

Modeling Perception Performance in Traffic Simulation

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CTR Day - 2023

Background

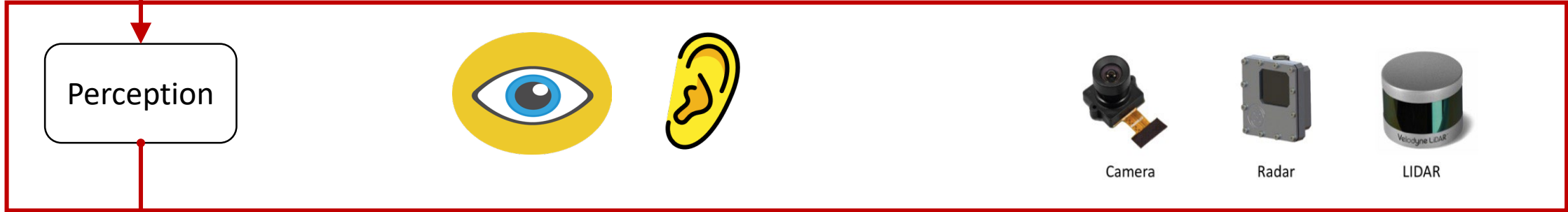
- Automated driving systems (ADS) are expected.
- Road authorities concern of traffic performance.
- Microscopic traffic simulation tools need to be made ready to assess mixed traffic with automated driving.
- Microscopic models for automated driving are developed based on expectations with limited possibility for validation.

Driving as a dynamic process

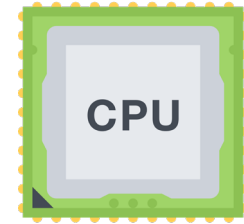


Human driving

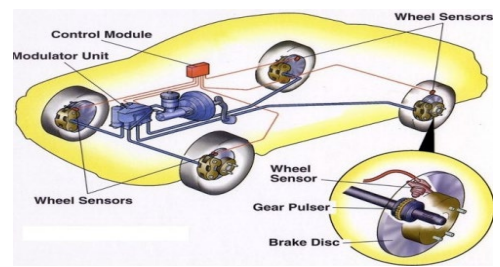
Automated driving



Decision



Action



Problem

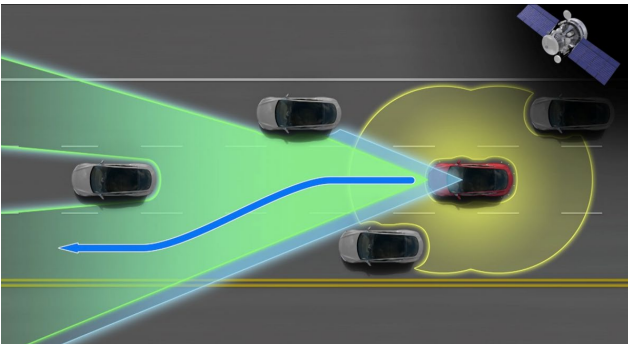
- The perception is essential for the driving activity → situational awareness.
- In previous simulation experiments the perception is oversimplified⁽¹⁾
 - Implicit modeling of perception.
 - Perfect perception / no perception errors.
 - Little / no difference in perception between automated and human driving.

(1) Postigo et al. 2021, Effects on Traffic Performance Due to Heterogeneity of Automated Vehicles on Motorways : A Microscopic Simulation Study

Aim

- Develop a model that explicitly deals with the perception which ensures consistency and transparency about assumptions.
- Describe differences in **perception performance** for the types of perception expected in mixed traffic.

Vehicle perception

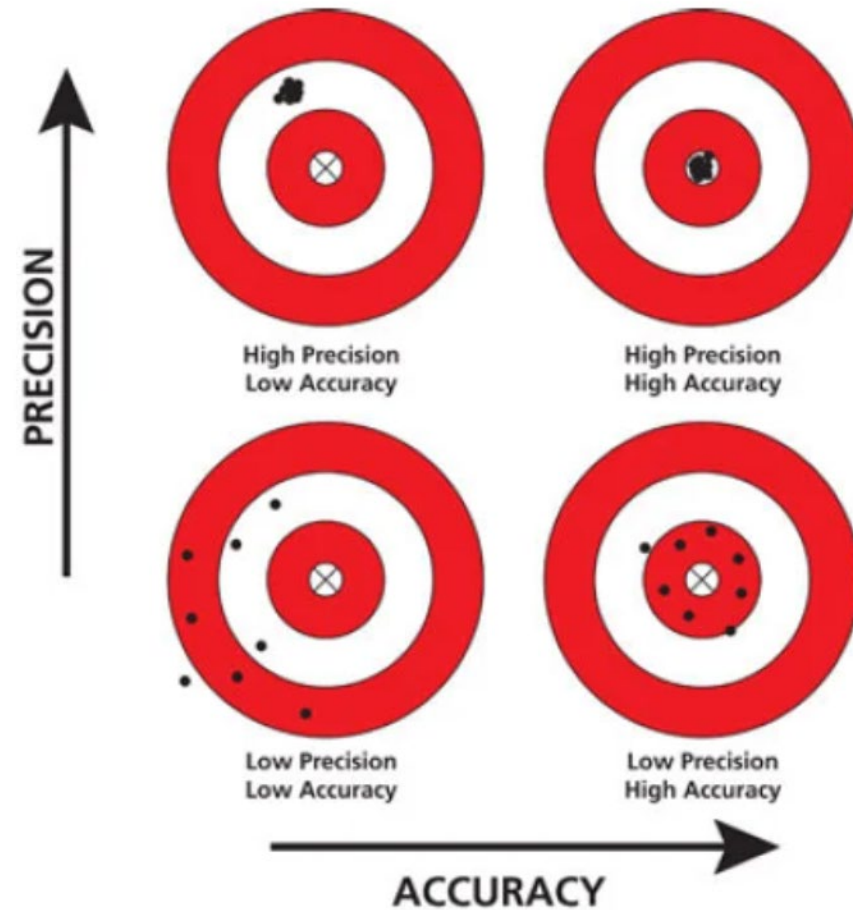


- How is the information obtained/what are the sensing capabilities?
 - Type of perception – e.g., sensors, v2x.
 - Accuracy - Precision - Range
- Which vehicles/objects can be perceived?
- What information can be known?
 - Position - Speed - Intentions
- When is the information obtained?
 - Delay

