Model Predictive Motion Cueing: Online Prediction and Washout Tuning

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Max Planck Institute
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Potential advantages of MPMCA

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- Exploit all Euler equations of motion
- Zero phase distortion filtering (potentially less motion sickness)
- Compensate for simulator vibrations [Kat18]

Model Predictive Control based Motion Cueing

MPC minimizes a cost function over the *prediction horizon* of length N

$$\frac{1}{N}\sum_{k=0}^{N} \underbrace{\|\mathbf{y}(\mathbf{x}_k,\mathbf{u}_k)-\hat{\mathbf{y}}_k\|^2_{W_\mathbf{y}}}_{\substack{\text{input tracking}\\ \text{“inertial signals” term}}} + \underbrace{\|\mathbf{x}_k-\hat{\mathbf{x}}\|^2_{W_\mathbf{x}}}_{\substack{\text{state tracking}\\ \text{“washout” term}}} + \underbrace{\|\mathbf{u}_k\|^2_{W_\mathbf{u}}}_{\substack{\text{input tracking}\\ \text{“aggressiveness” term}}} \tag{1}$$

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such that, for all k:

$$\underline{\mathbf{x}} \le \mathbf{x}_k \le \overline{\mathbf{x}} \tag{2}$$

$$\underline{\mathbf{u}} \le \mathbf{u}_k \le \overline{\mathbf{u}} \tag{3}$$

$$\underline{\ell} \le \ell_k \le \overline{\ell} \tag{4}$$

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Our implementation:

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1. Basics: yaw maneuver smaller than limits.

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2. Limits: yaw maneuver larger than limits.

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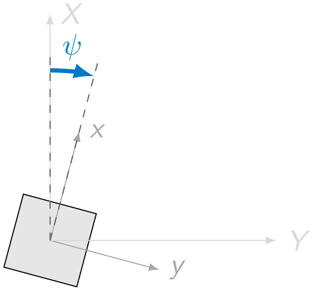
Examples:

1. Basics: yaw maneuver smaller than limits.
2. Limits: yaw maneuver larger than limits.
3. Optimization: yaw maneuver for different weights.
4. Synthetic car turn involving multiple DOF on hexapod motion system with non-linear constraints.

Example 1: yaw maneuver smaller than limits



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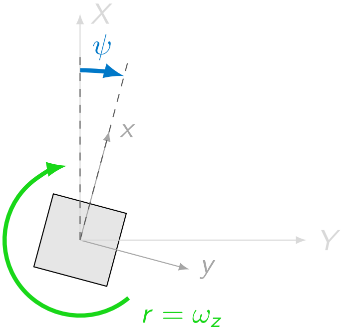

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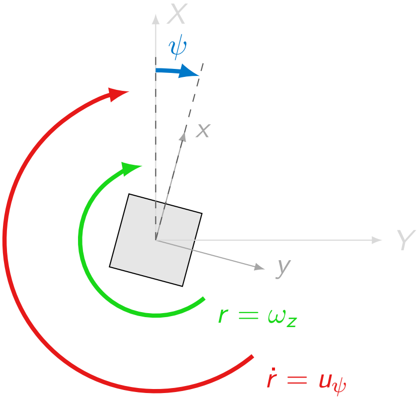

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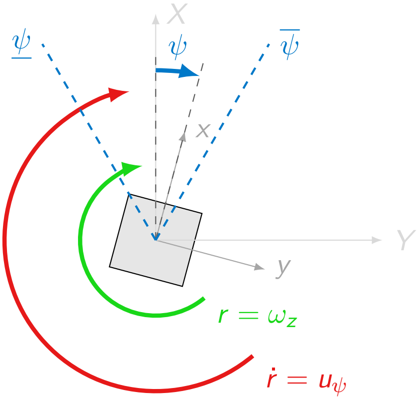

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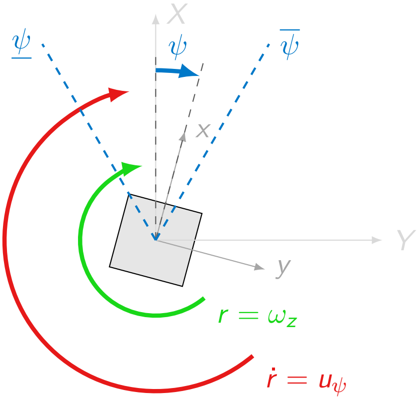

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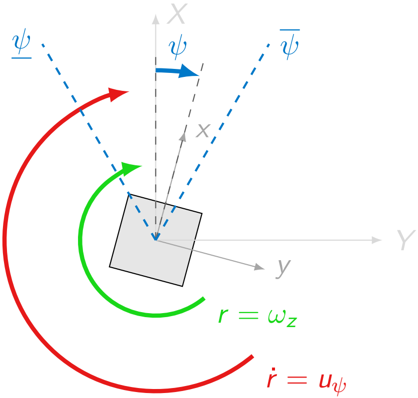

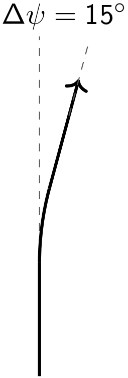

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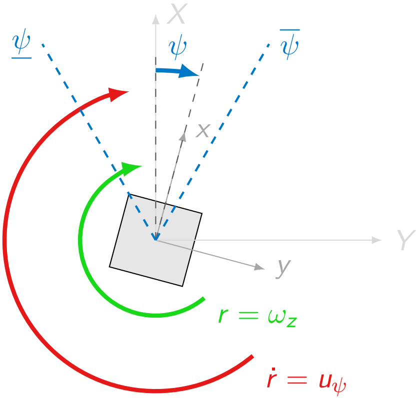

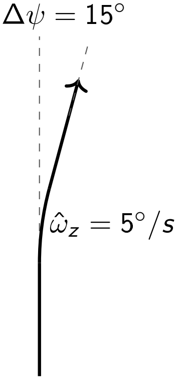

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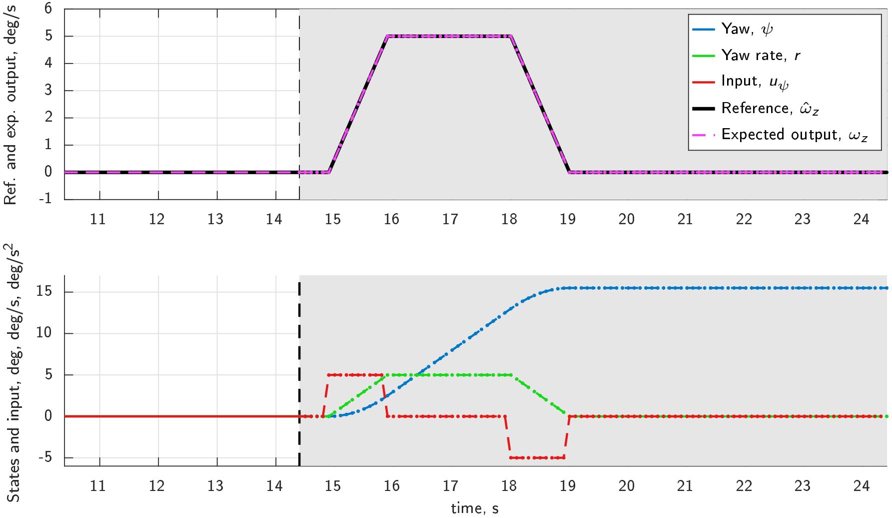

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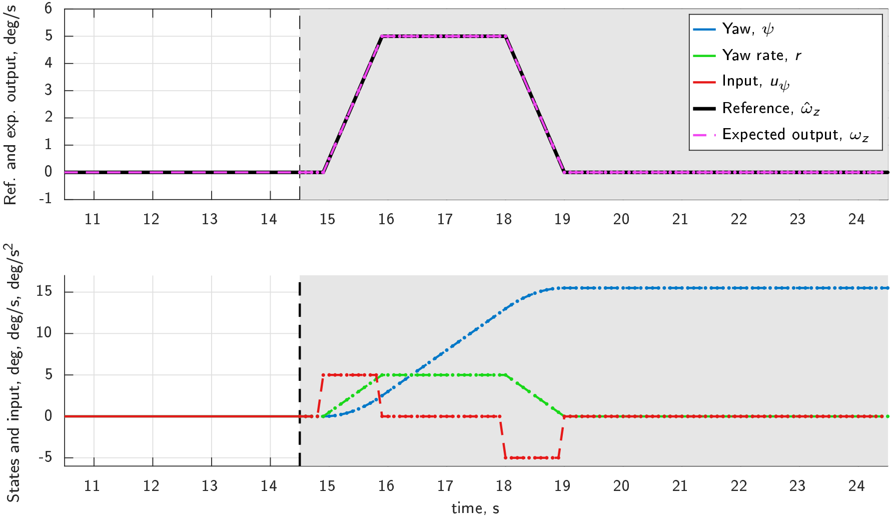

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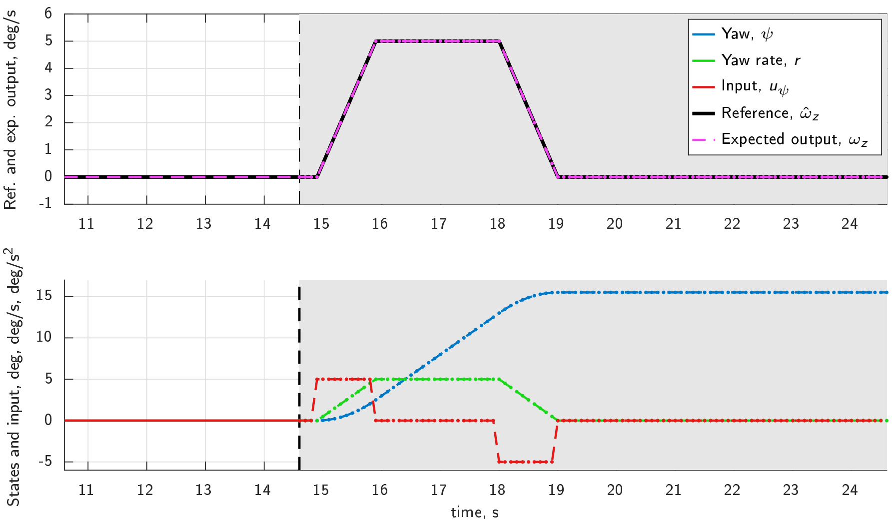

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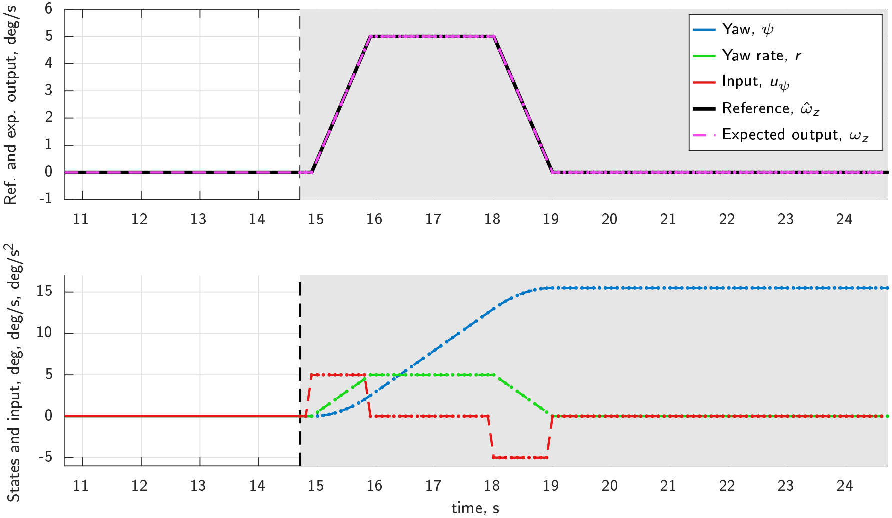

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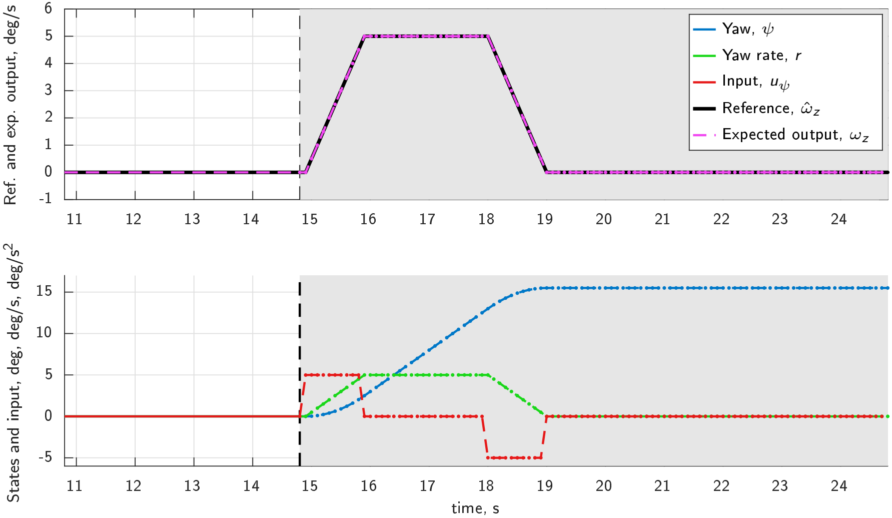

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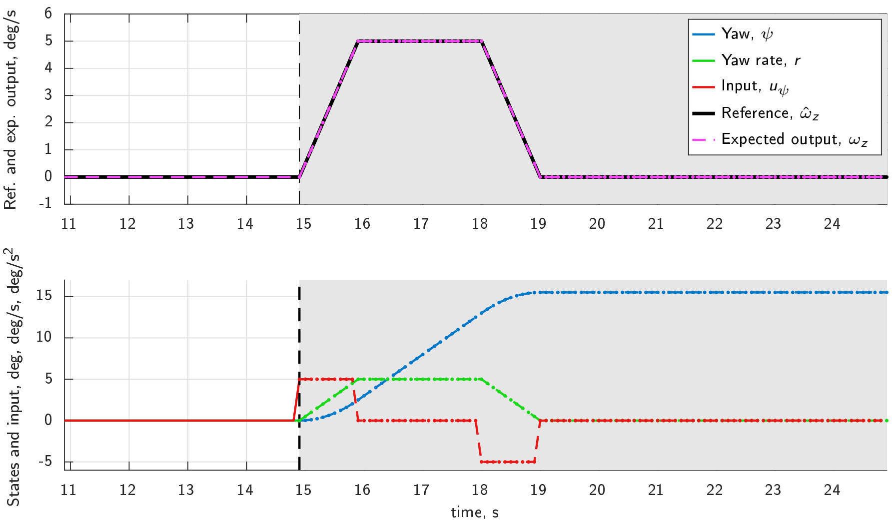

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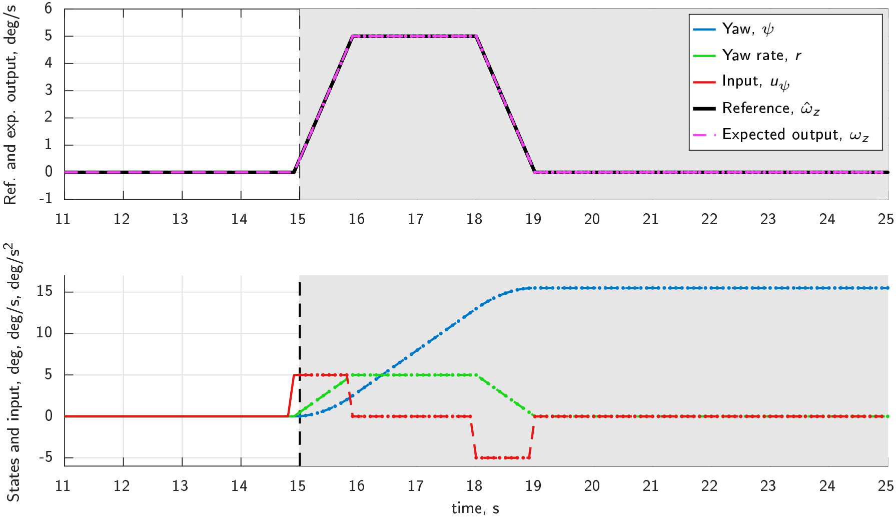

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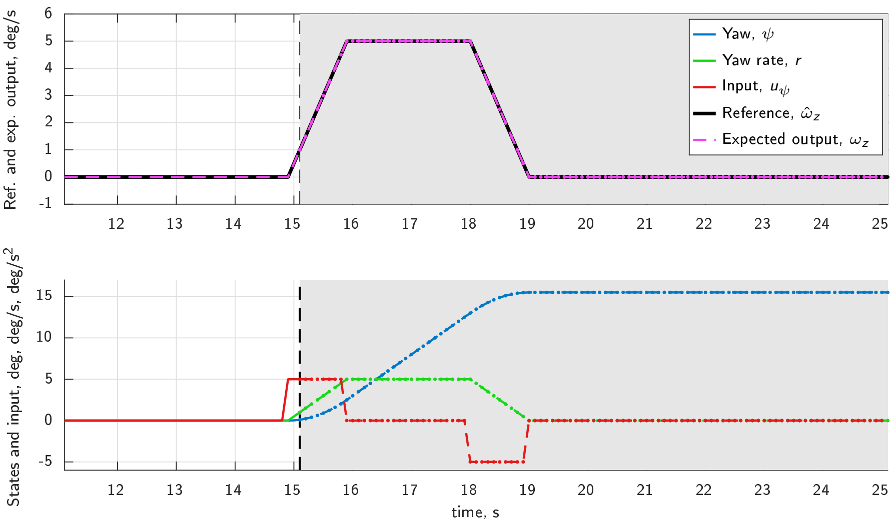

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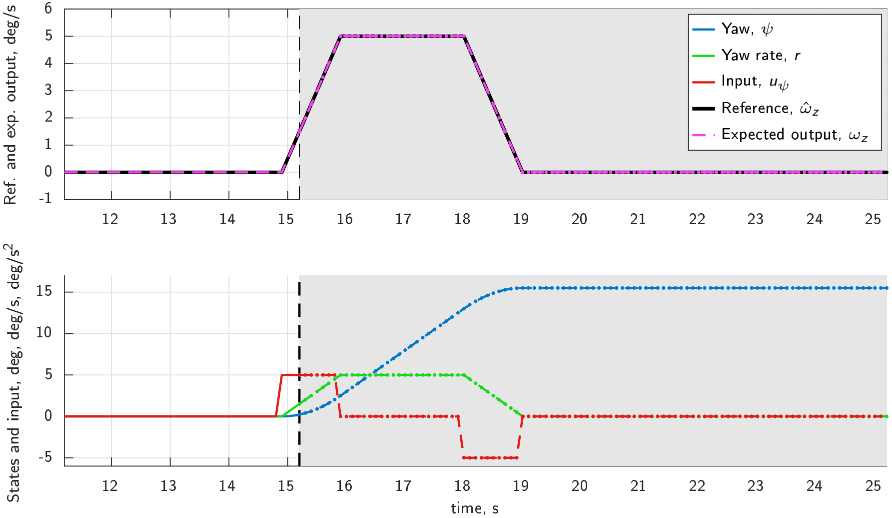

