On top of them are a set of transportation simulators (or simulation software packages), such as AIMSUN, CORSIM, HUTSIM, Integration, Paramics, and VISSIM. The intersection of a horizontal line (a modeling approach) and a vertical line (a simulator) denotes potential implementation of a car-following model of this approach in the simulator. If the implementation is true, a diamond-shaped dot is placed at the intersection. Therefore, it is clear that car following in CORSIM is based on a *desired measure* model, car following in VISSIM is based on a *psychophysical* model, and car following in HUTSIM is based on a *rule-based* model. The connection of simulators and models in other modules can be interpreted in a similar way.

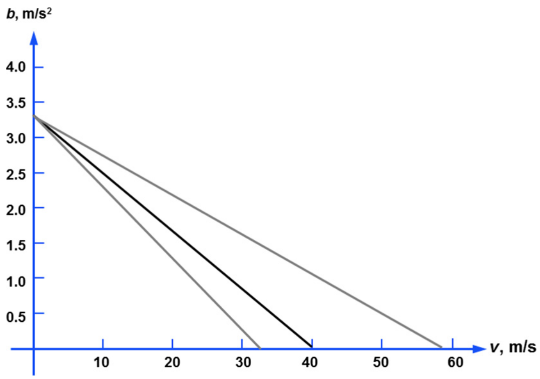
PROBLEMS

1. The figure below was used by Wiedemann in his psychophysical model to determine the desired minimum following distance as a function of speed. Use the figure to answer the following questions and do the following task:



   a. What is the assumed nominal vehicle length (i.e., the average spacing when traffic is jammed)?
   b. According to the middle curve, what is the desired minimum following distance when the speed is 30 m/s?
   c. Plug the results of (a) and (b) into the Pipes model to estimate the corresponding perception-reaction time.
2. The figure below was used by Wiedemann in his psychophysical model to determine the maximum acceleration of passenger cars as a function

of speed. Use the figure to answer the following questions and do the following tasks:



a. What is the assumed maximum acceleration?

b. What is the assumed cruise speed according to the middle curve?

c. Formulate the underlying acceleration profile—that is, express acceleration as a function of speed.

d. Derive the corresponding equations to calculate acceleration, speed, and displacement from initial conditions $x(t = 0) = x_0$ and $v(t = 0) = v_0$.

e. If the vehicle is traveling at 20 m/s, determine its speed after 5 s of acceleration and the distance traveled during that time.

3. Figure 17.2 depicts typical acceleration rates on a level road used by the CARSIM model. Convert the units to the metric system and plot the data on top of the figure in problem 2 (use the column for cars and take the midpoint of each speed range). Comment on how the acceleration profiles differ in the CARSIM model and the psychophysical model.

4. Determine all the rules that apply and the rule that actually takes effect in each of the following scenarios according to the rule-based model:

a. A vehicle is entering an empty freeway at a speed of 60 km/h. The freeway speed limit is 90 km/h.

b. A vehicle is cruising on the freeway at a desired speed of 95 km/h. There is no other vehicle in the visible range in front.

c. A vehicle at a speed of 100 km/h is approaching a leader at a speed of 90 km/h. Their current spacing is 70 m, and the minimum safe distance 100 m.

   d. A vehicle with a desired speed of 95 km/h is following its leader, both traveling at a speed 90 km/h with a spacing of 120 m. The minimum safe distance is 100 m, and the stable area is 25 m.
   e. A vehicle at a speed of 70 km/h is changing to the target lane, where there is a leader traveling at a speed of 90 km/h. The spacing between the two vehicles is 70 m, and the minimum safe distance is 100 m.

5. The minimum safe distance in the rule-based model can be formulated in many ways. Use your car-following knowledge learned in previous chapters to propose two ways to determine the minimum safe distance.