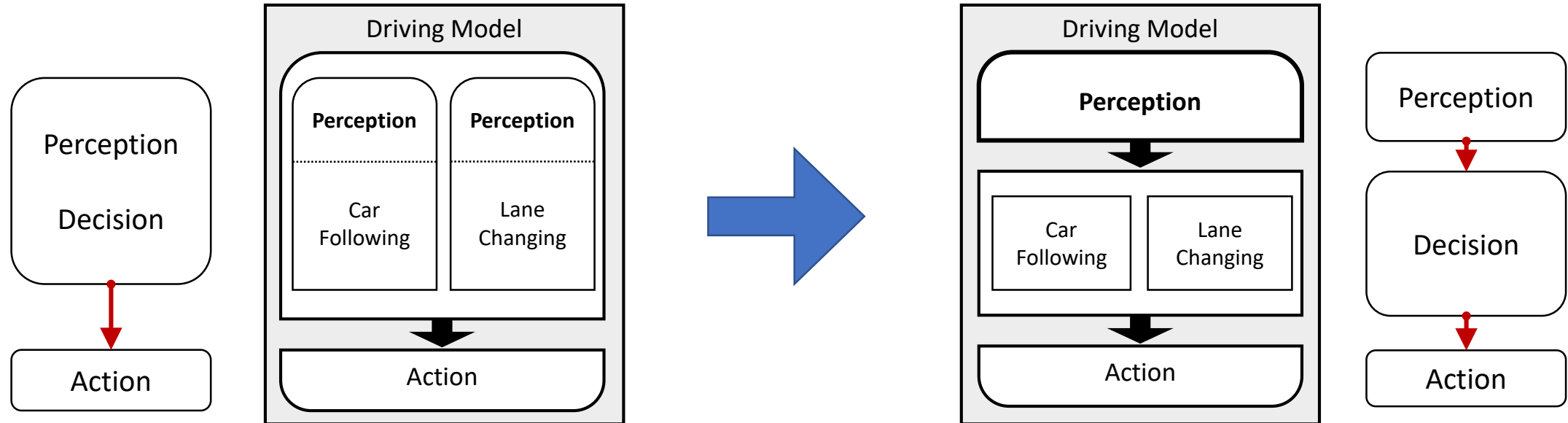
Perception performance

Four dimension to characterize the perception performance:

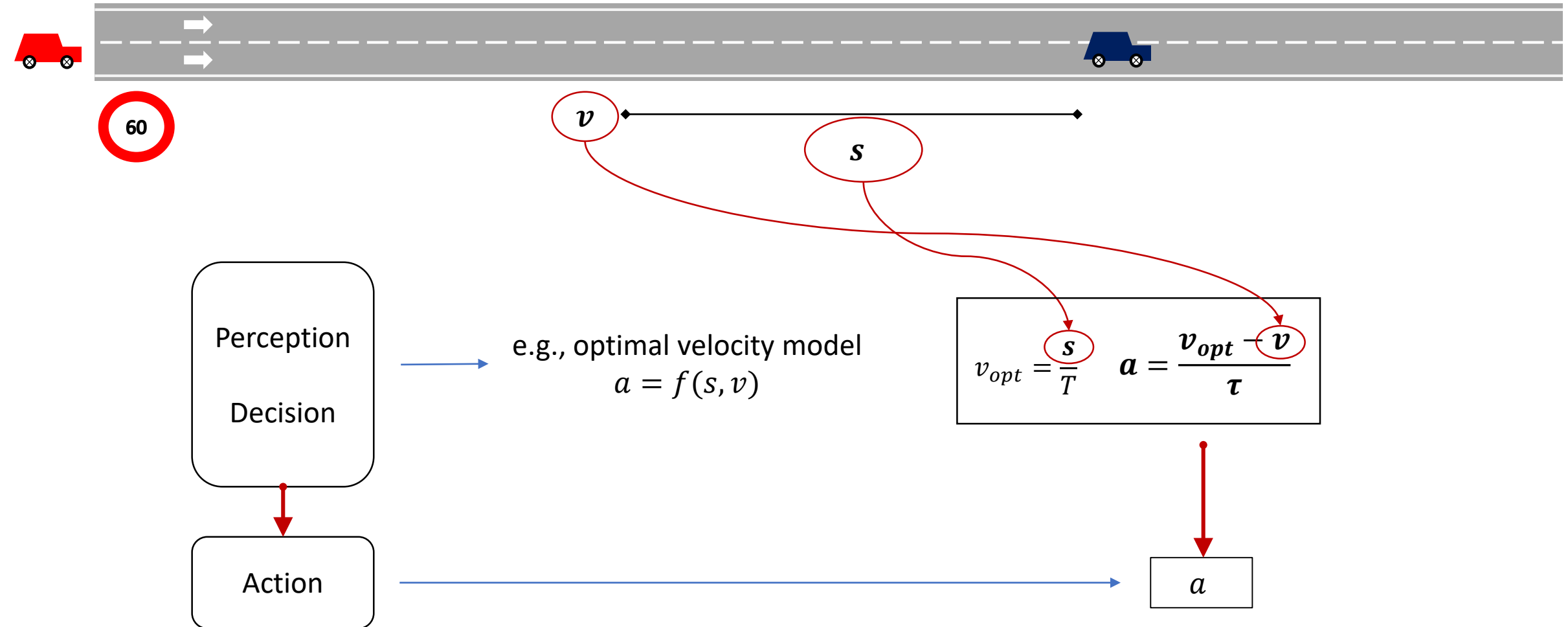
- Accuracy
- Precision
- Detection speed – Delay
- Range