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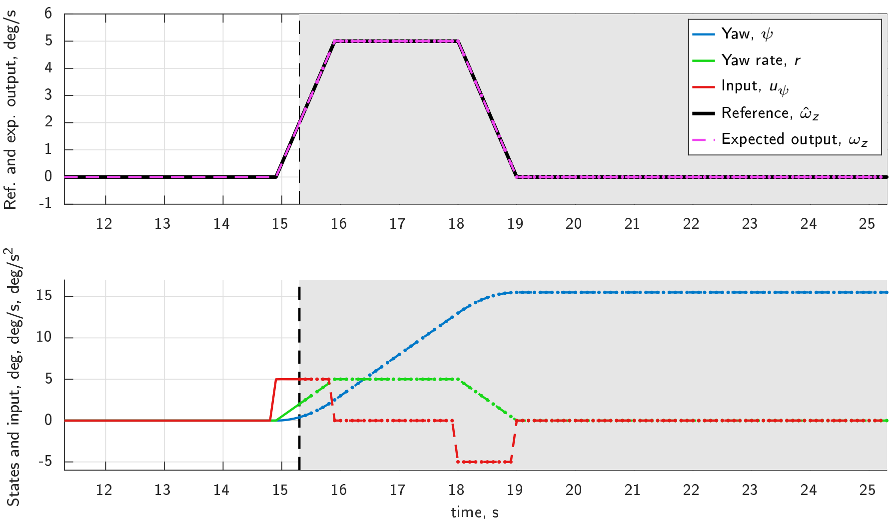

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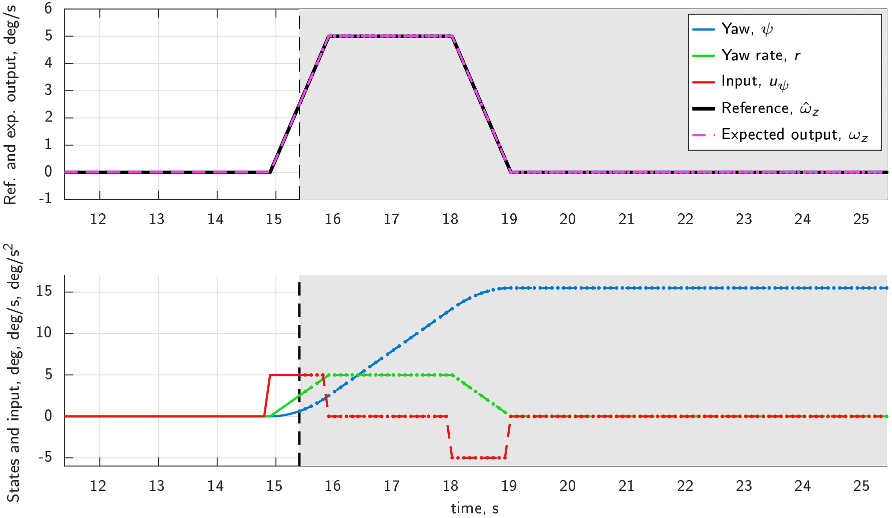

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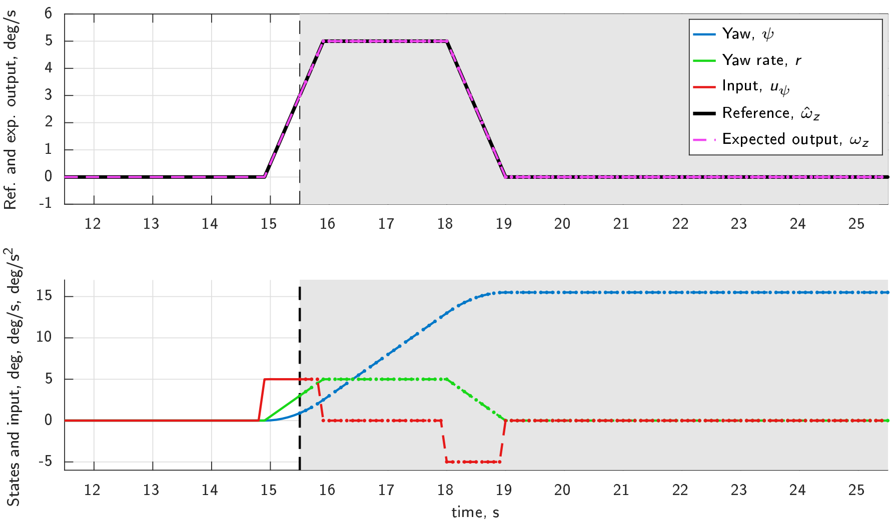

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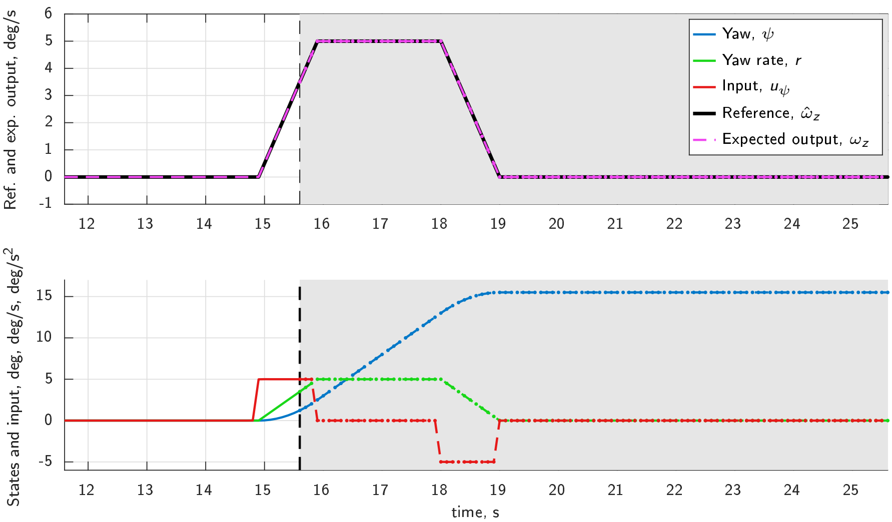

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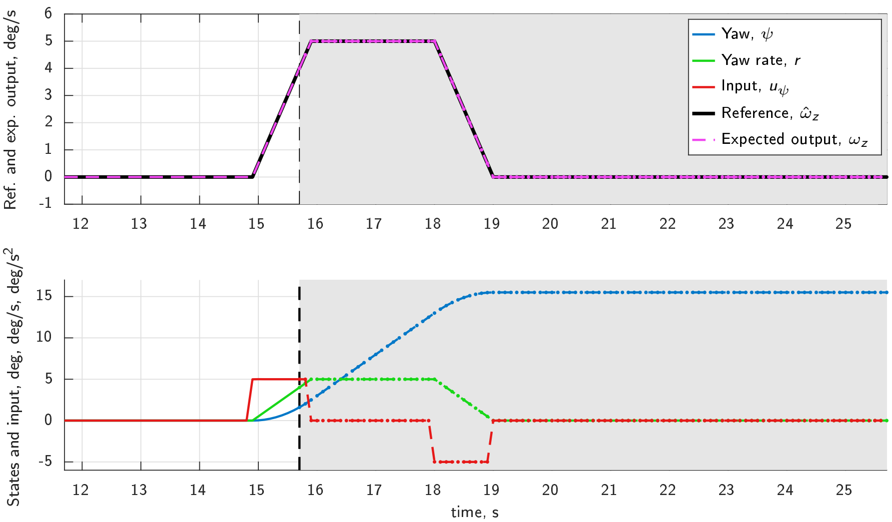

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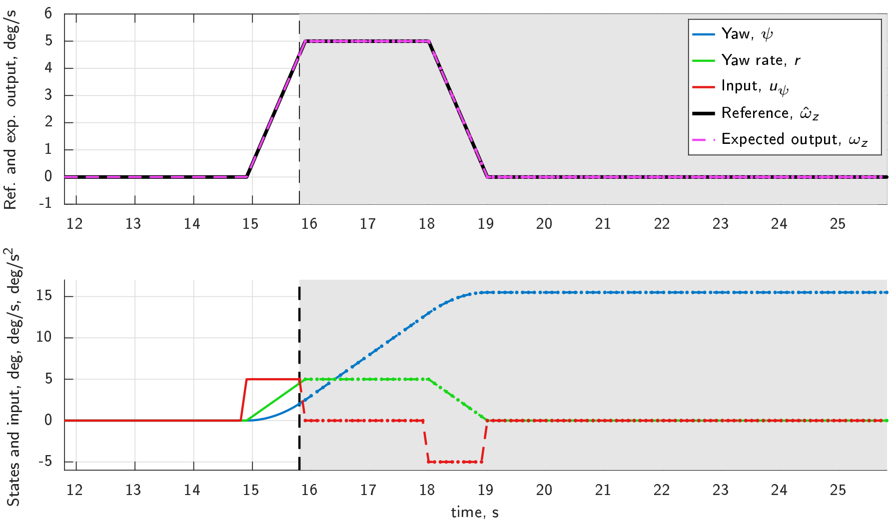

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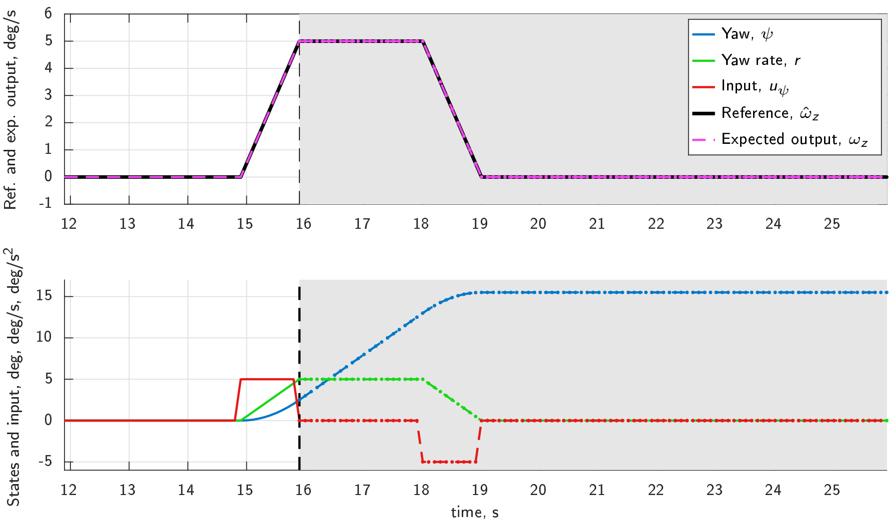

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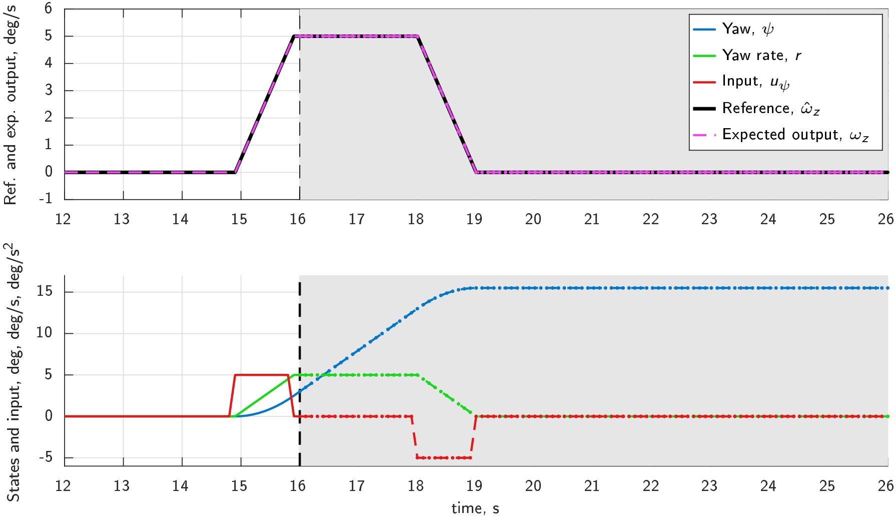

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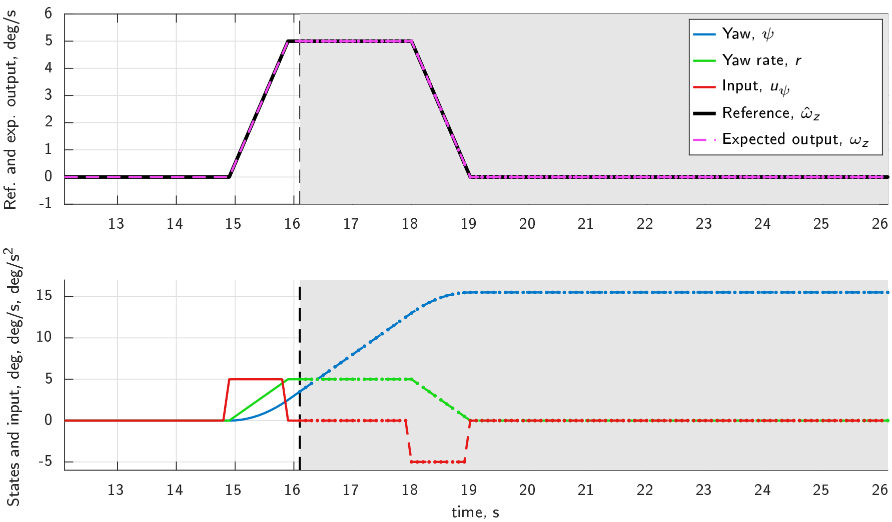

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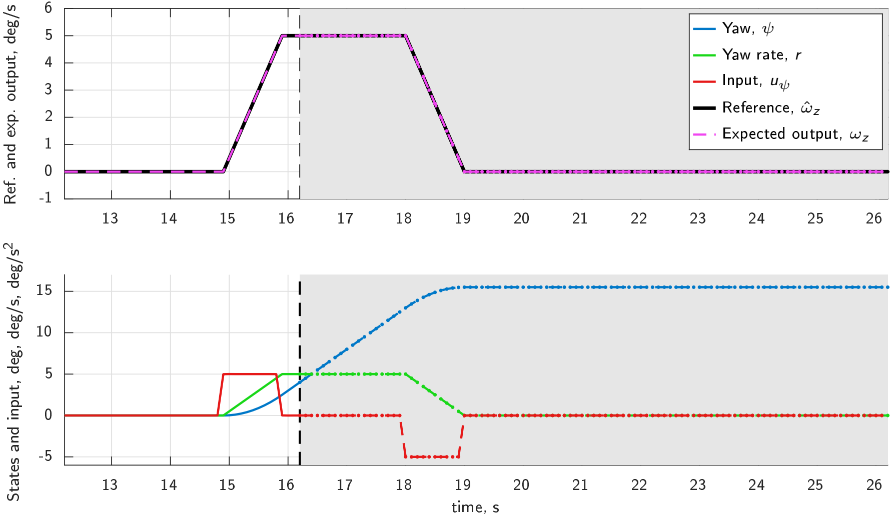

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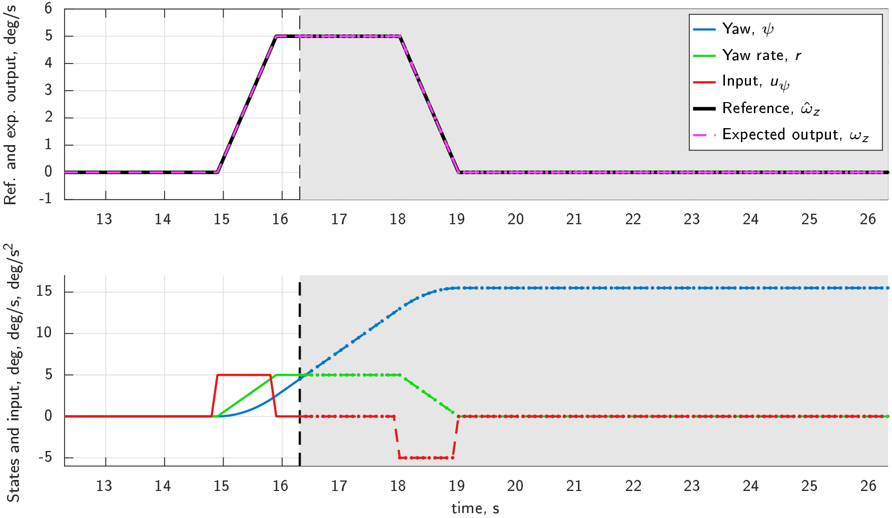

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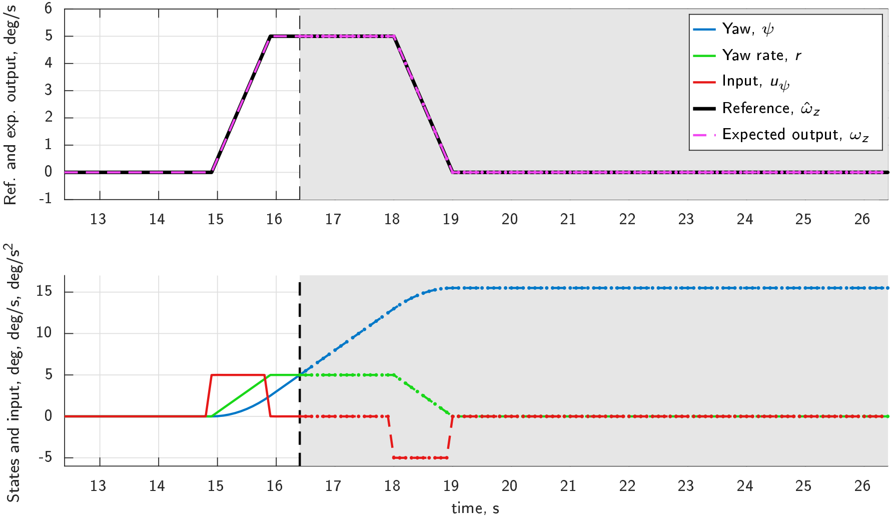

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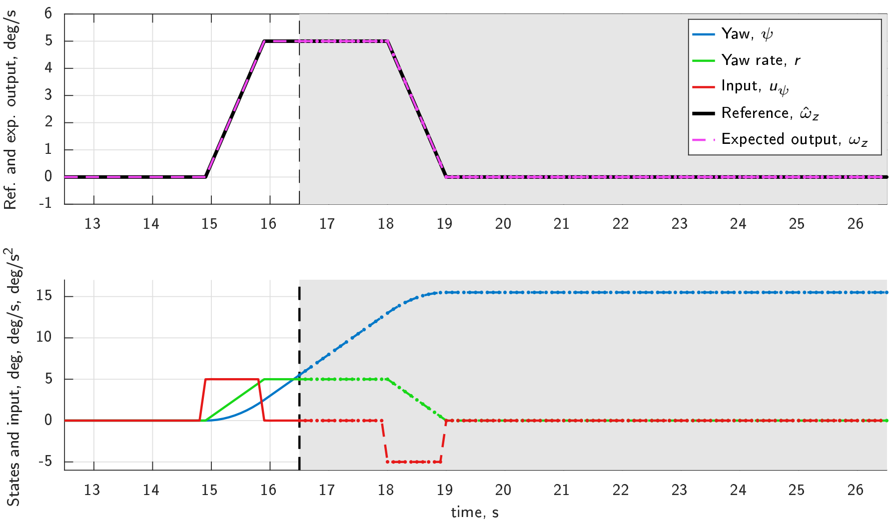

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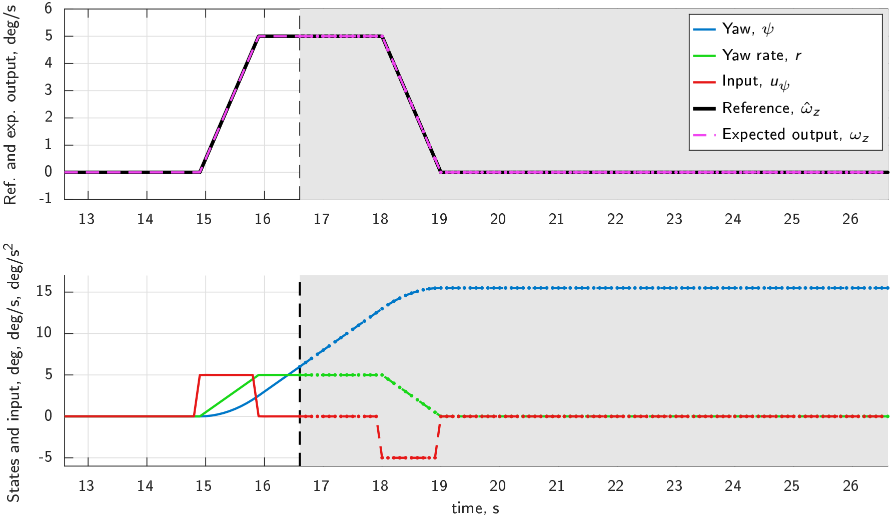