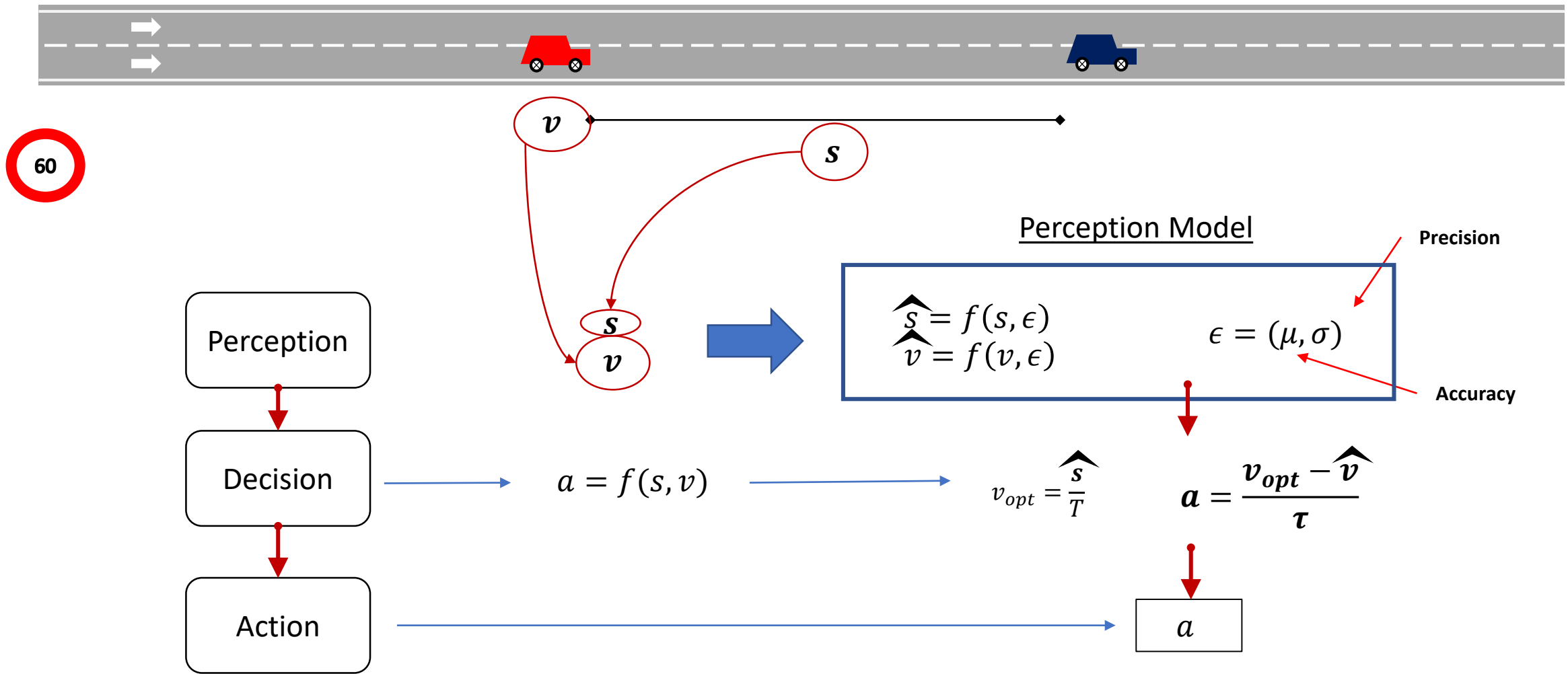
Change in microscopic driving model



Example current approach – following regime



Proposed approach – following regime



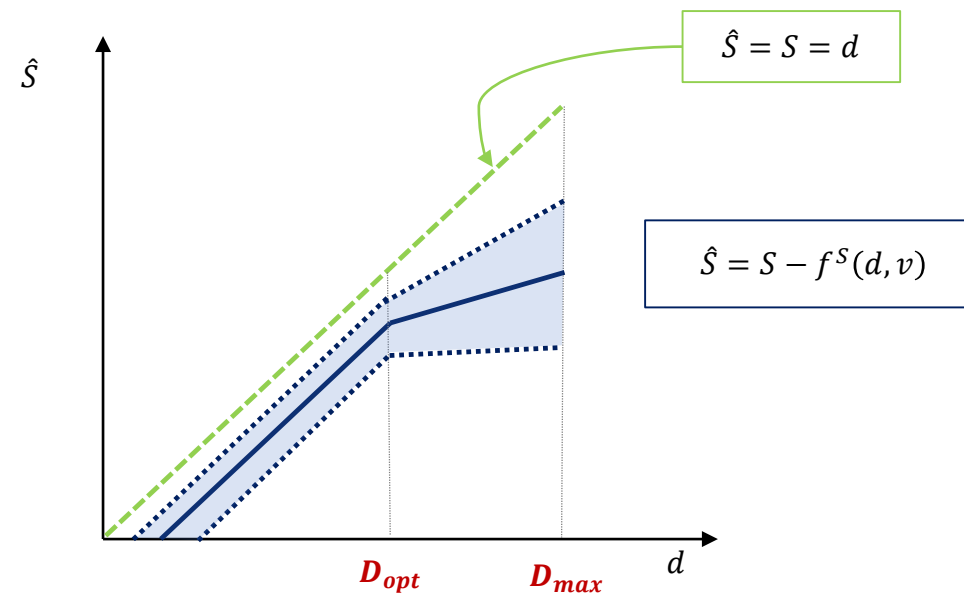
60

Error function - $f^\Omega(d, v)$

$$f^\Omega(d, v) = \underbrace{\varepsilon^\Omega(d)}_{\text{accuracy}} + \underbrace{W_{trans} * (\sigma^\Omega(d) + \sigma^\Omega(v))}_{\text{precision}}$$

accuracy

precision



S : Front space gap or space headway

d : Distance

v : Speed

Simulation experiment

Base scenario

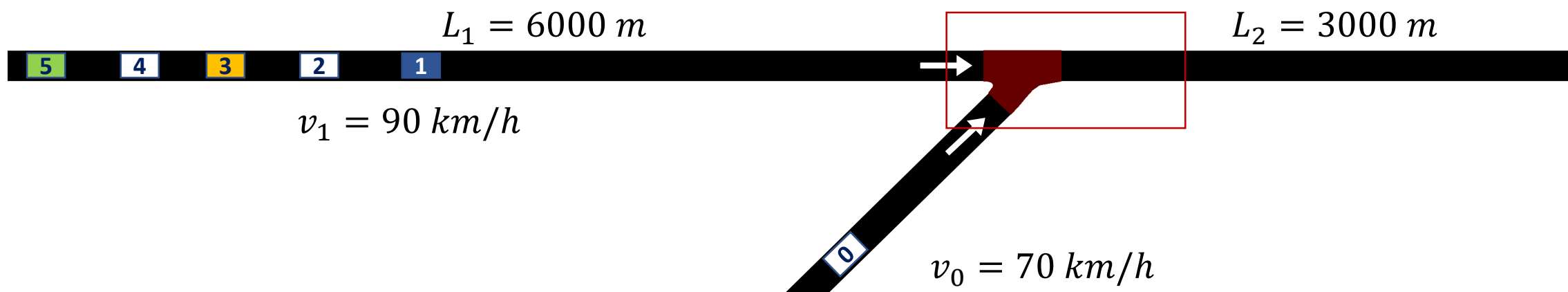
No errors

Scenario 1

Low accuracy + high precision

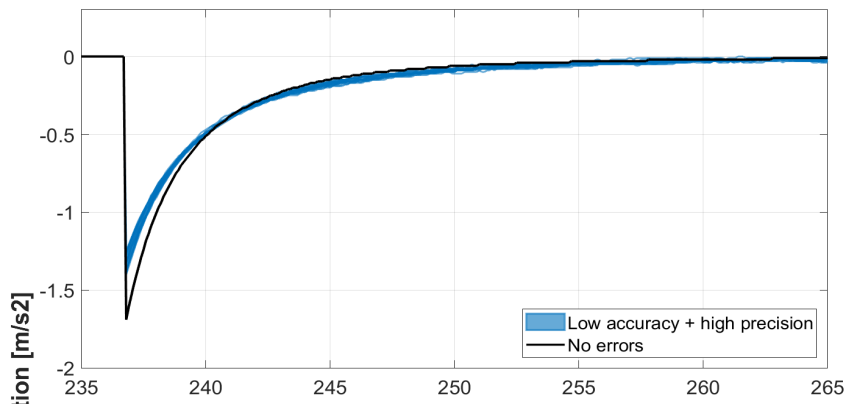
Scenario 2

High accuracy + low precision

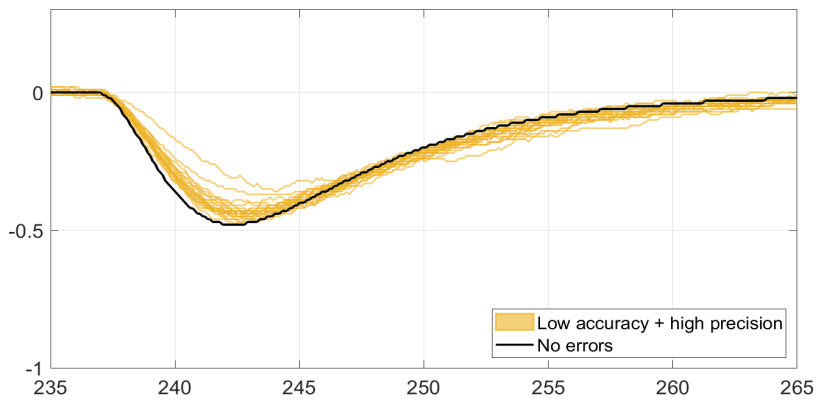


Simulation results

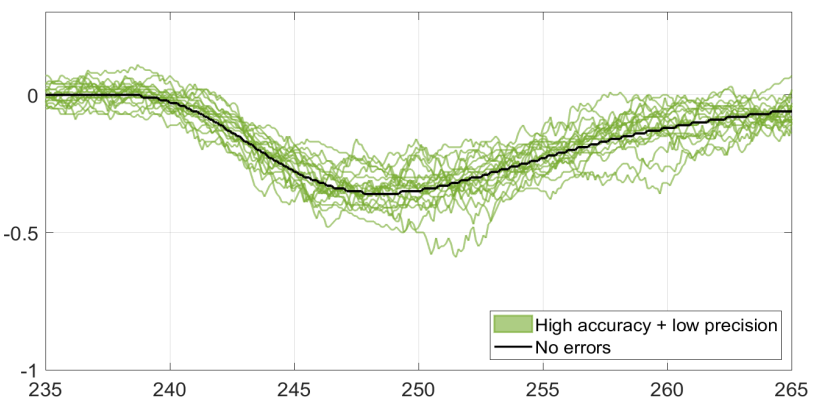
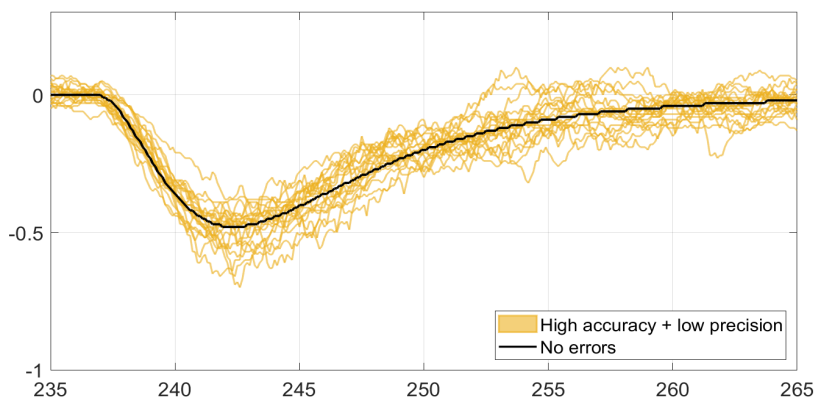
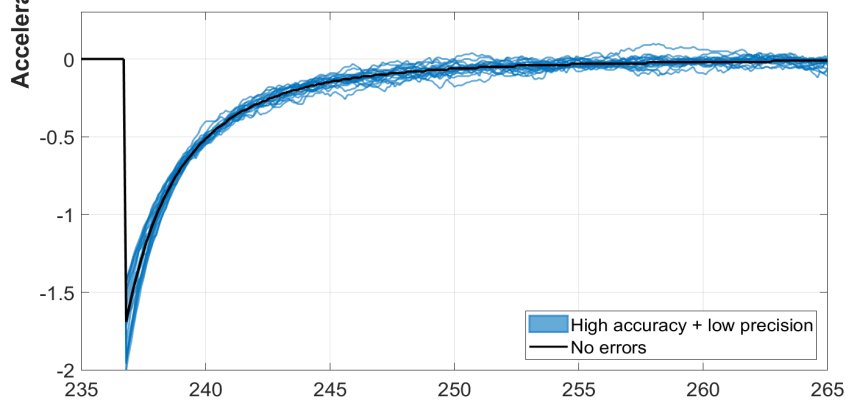
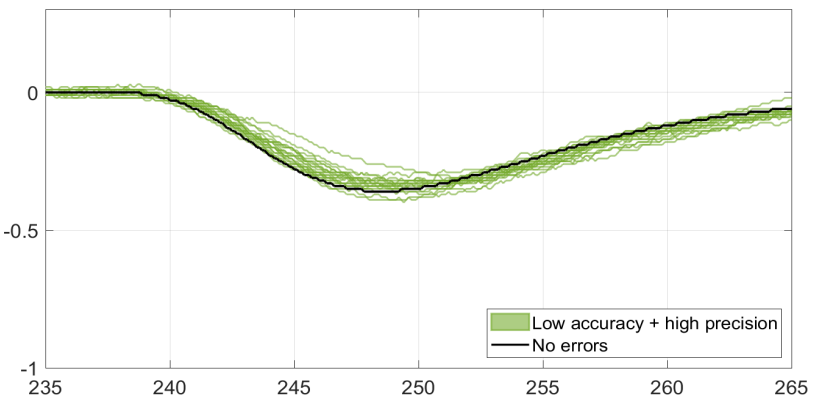
Vehicle 1



Vehicle 3



Vehicle 5



Time [s]

Conclusions and future work

- Conclusions
 - Results show that perception errors affect the acceleration response and thereby the traffic flow dynamics.
 - Improved transparency for microscopic traffic simulation.
 - Enable explicit assumptions for different types of perception.
 - Improved consistency on the level of detail for different types of perception.
 - Improved modeling of mixed traffic in different driving conditions.
- Future work
 - Implement perception errors for other submodels.
 - Evaluate perception errors in a realistic simulation experiment.

Thanks for your attention!