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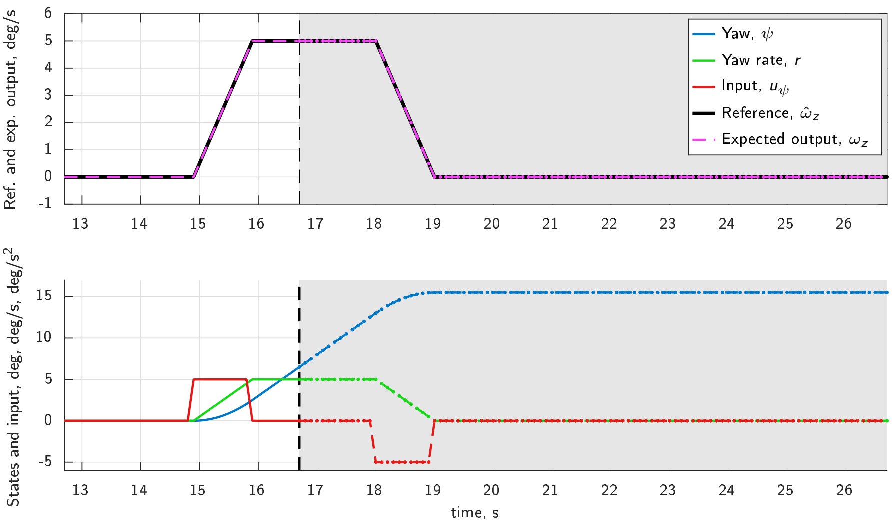

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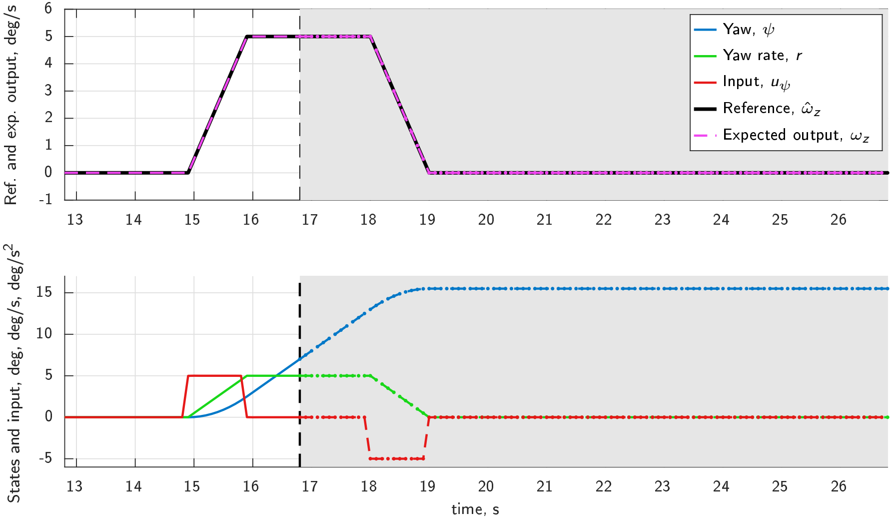

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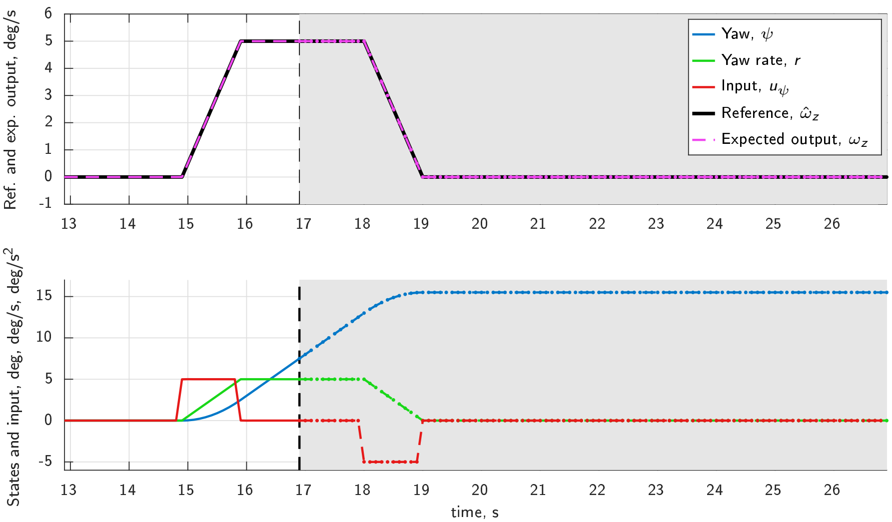

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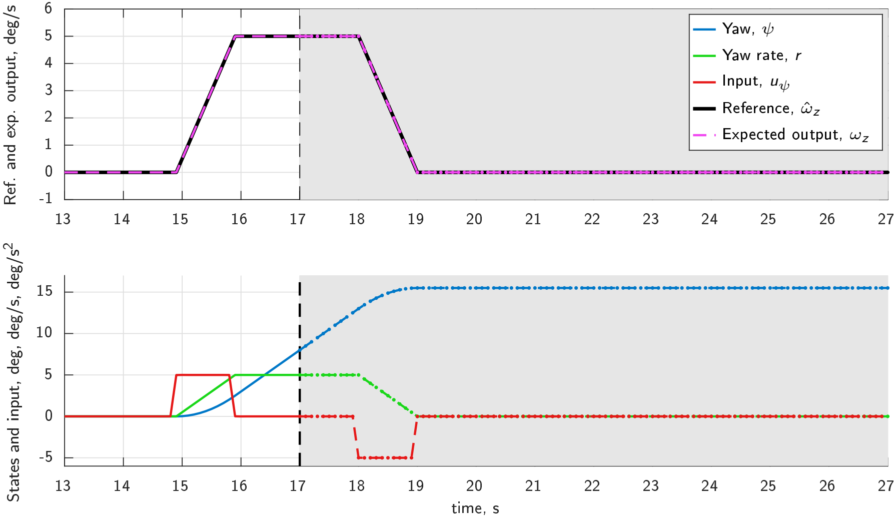

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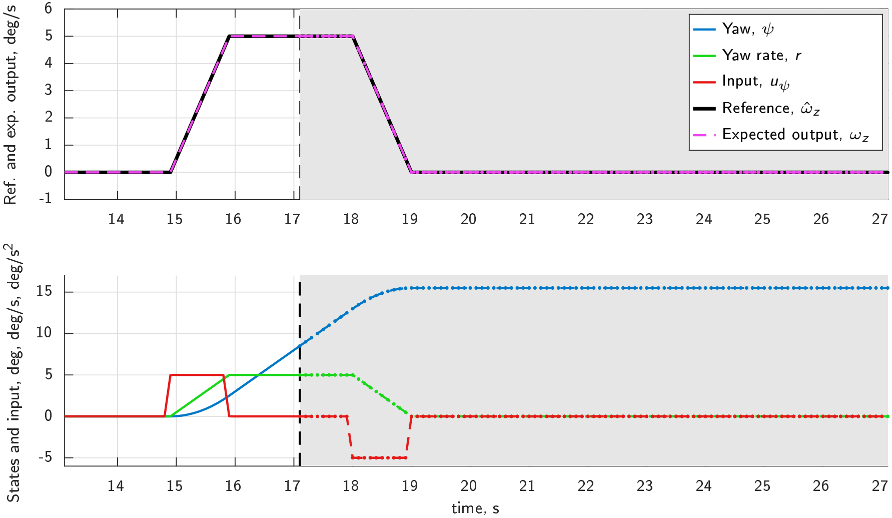

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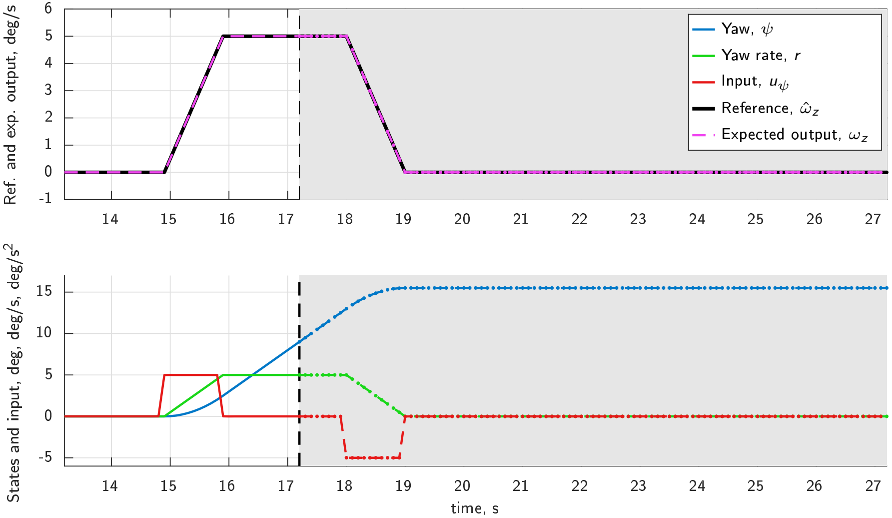

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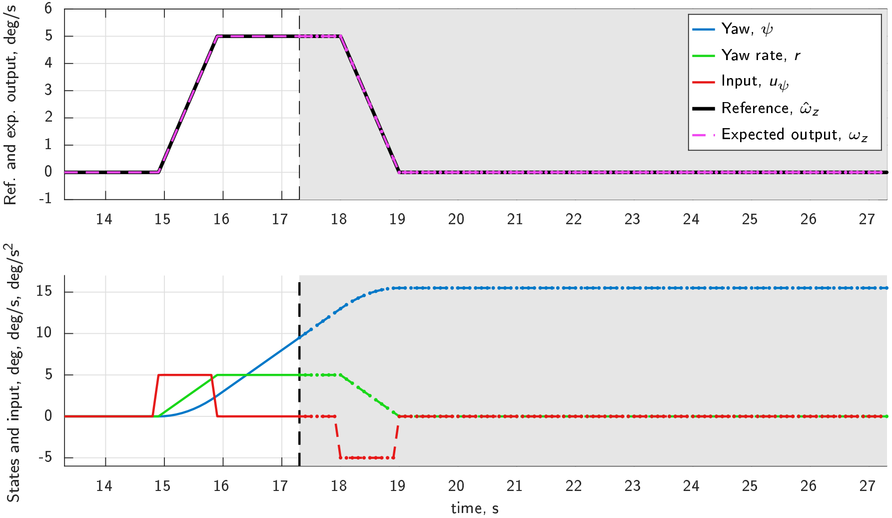

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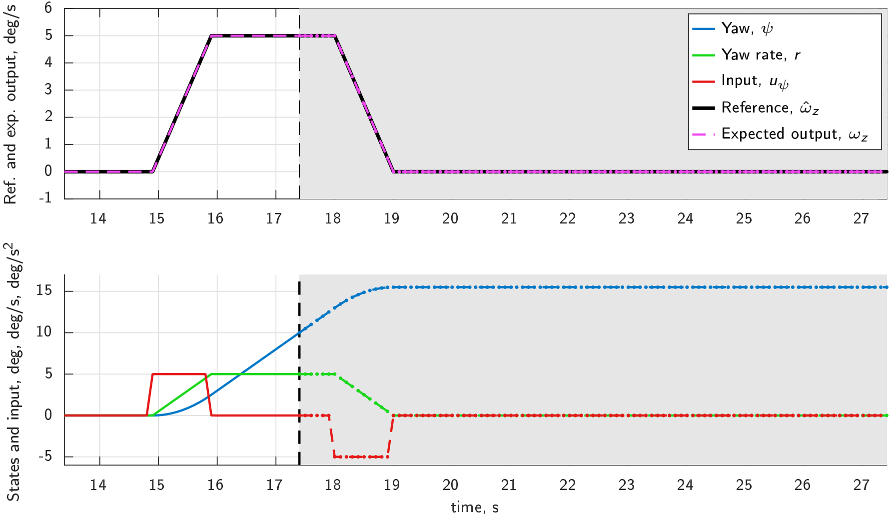

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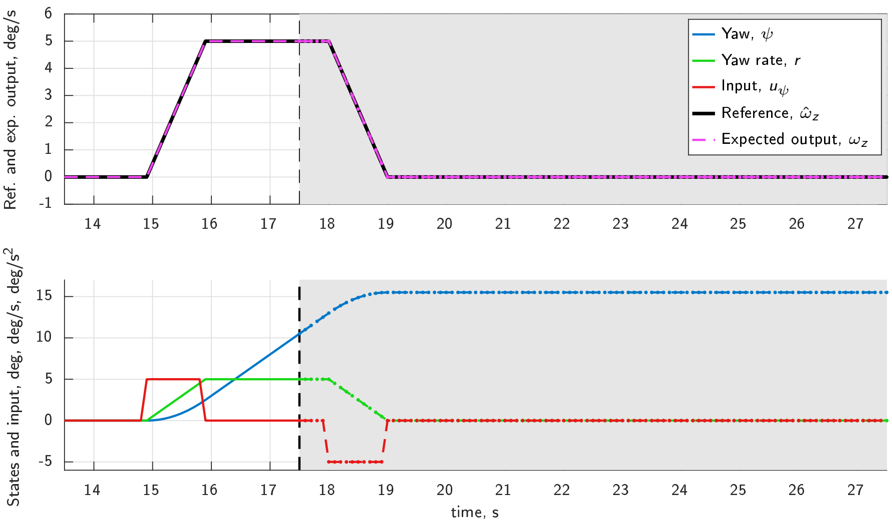

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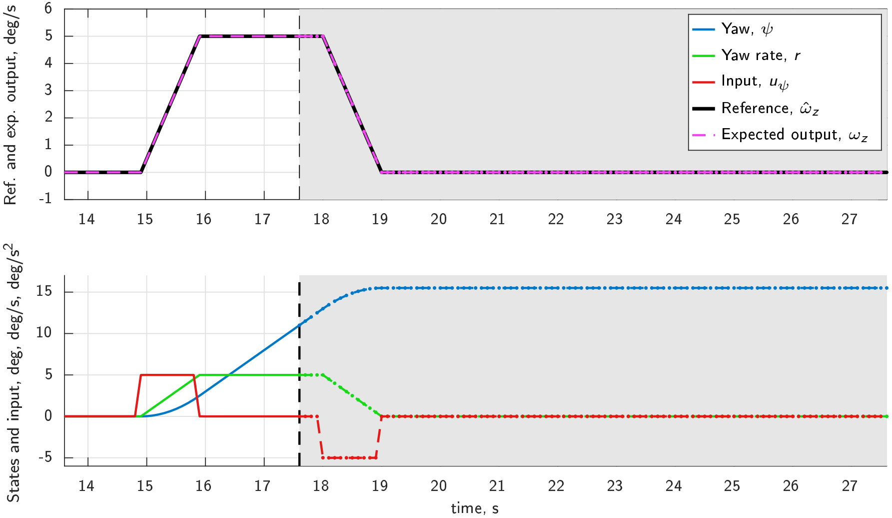

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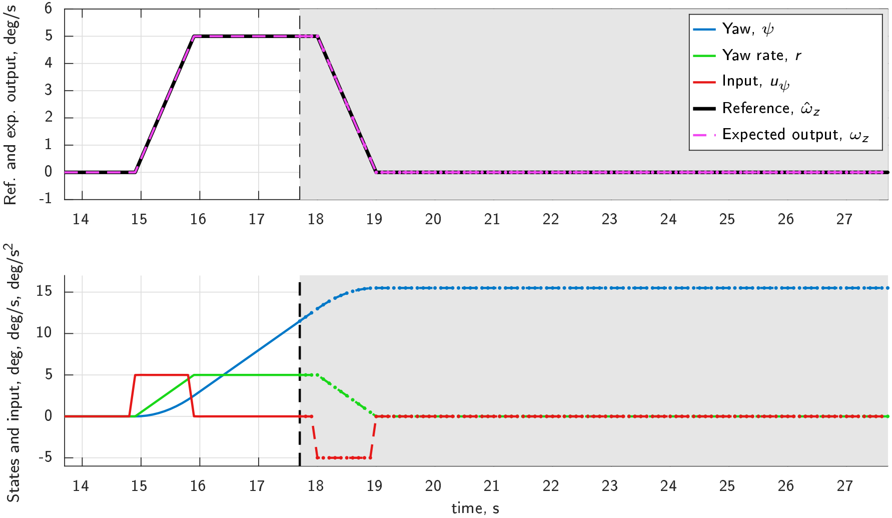

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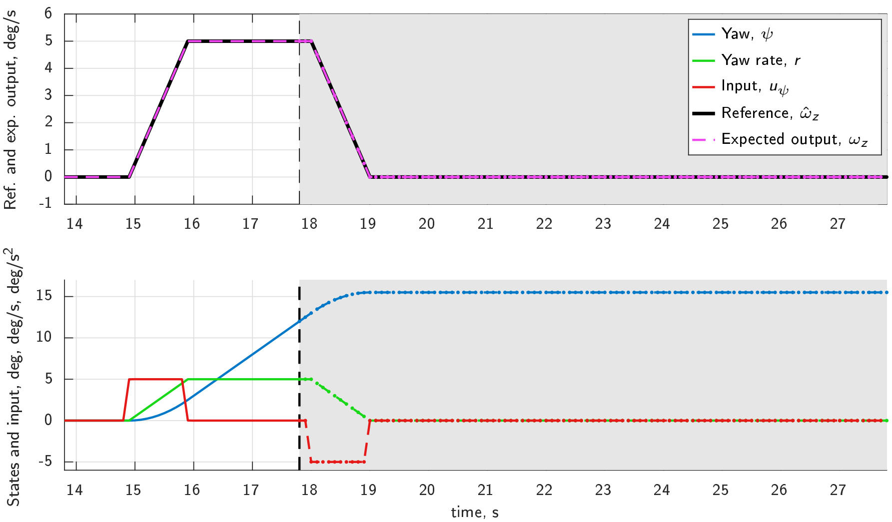

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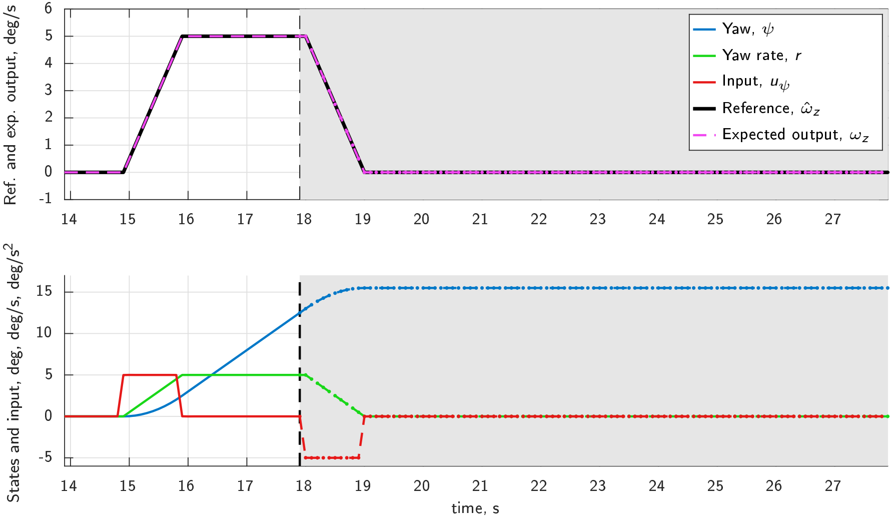