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Accuracy (i)

$$f^{\Omega}(d, v) = \boxed{\varepsilon^{\Omega}(d)} + W_{trans} * (\sigma^{\Omega}(d) + \sigma^{\Omega}(v))$$

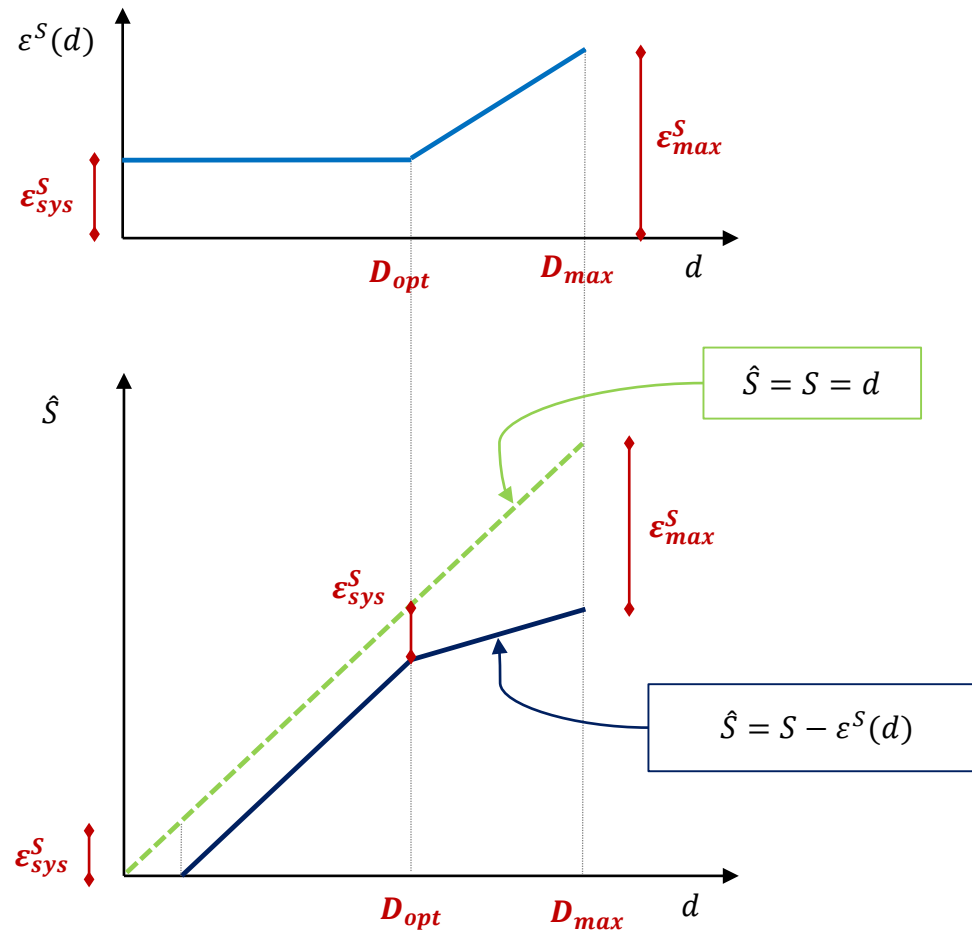
$\varepsilon^{\Omega}(d)$ - Parameters :

$\varepsilon_{sys}^{\Omega}$: Systematic, persistent or minimum error

$\varepsilon_{max}^{\Omega}$: Error at maximum detection range

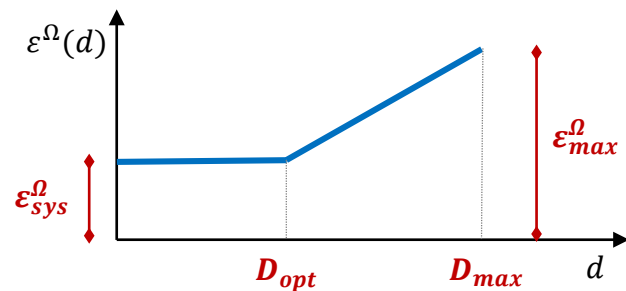
D_{opt} : Optimal operational range

D_{max} : Maximum detection range

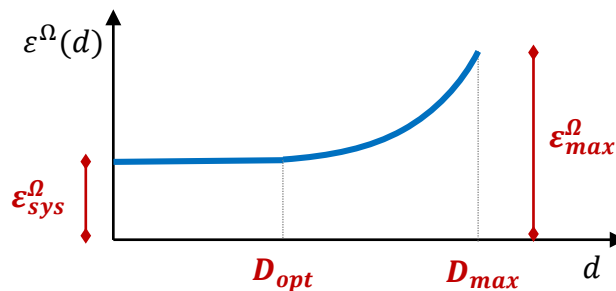


Accuracy (ii)

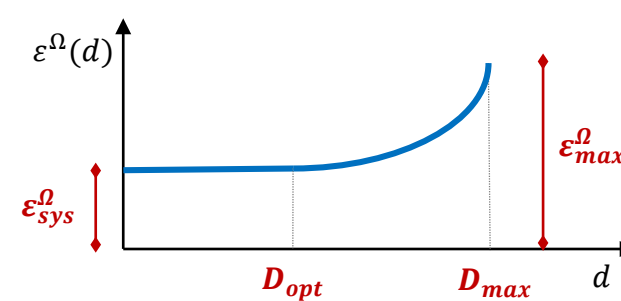
$$f^\Omega(d, v) = \boxed{\varepsilon^\Omega(d)} + W_{trans} * (\sigma^\Omega(d) + \sigma^\Omega(v))$$



linear



quadratic



ellipse

Precision (i)

$$f^{\Omega}(d, v) = \varepsilon^{\Omega}(d) + W_{trans} * (\sigma^{\Omega}(d) + \sigma^{\Omega}(v))$$