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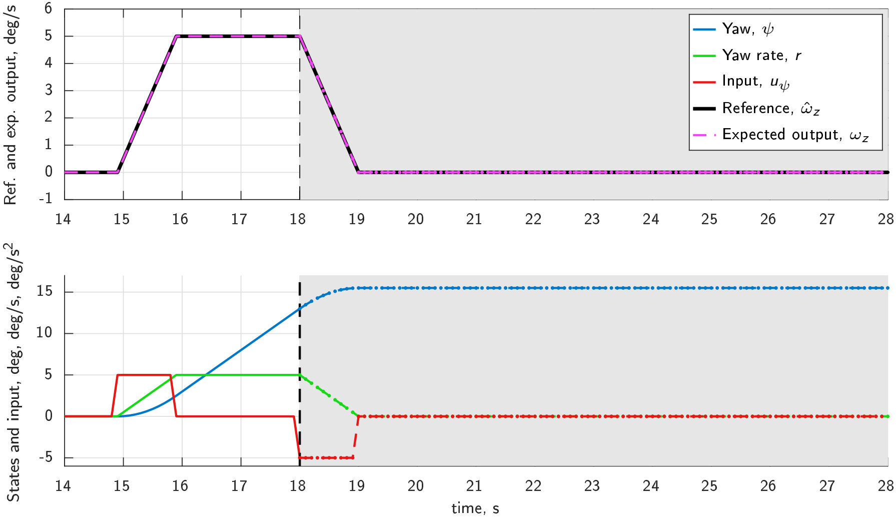

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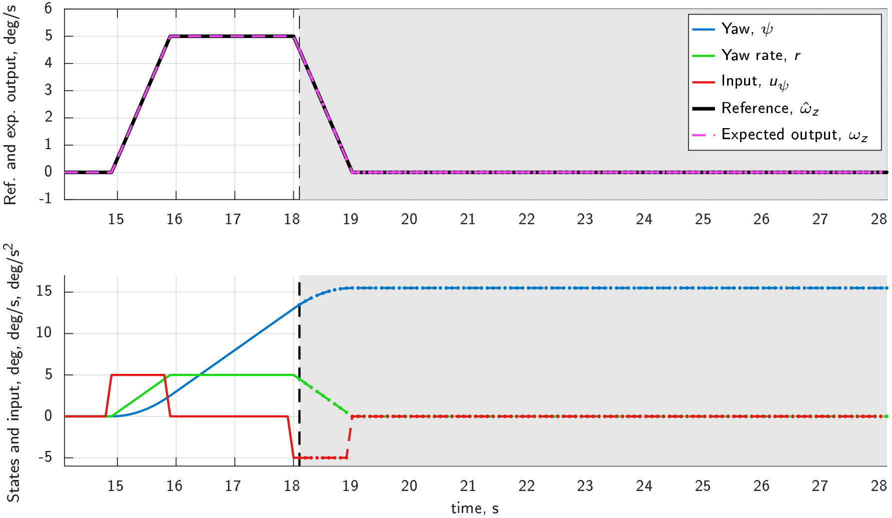

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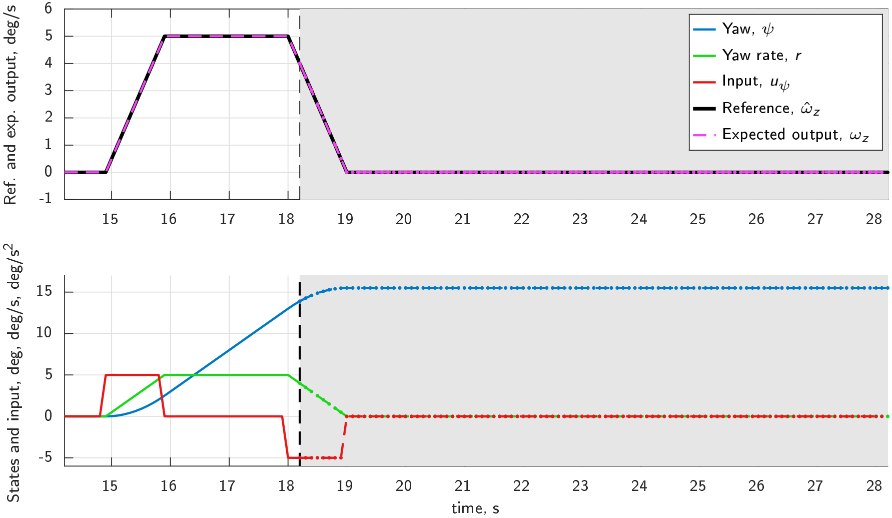

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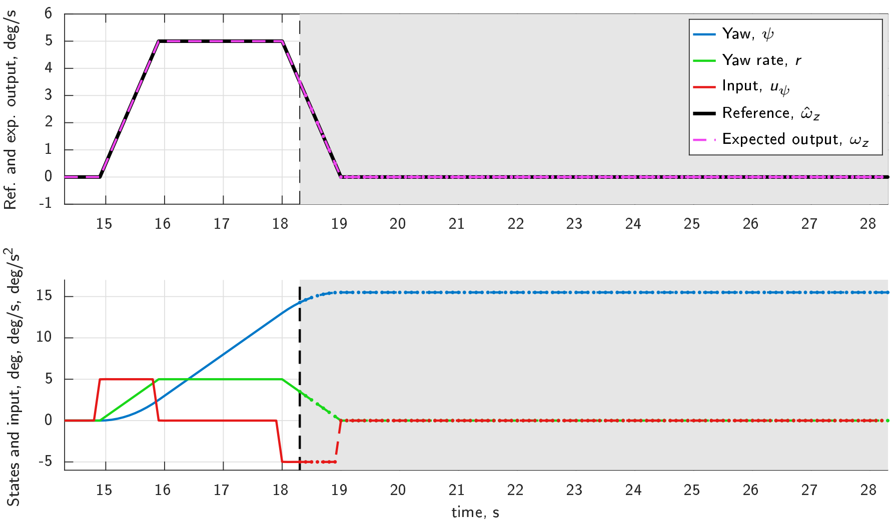

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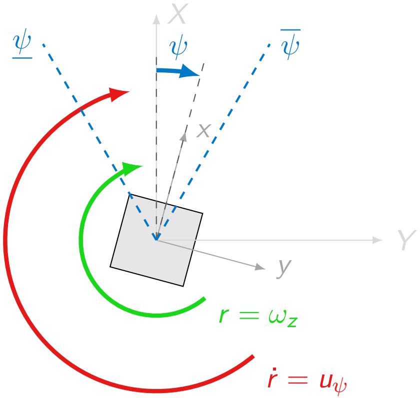

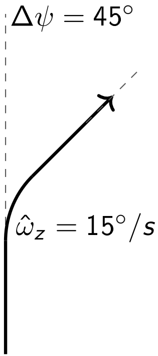

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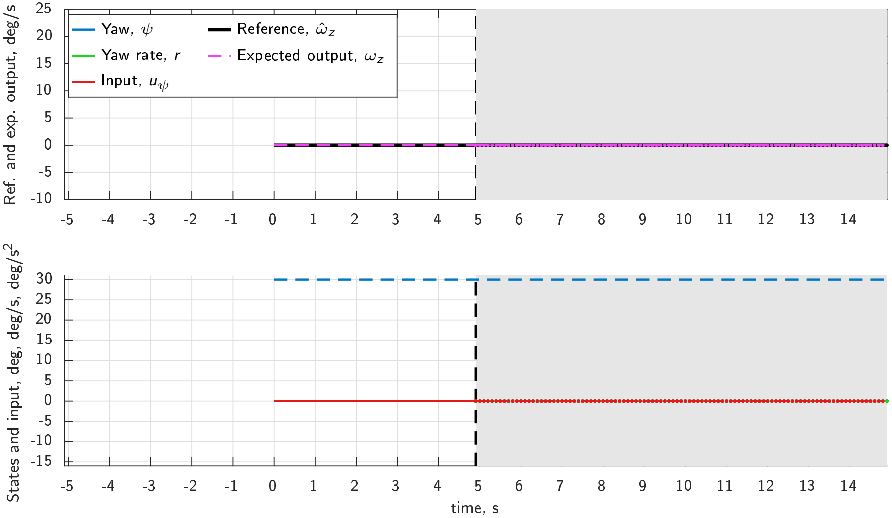

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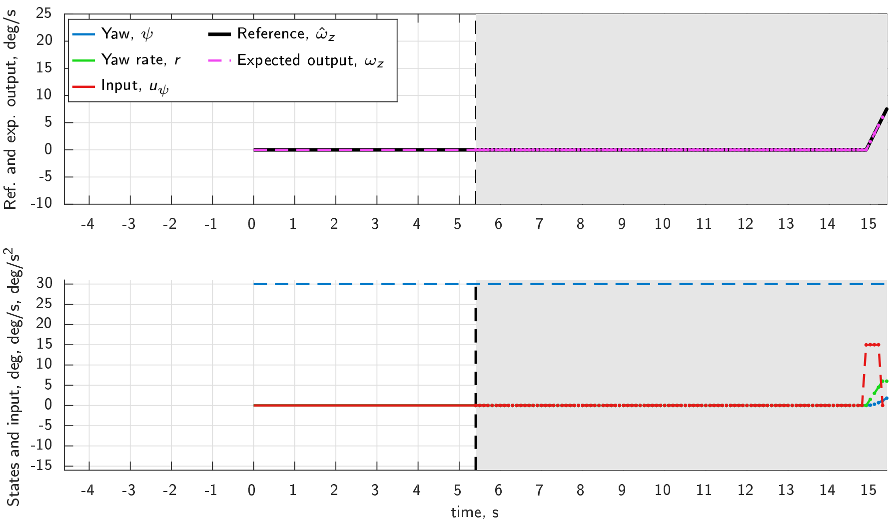

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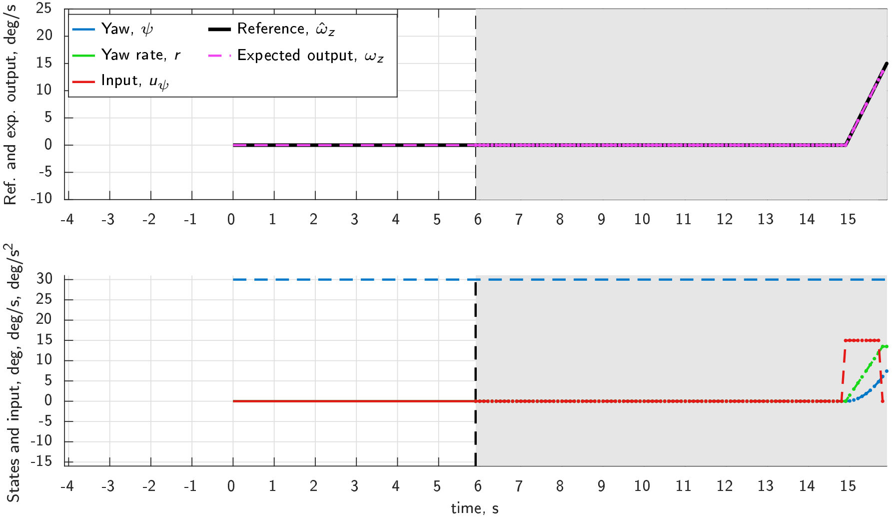

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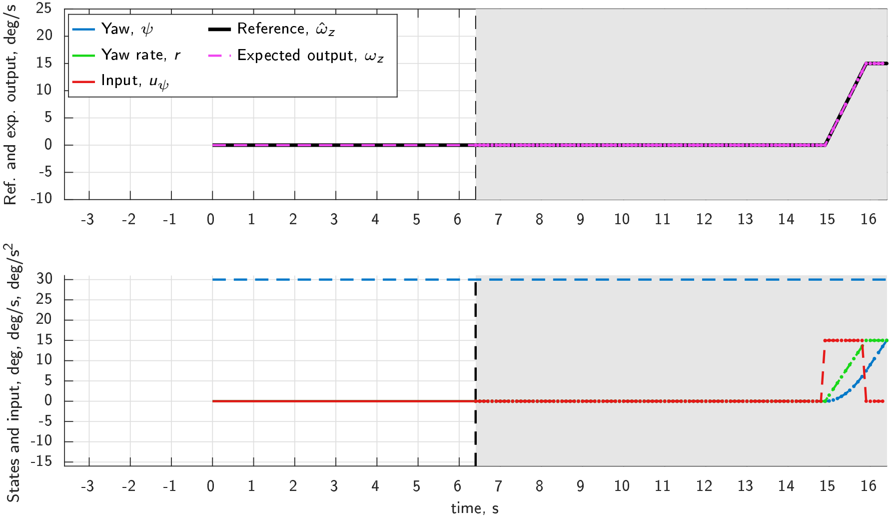

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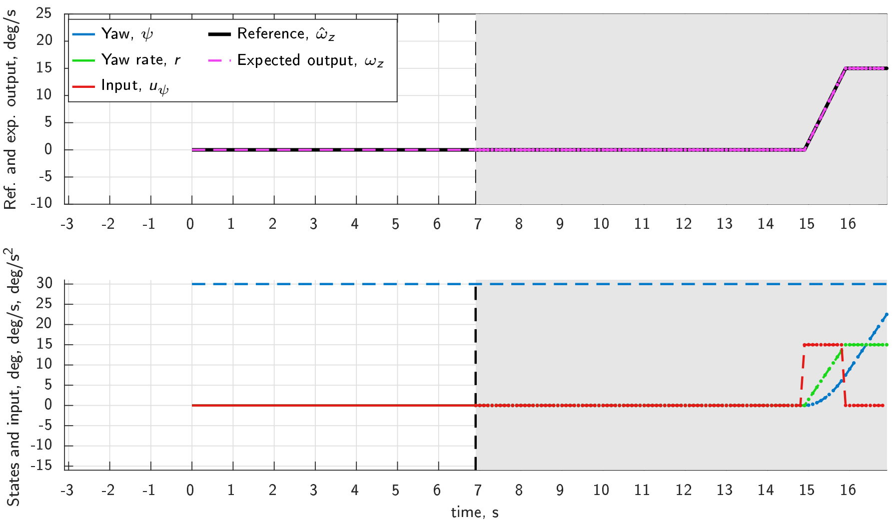

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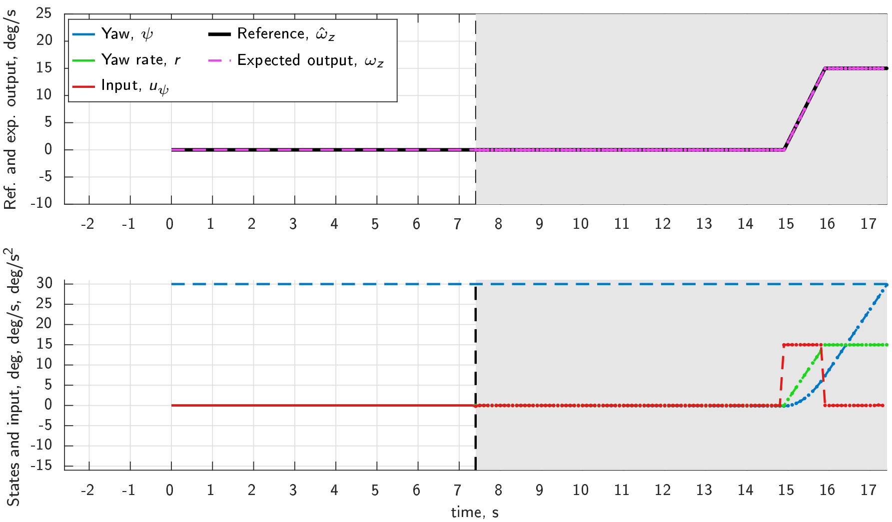

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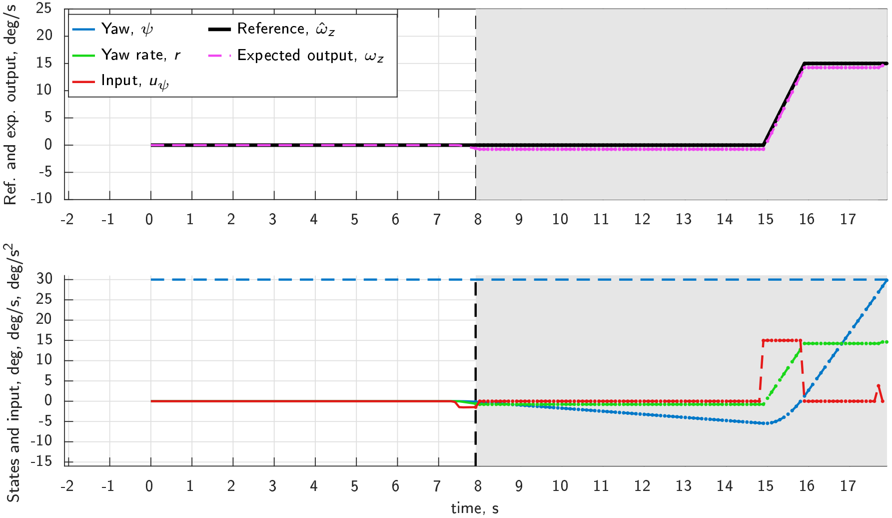
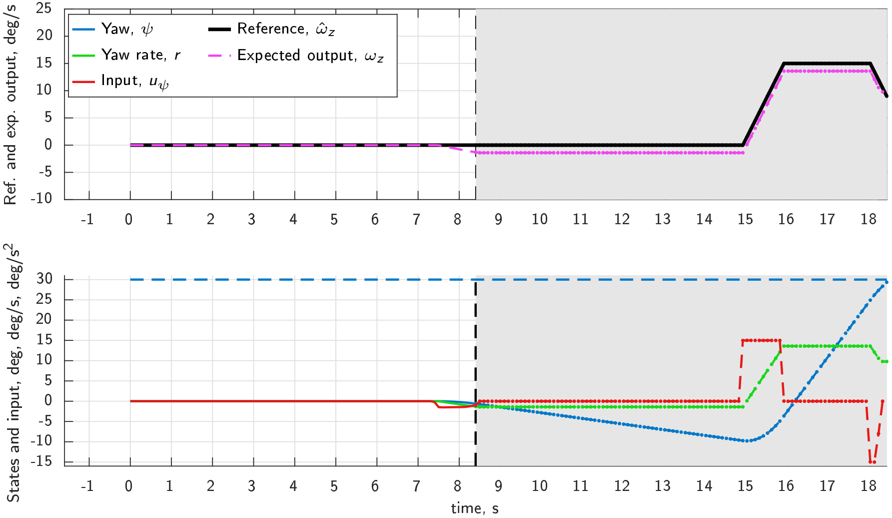
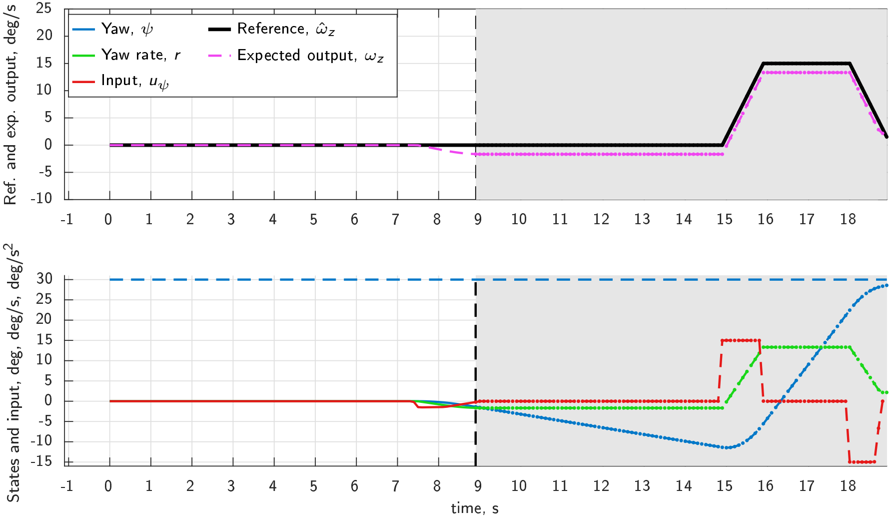


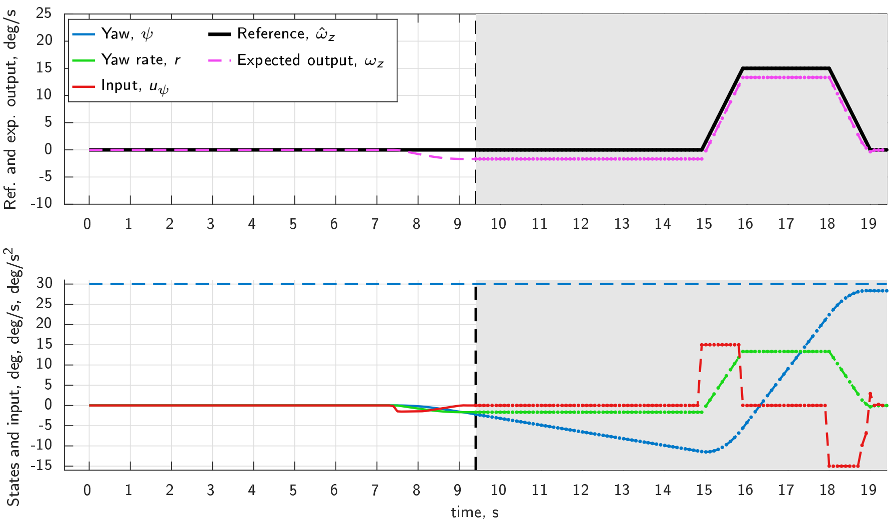
Example 2: yaw maneuver larger than limits



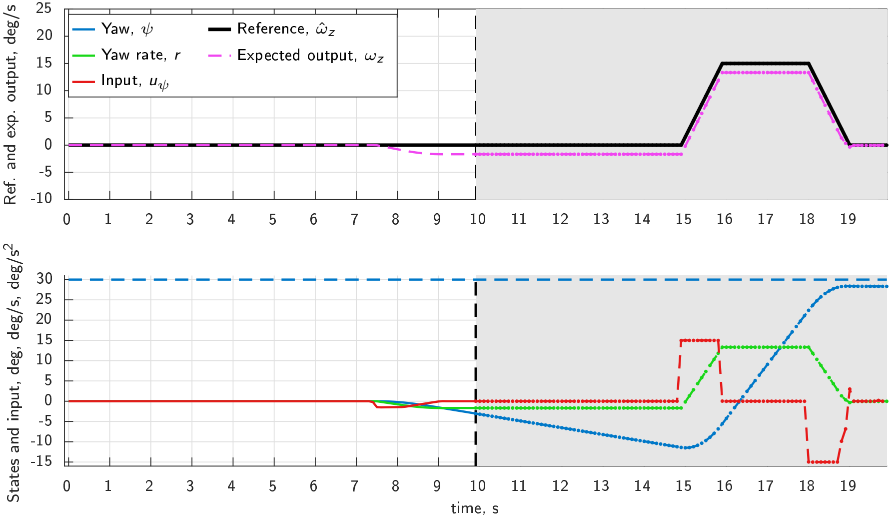
Example 2: yaw maneuver larger than limits



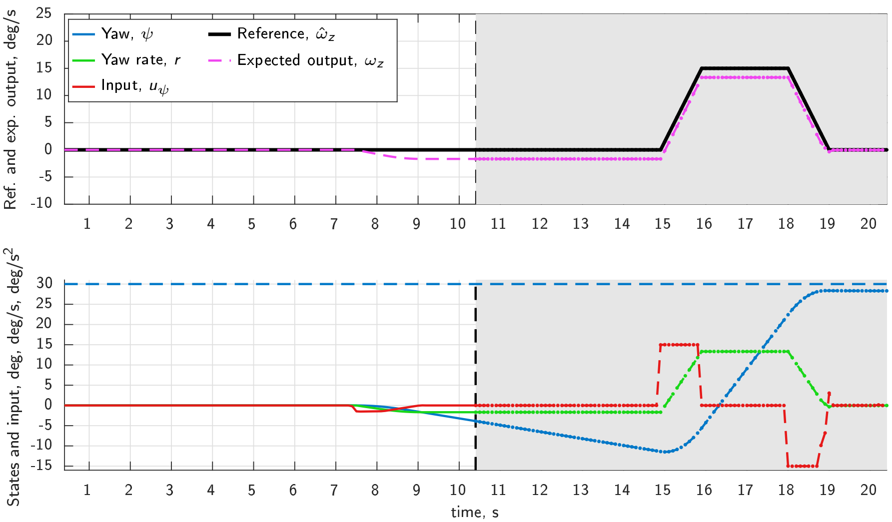
Example 2: yaw maneuver larger than limits



Example 2: yaw maneuver larger than limits



Example 2: yaw maneuver larger than limits



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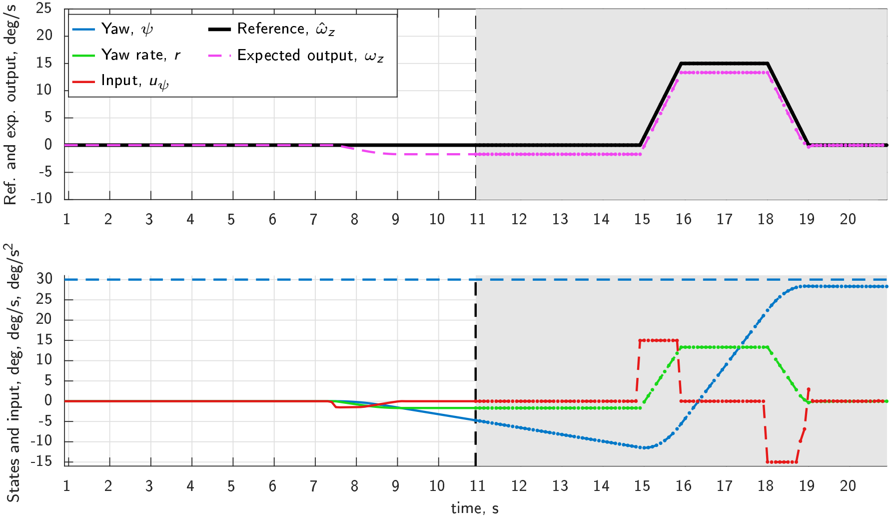

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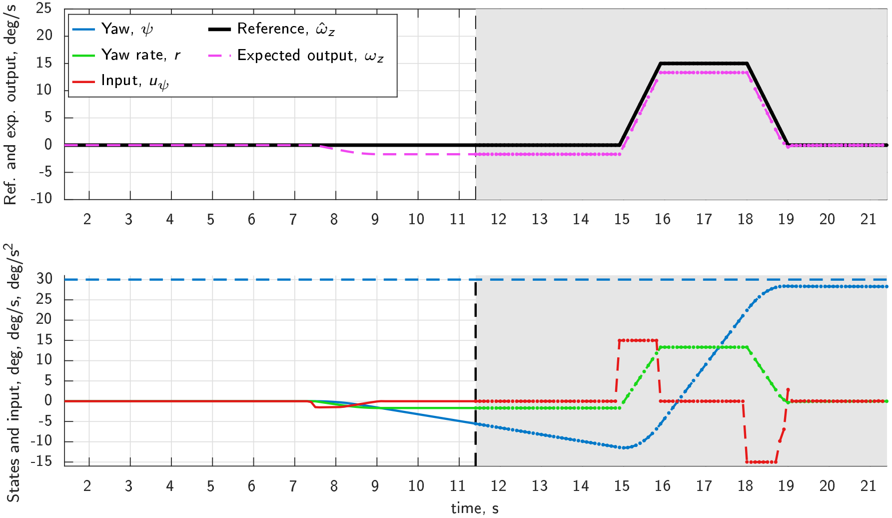
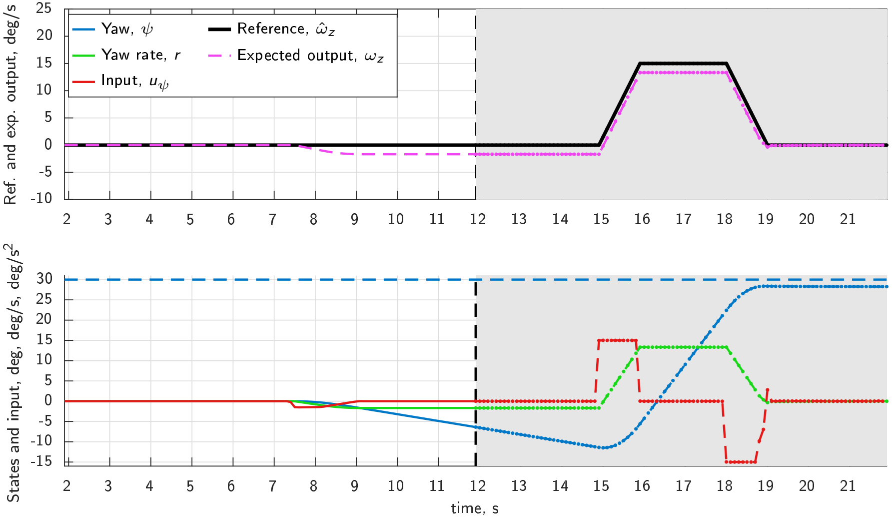
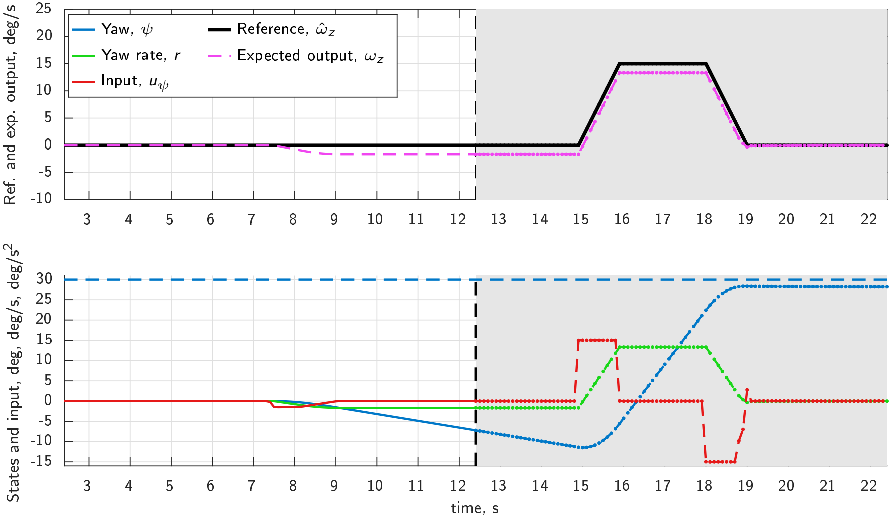


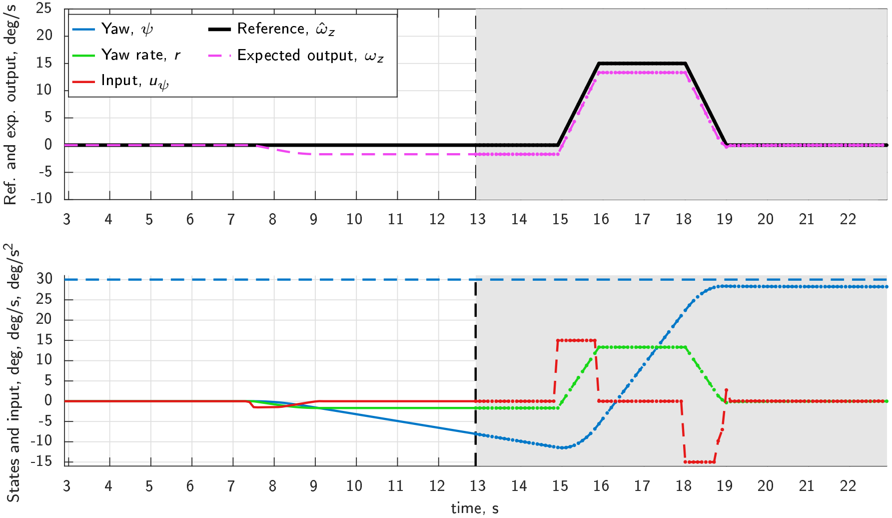
Example 2: yaw maneuver larger than limits



Example 2: yaw maneuver larger than limits



Example 2: yaw maneuver larger than limits



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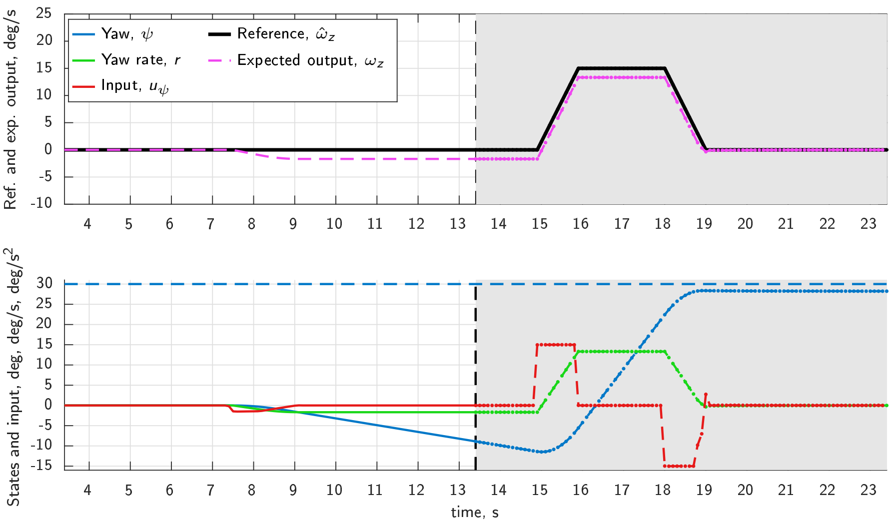

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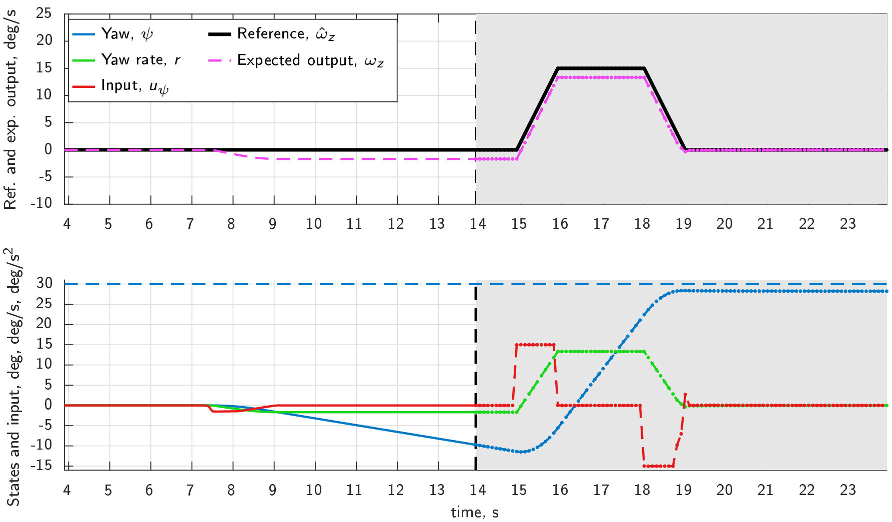

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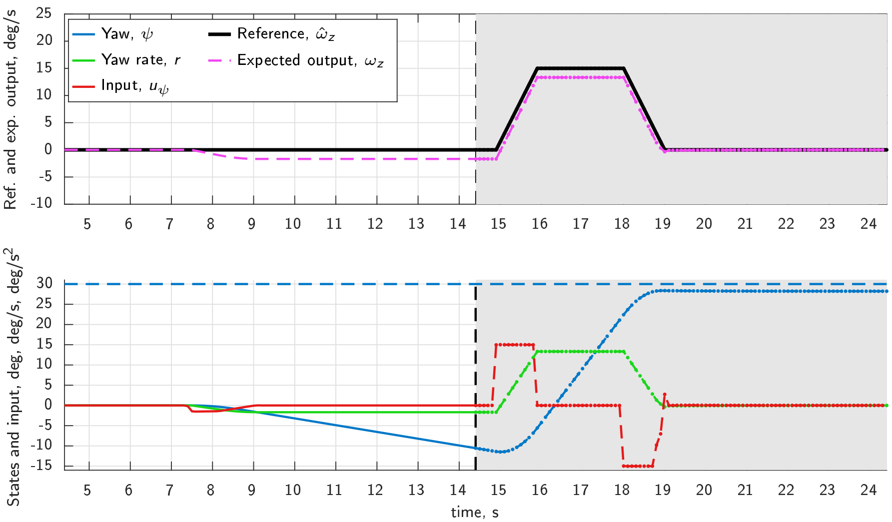

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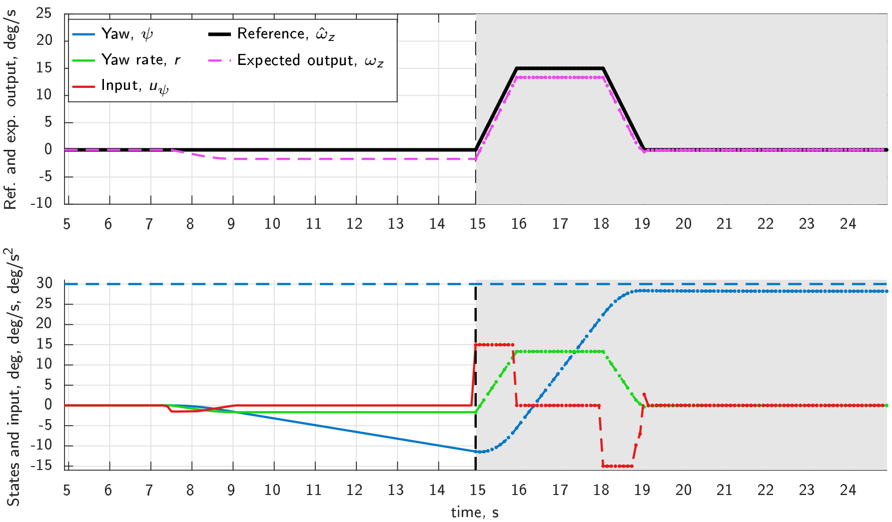

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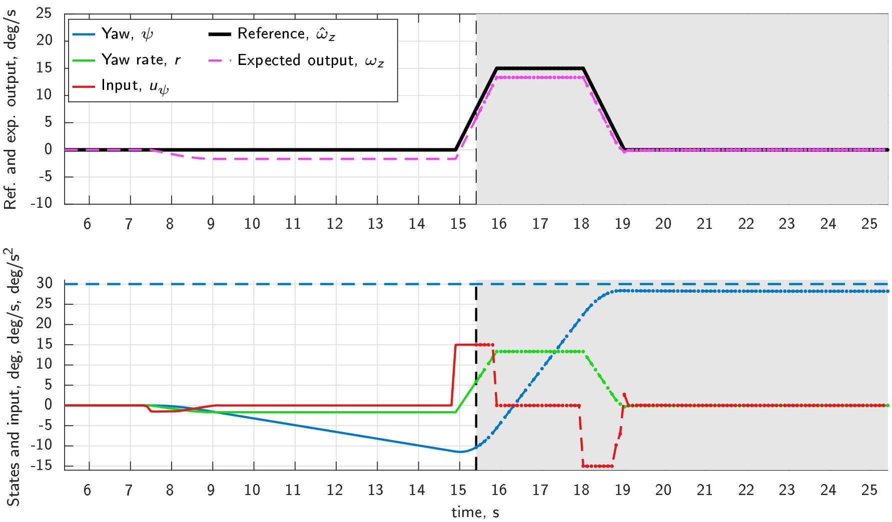