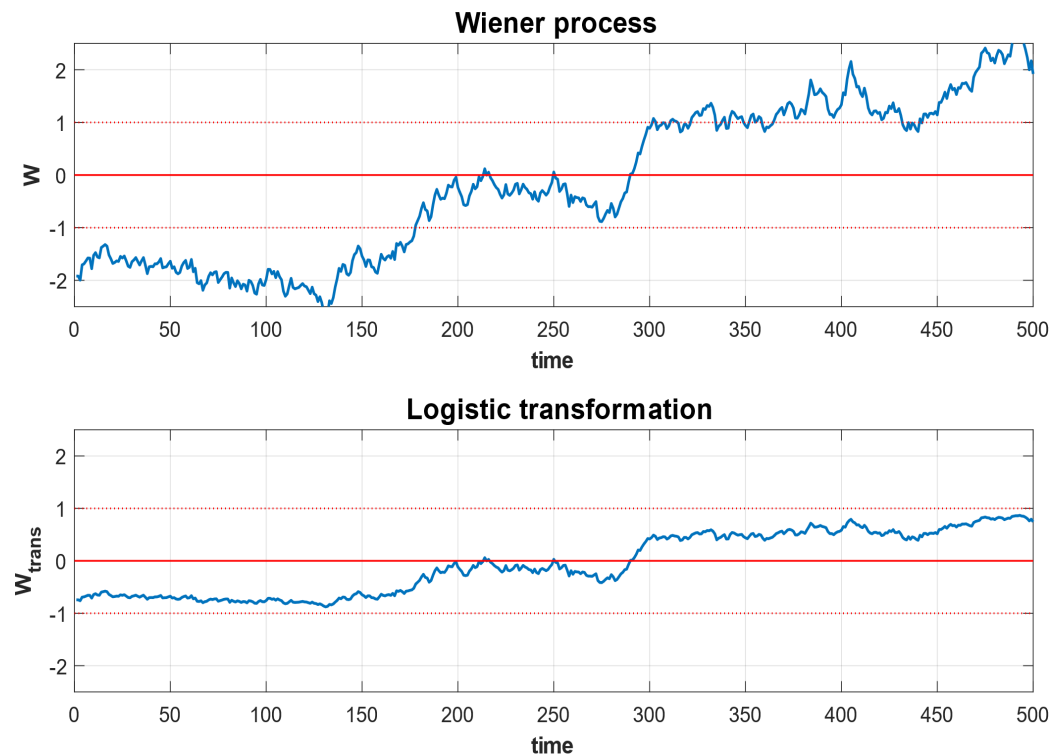
$$W_{trans} \in [-1, 1]$$

$$W_{trans} = \frac{2}{1 + \exp(-W)} - 1$$

$$W(t + \Delta t) = \begin{cases} \eta, & \text{initial} \\ \exp\left(-\frac{\Delta t}{\tau}\right) * W(t) + \eta \sqrt{\frac{2\Delta t}{\tau}}, & \text{otherwise} \end{cases}$$

$$\eta \in N(0,1)$$

τ : Time-window correlation



Precision (ii)

$$f^{\Omega}(d, v) = \varepsilon^{\Omega}(d) + W_{trans} * (\sigma^{\Omega}(d) + \sigma^{\Omega}(v))$$

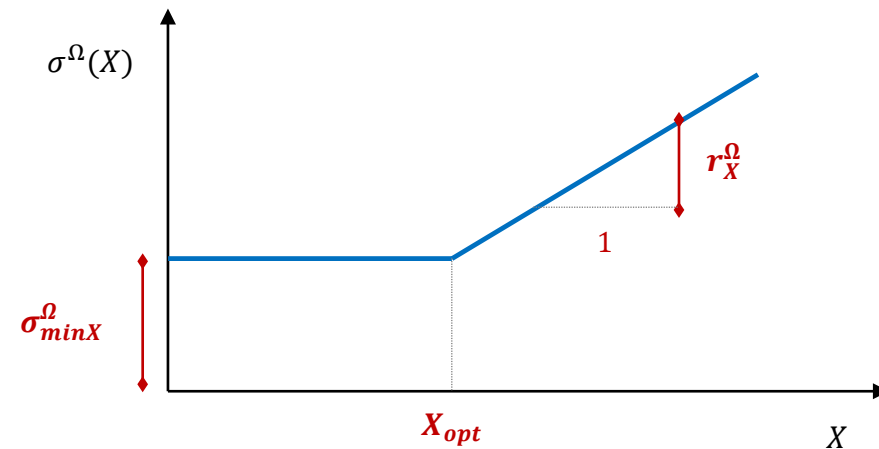
$$X = \{d, v\}$$

$\sigma^{\Omega}(X)$ - Parameters :

σ_{minX}^{Ω} : Minimum variation or noise

r_X^{Ω} : variation increase rate

X_{opt} : Optimal operational range



Accuracy and precision

Parameters :