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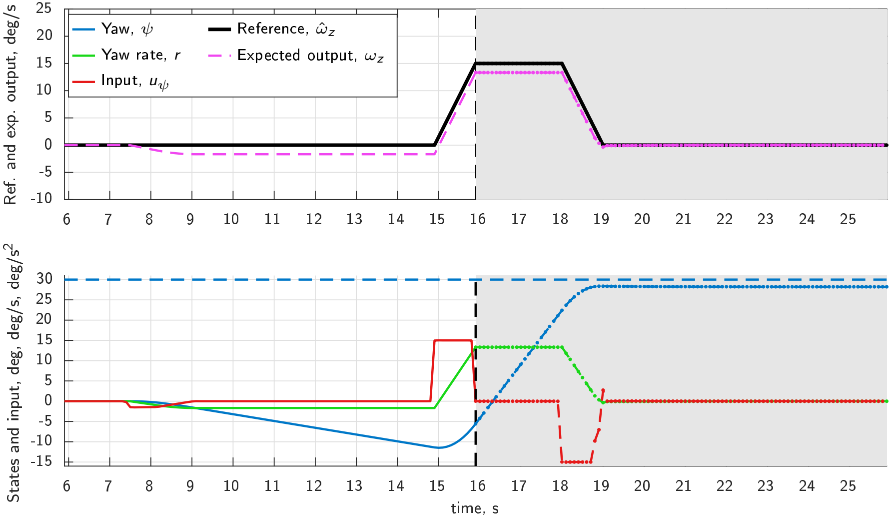

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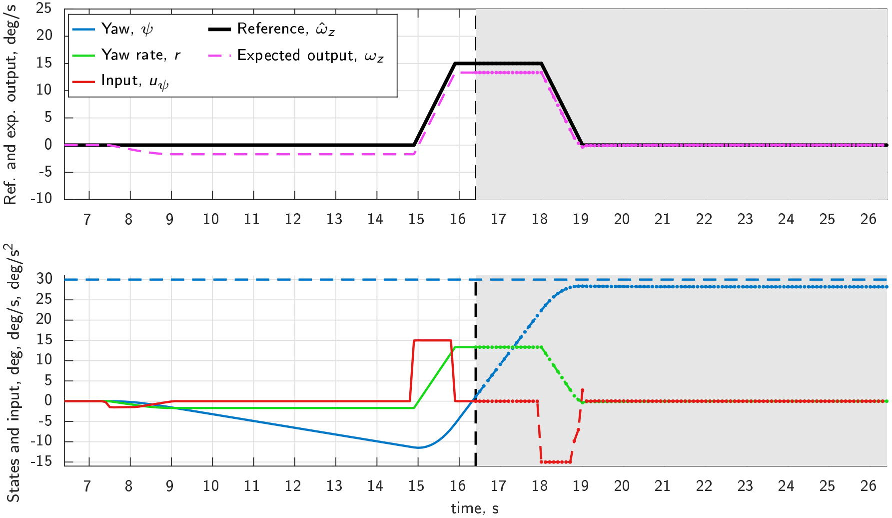

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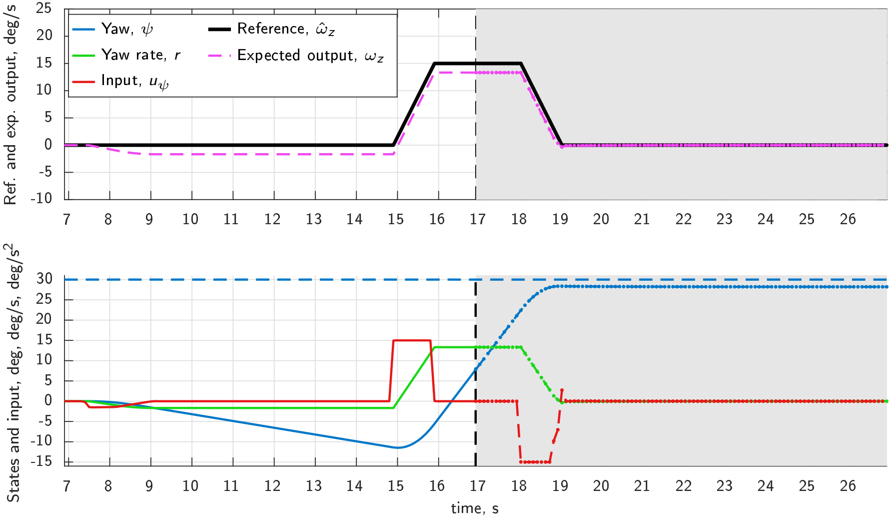
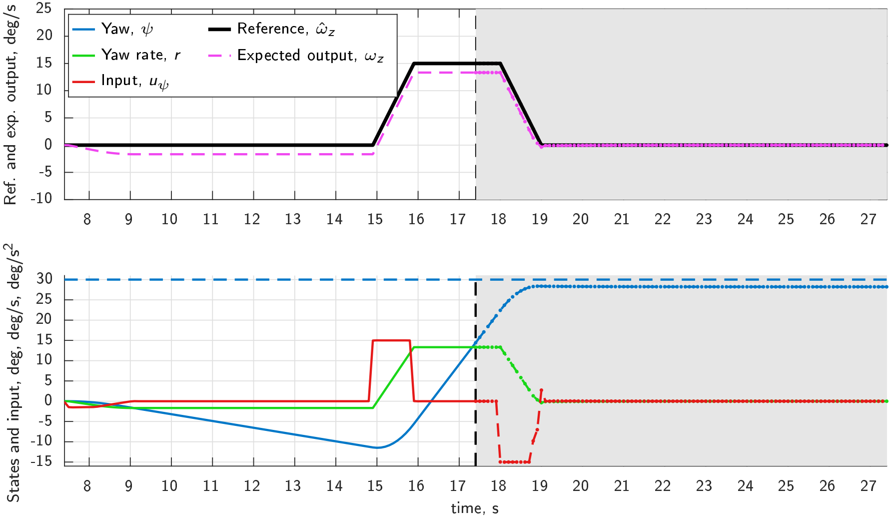
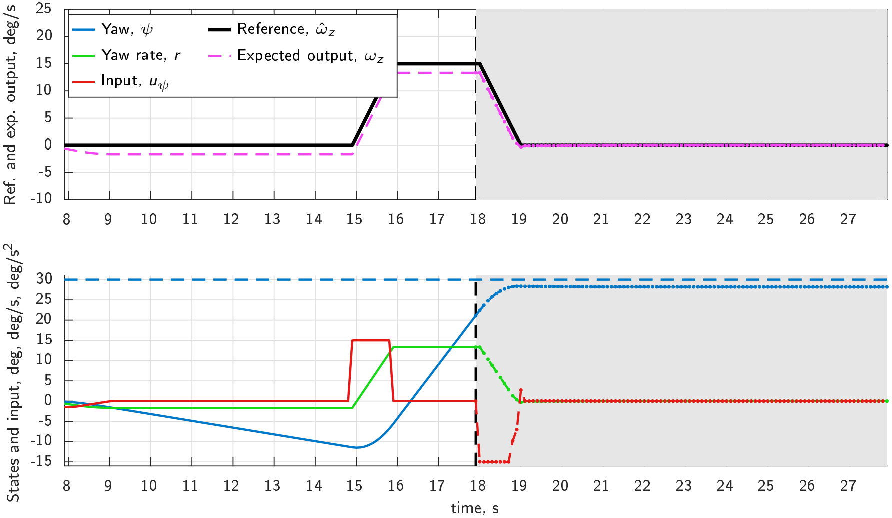


Example 2: yaw maneuver larger than limits



Example 2: yaw maneuver larger than limits



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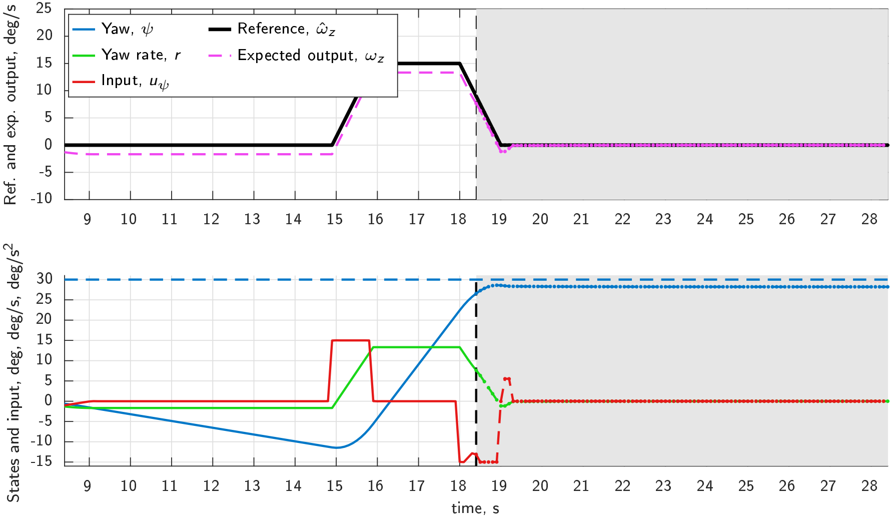

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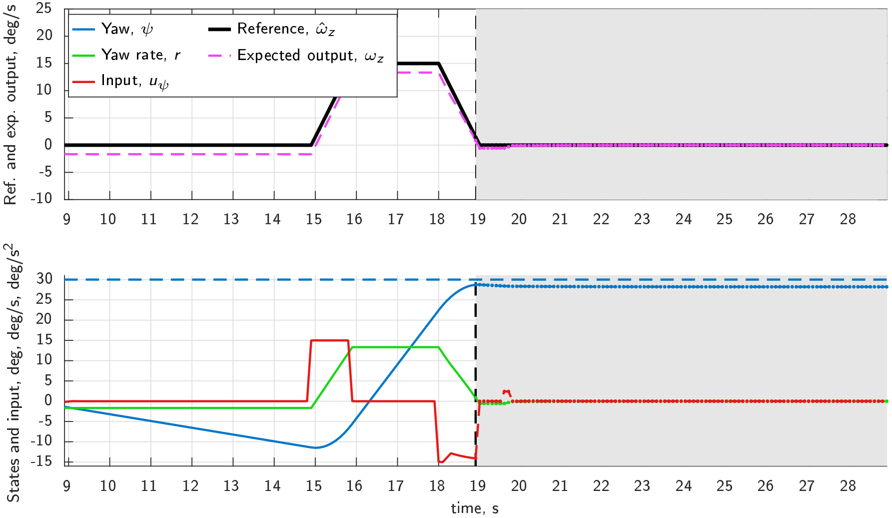

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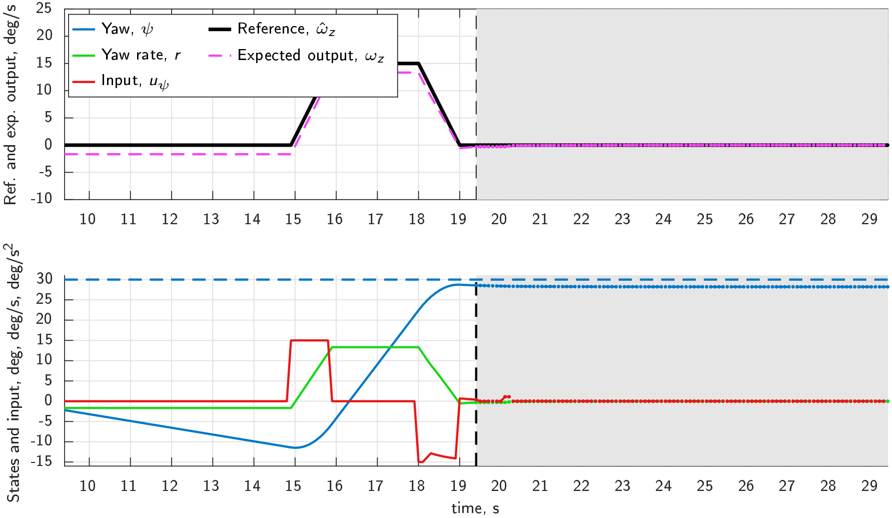

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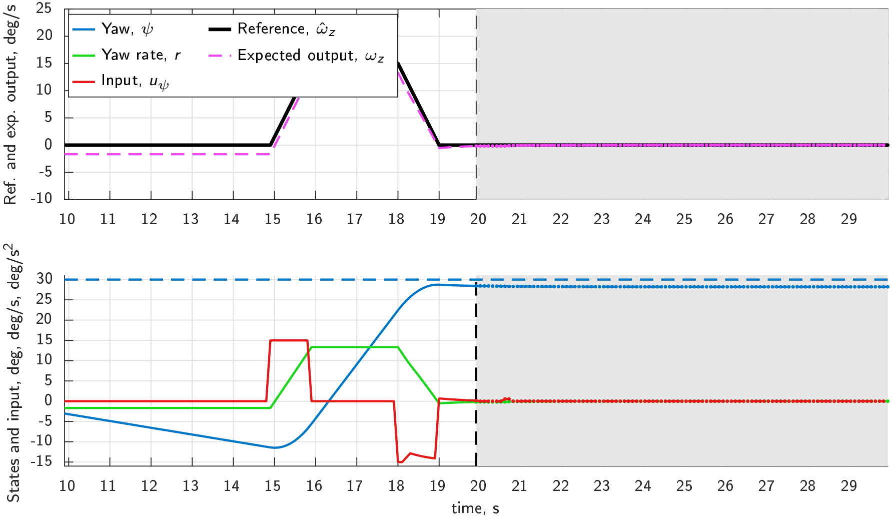

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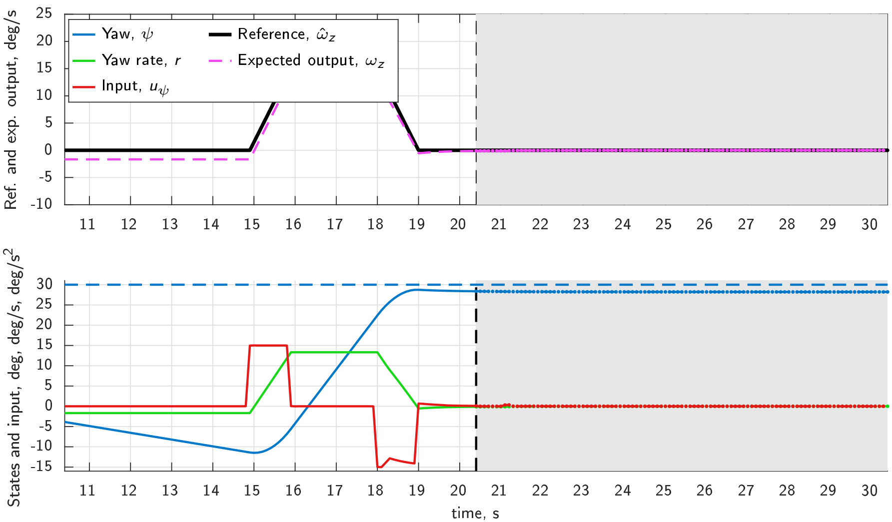

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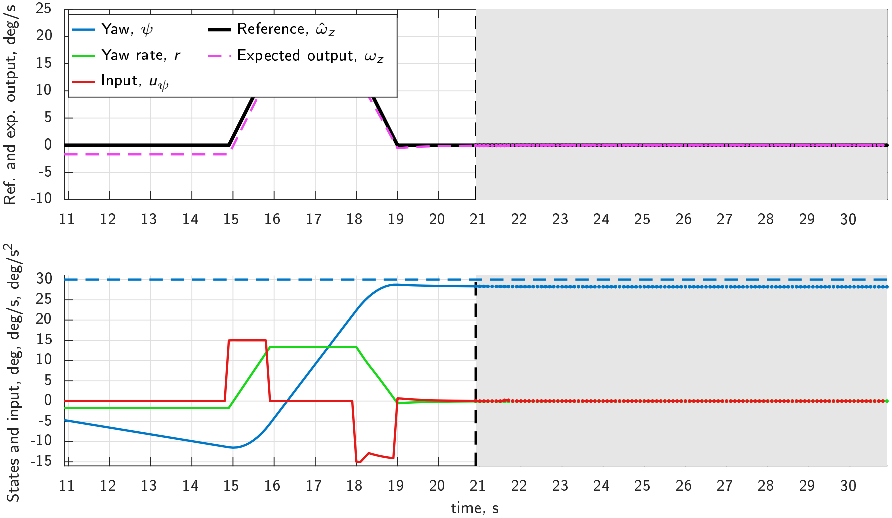

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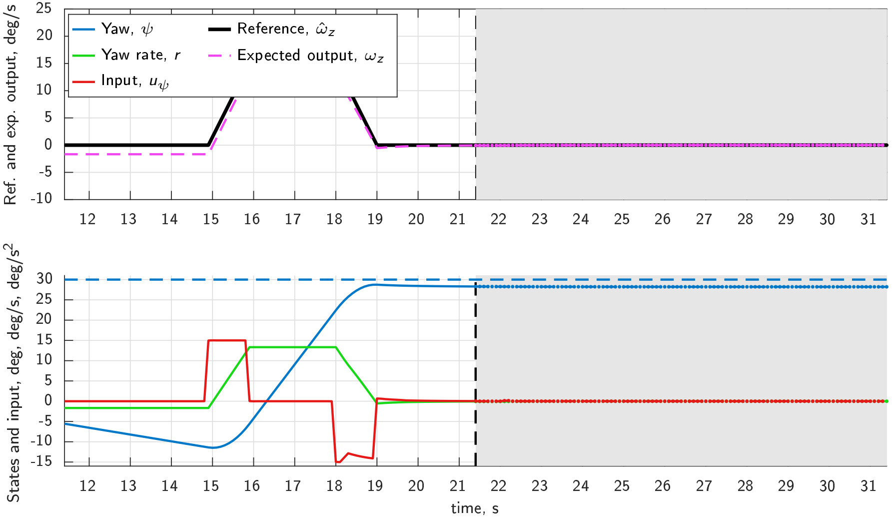

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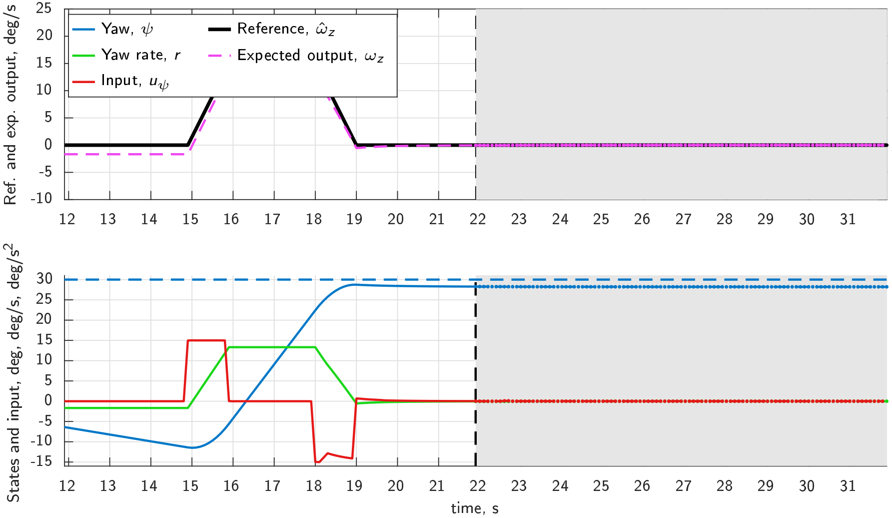

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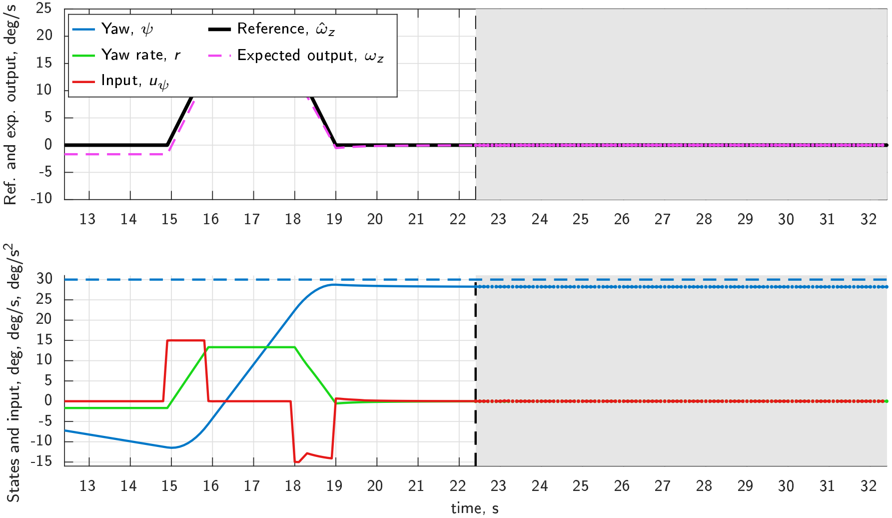

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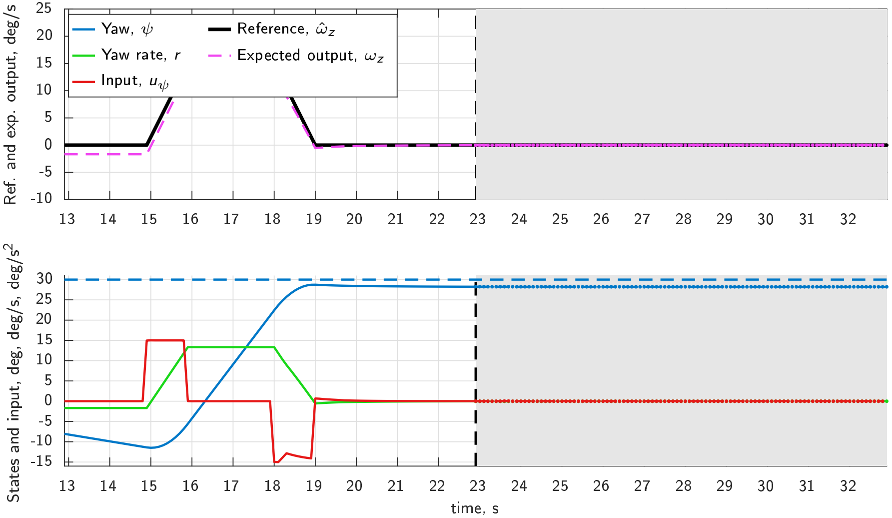

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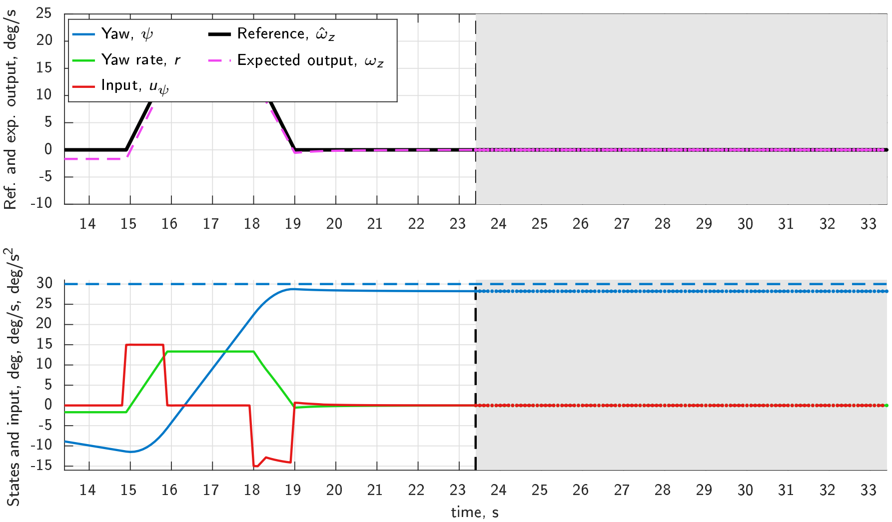

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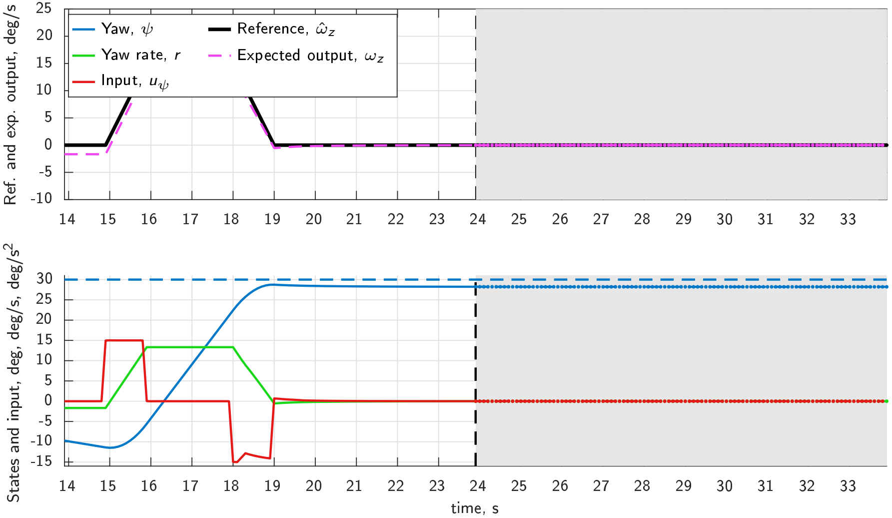

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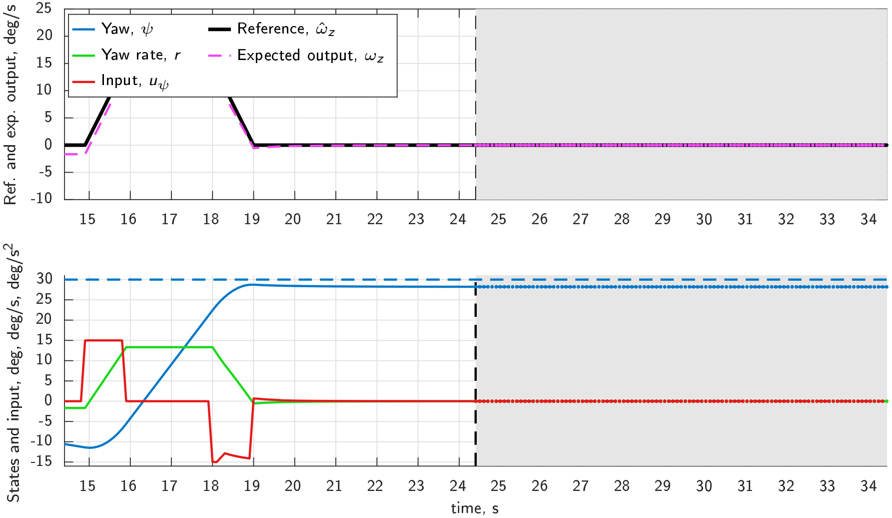
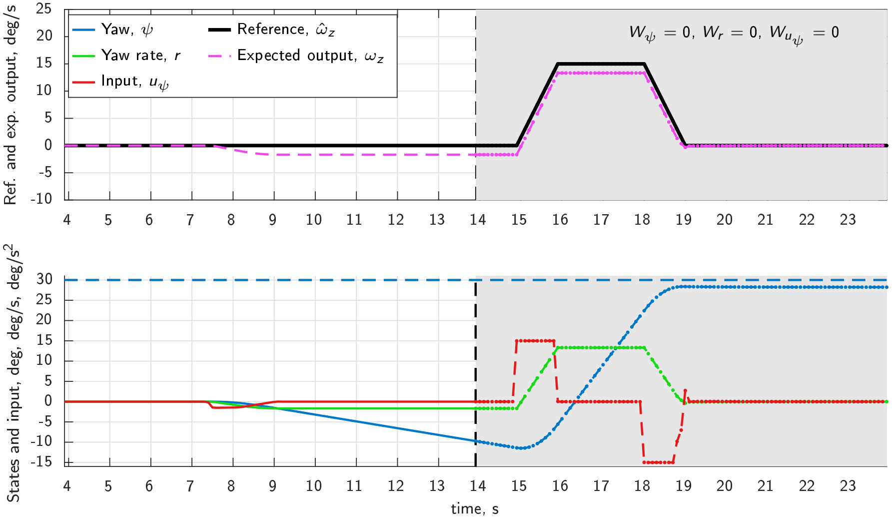
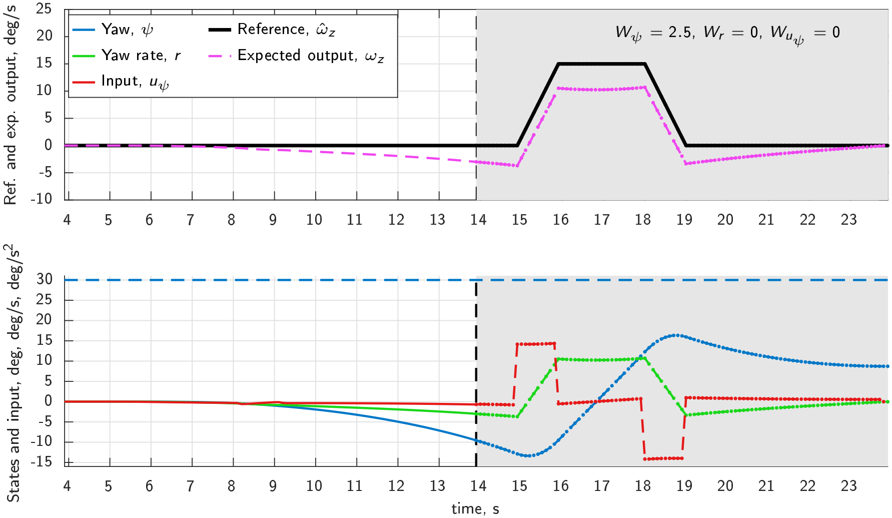


Example 3: yaw maneuver for different weights



Example 3: yaw maneuver for different weights



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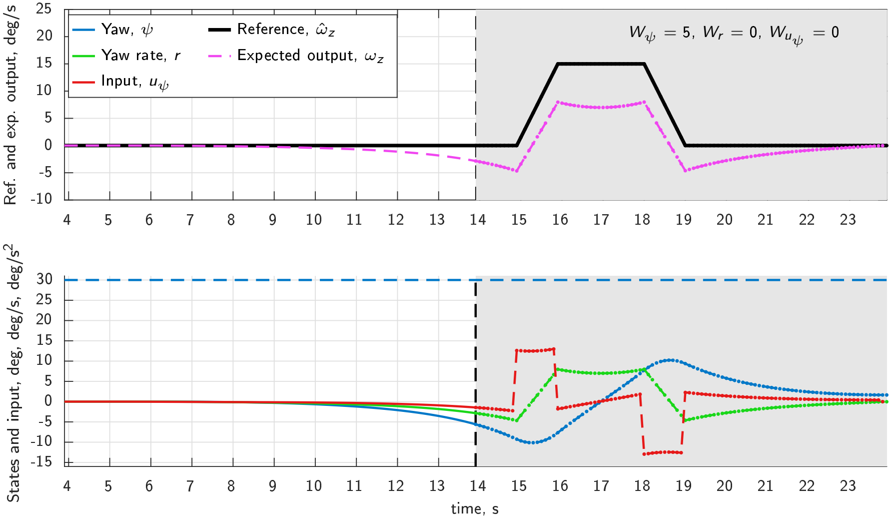

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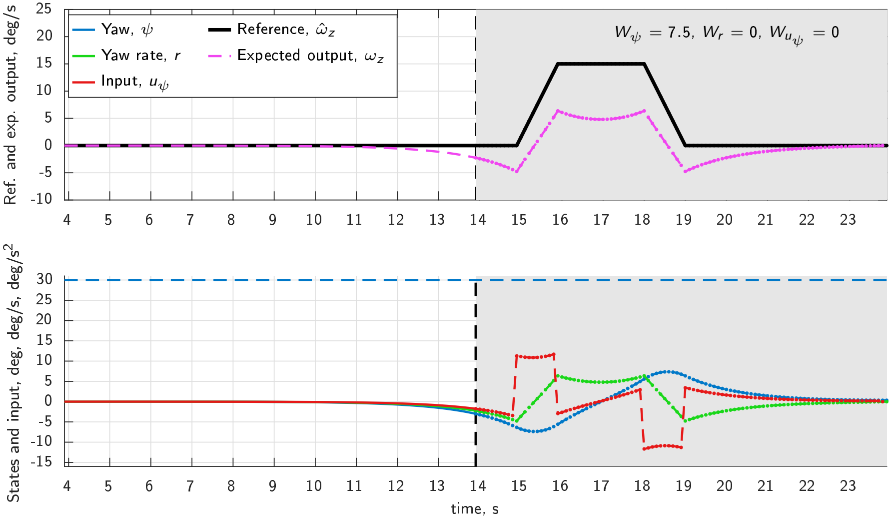

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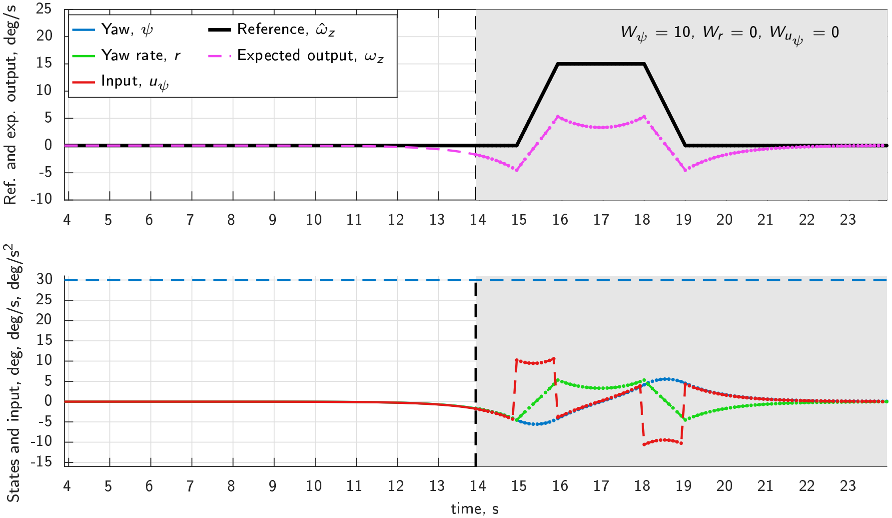

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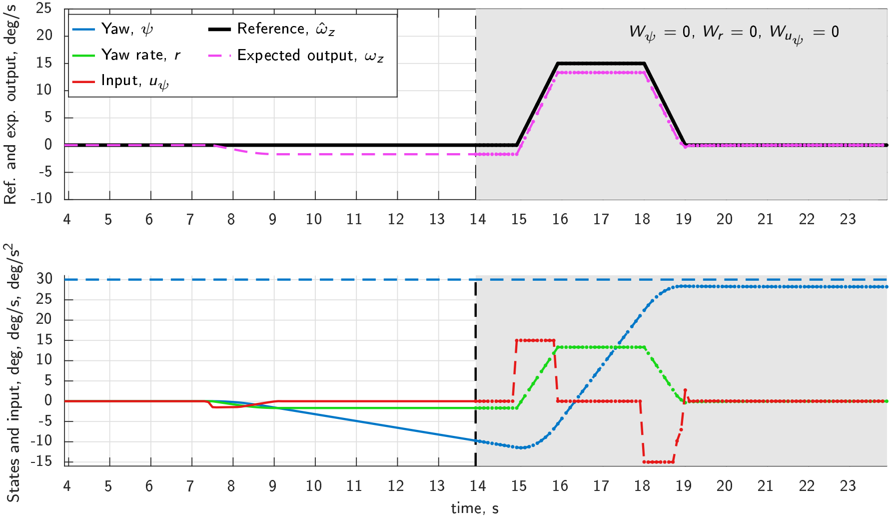

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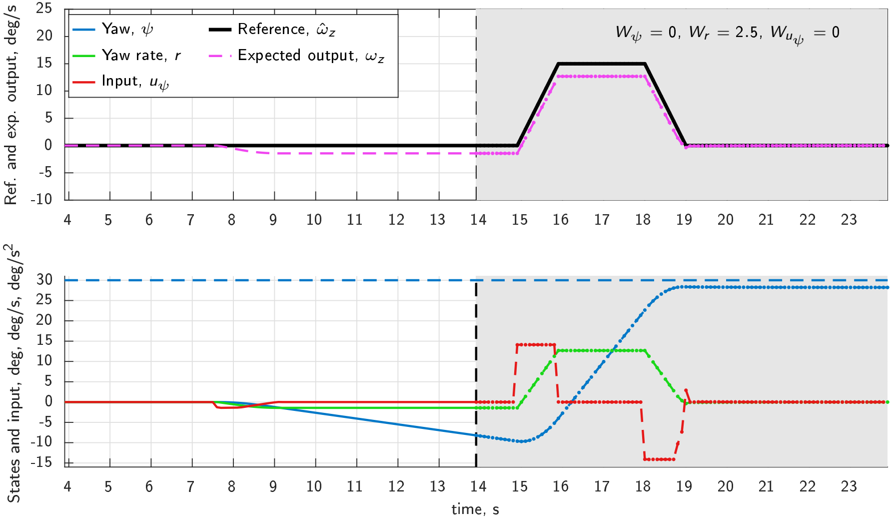
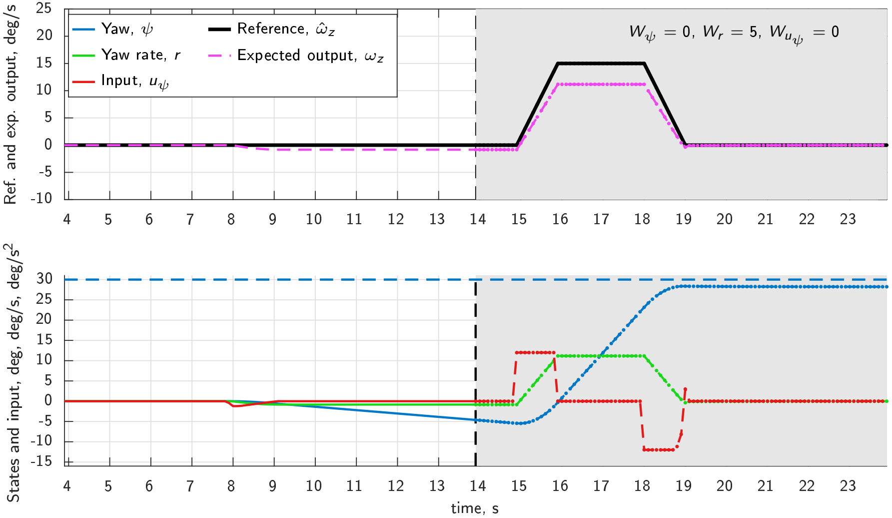


Example 3: yaw maneuver for different weights



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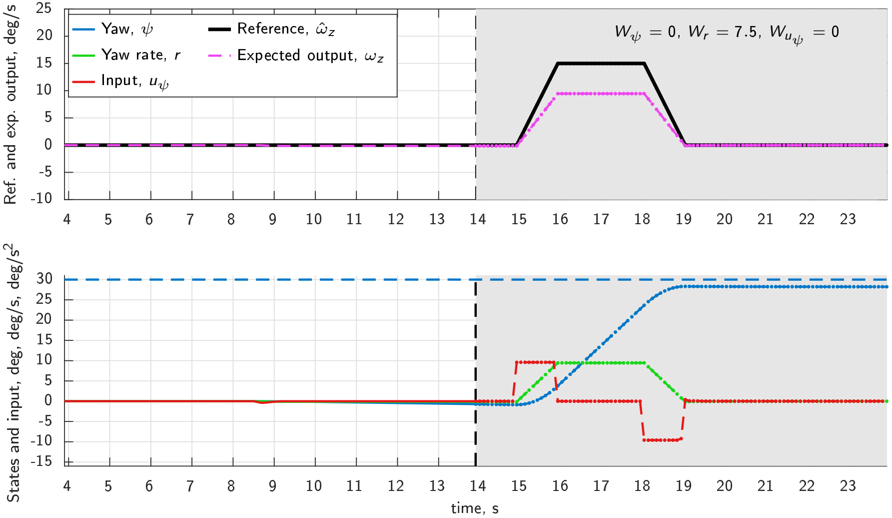