$\varepsilon_{sys}^{\Omega}$: Systematic, persistent or minimum error

$\varepsilon_{max}^{\Omega}$: Error at maximum detection range

D_{opt} : Optimal operational range

D_{max} : Maximum detection range

σ_{minD}^{Ω} : Minimum distance variation or noise

r_d^{Ω} : Distance variation increase rate

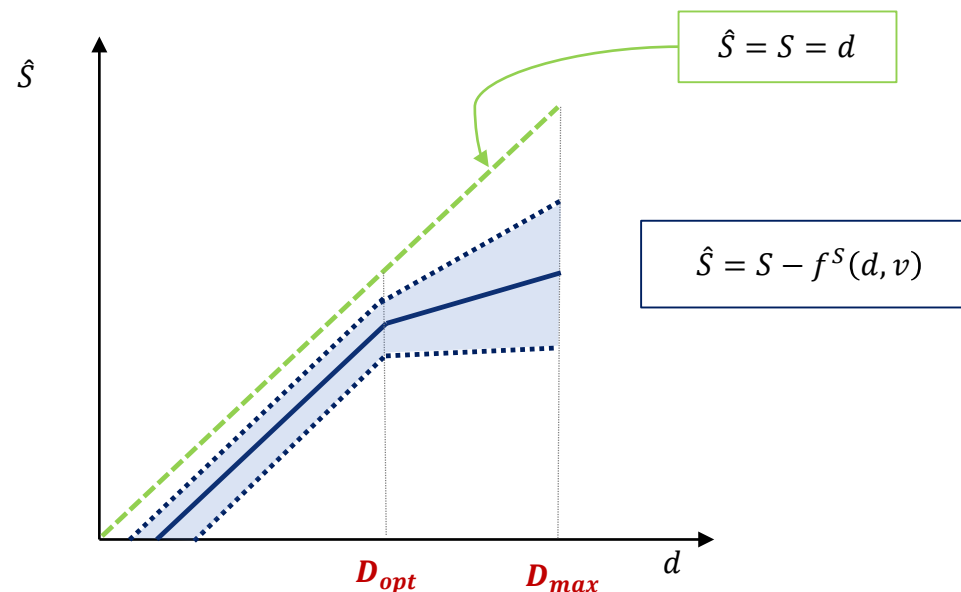
σ_{minV}^{Ω} : Minimum speed variation or noise

r_v^{Ω} : Speed variation increase rate

V_{opt} : Optimal operational speed

τ : Time-window variation correlation

$$f^{\Omega}(d, v) = \varepsilon^{\Omega}(d) + W_{trans} * (\sigma^{\Omega}(d) + \sigma^{\Omega}(v))$$



Intelligent driver model (IDM) sensibility

$$\dot{v} = a \cdot \left(1 - \left(\frac{v}{V_o} \right)^\delta - \left(\frac{S^*}{S} \right)^2 \right)$$

$$S^* = S_o + \max \left\{ \left(0, vT + \frac{v\Delta v}{2\sqrt{ab}} \right) \right\}$$

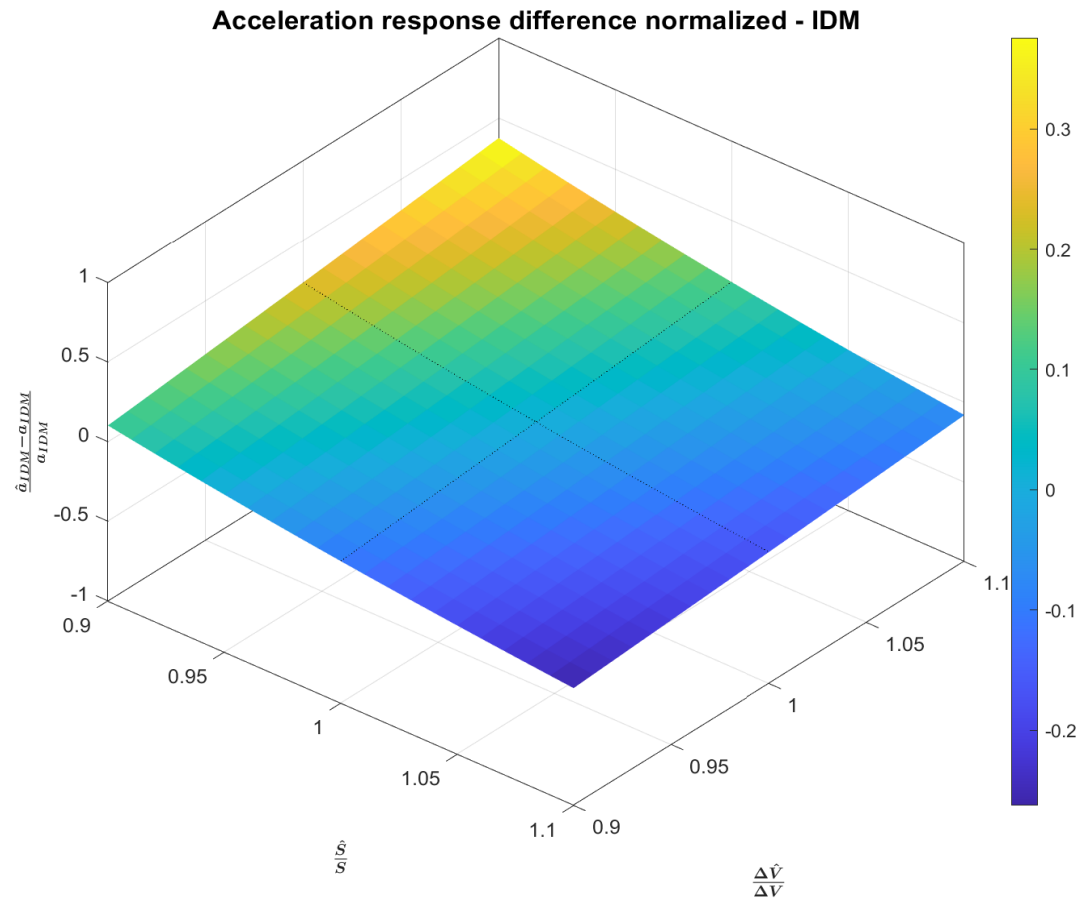
$$a = 1 \text{ m/s}^2$$

$$S = 65 \text{ m}$$

$$v = 25 \text{ m/s}$$

$$V_o = 25 \text{ m/s}$$

$$\Delta V = 5.55 \text{ m/s}$$



Change in fundamental diagram (IDM)

$$V_0 = 19.45 \text{ m/s}$$

$$S = Se(v) = \frac{so + vT}{\sqrt{1 - \left(\frac{v}{v_0}\right)^\delta}}$$

$$\rho = \frac{1}{S}$$

$$Q = \rho * V$$