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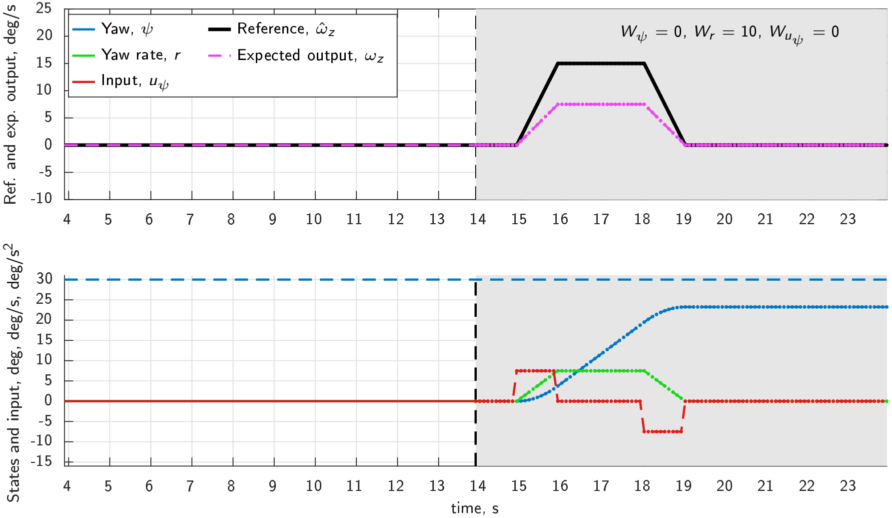

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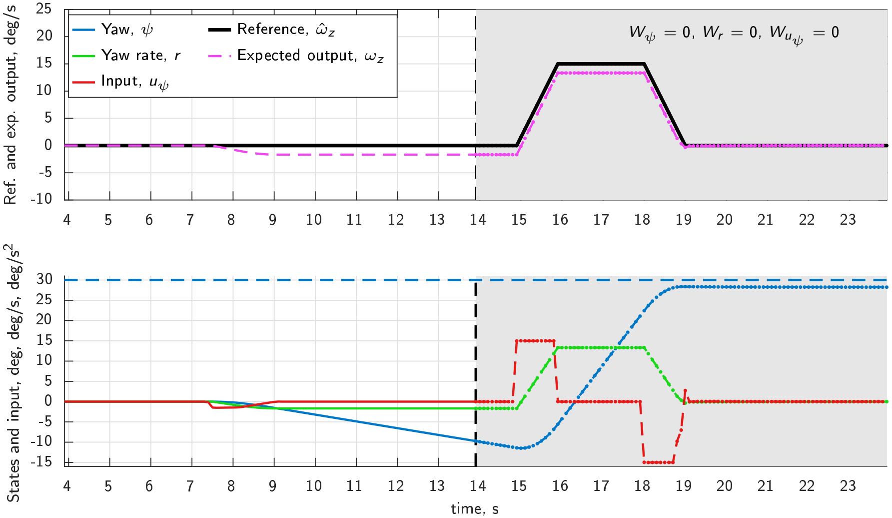

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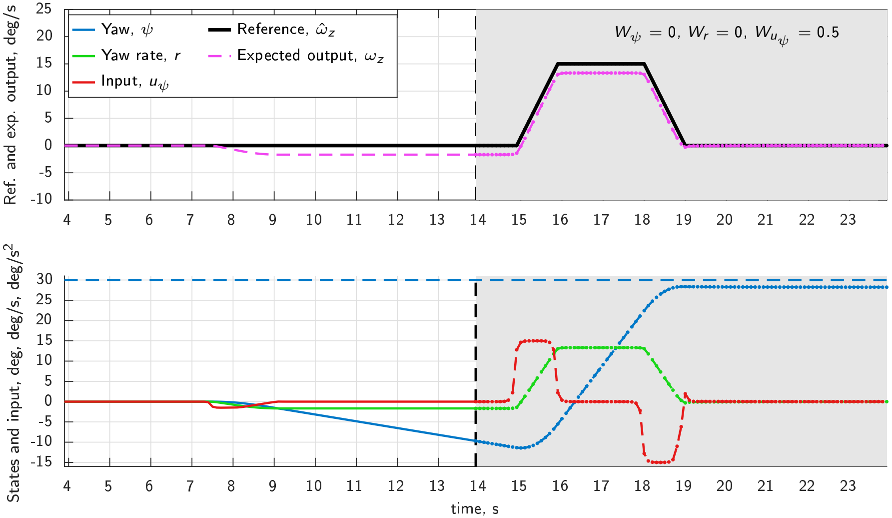

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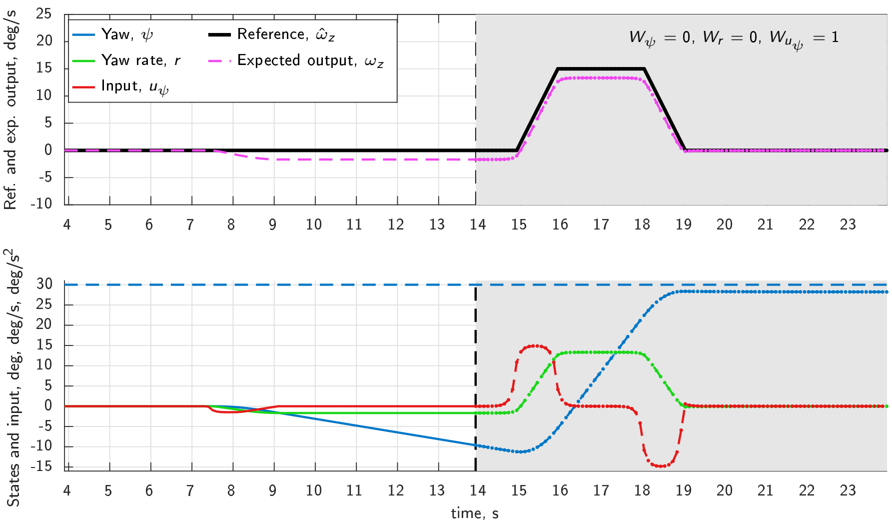

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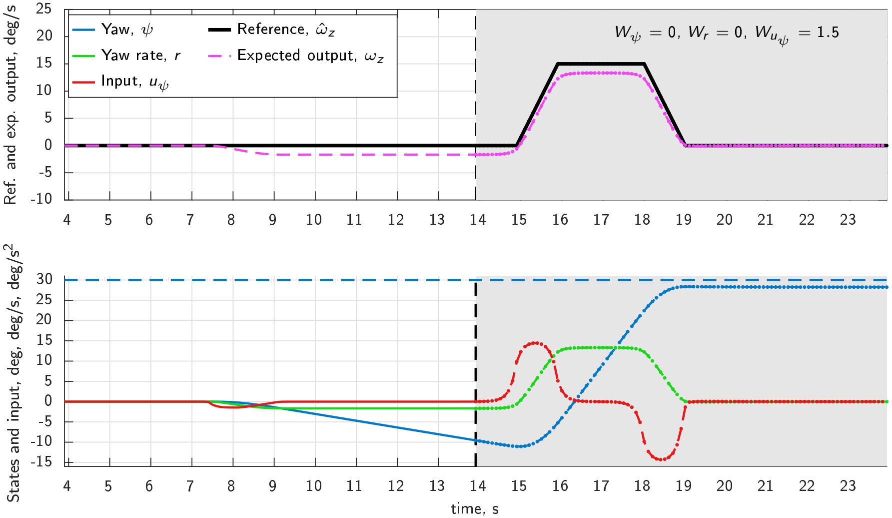

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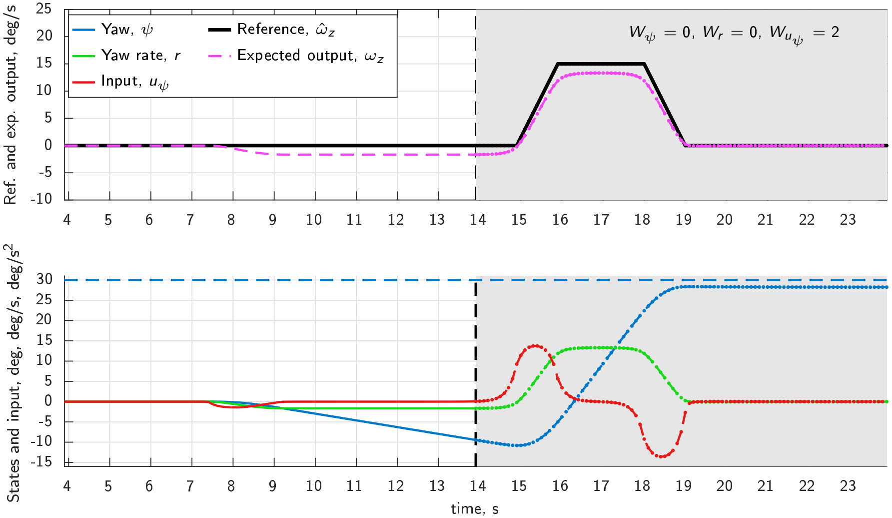
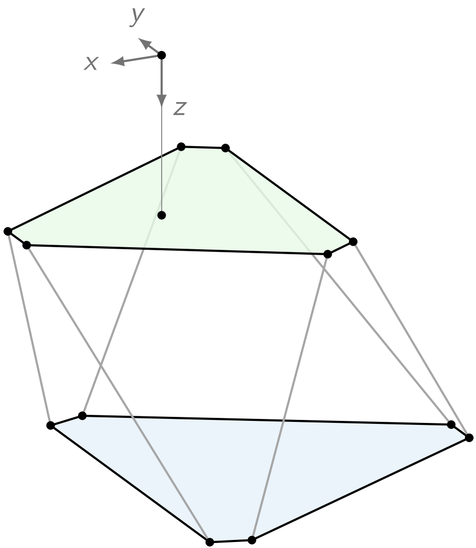


Example 4: A synthetic car turn on a hexapod



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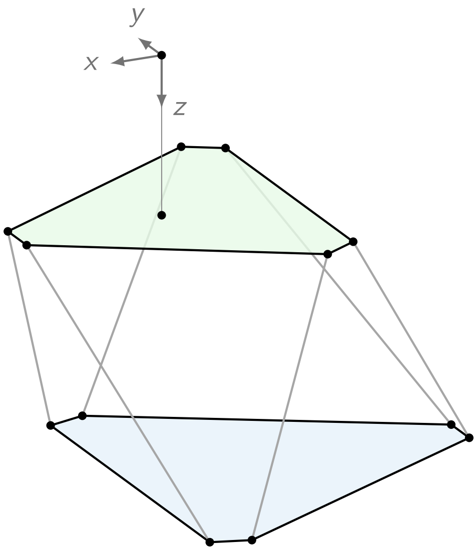

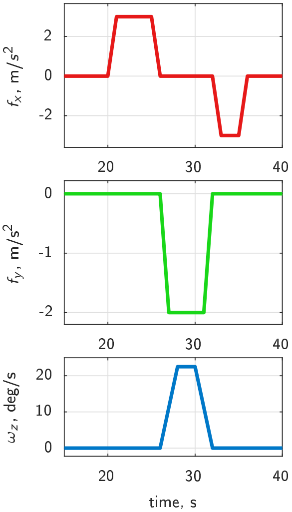

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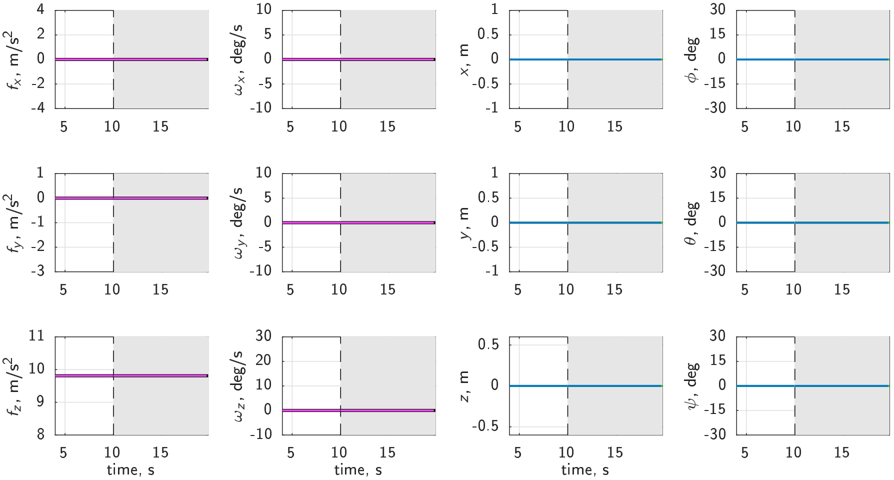

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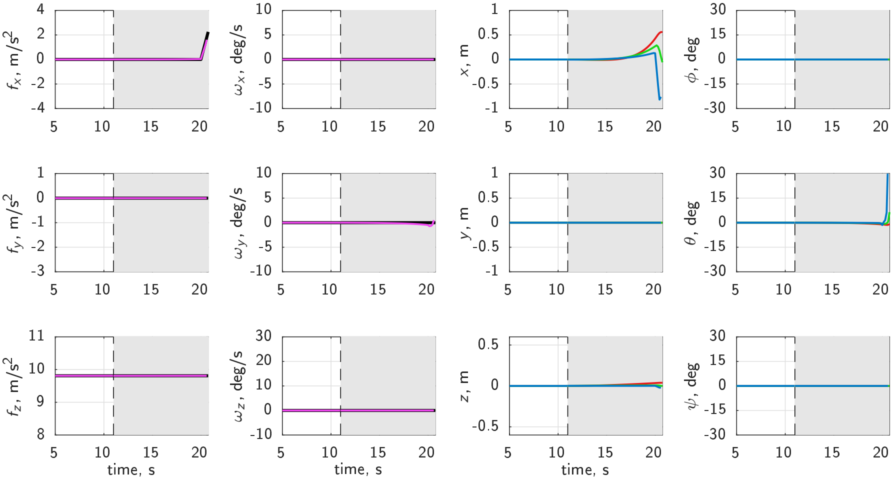

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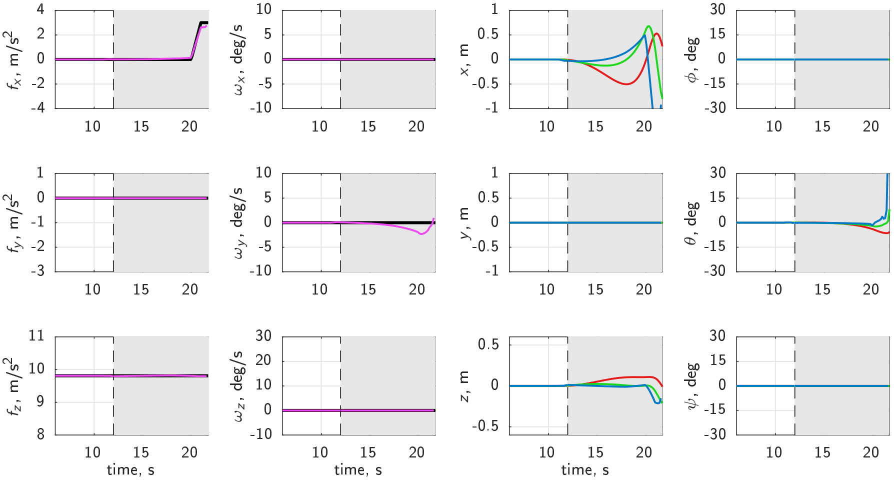

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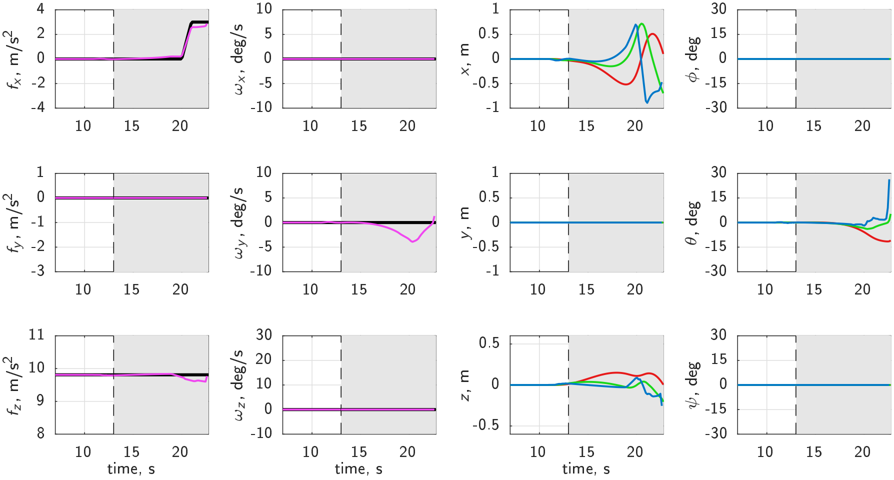

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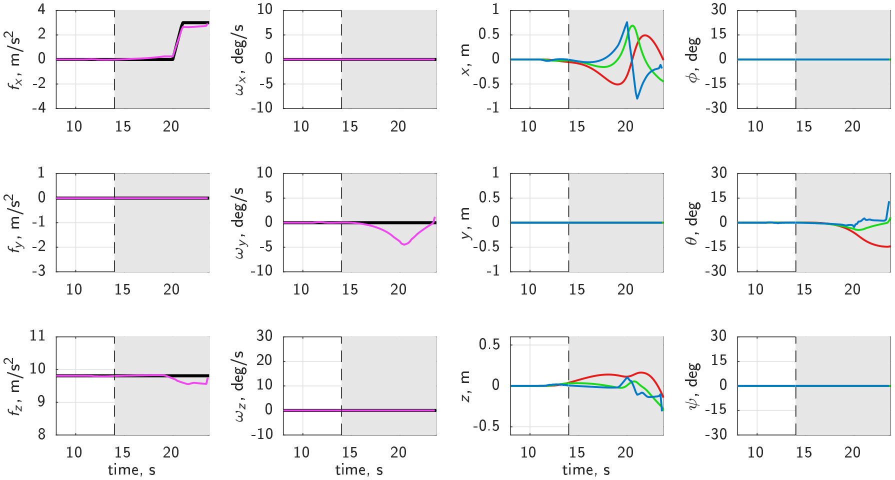

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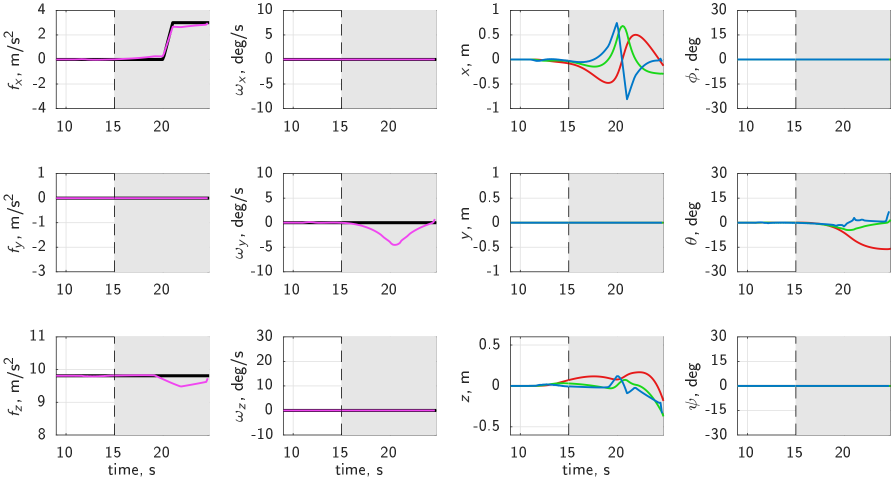

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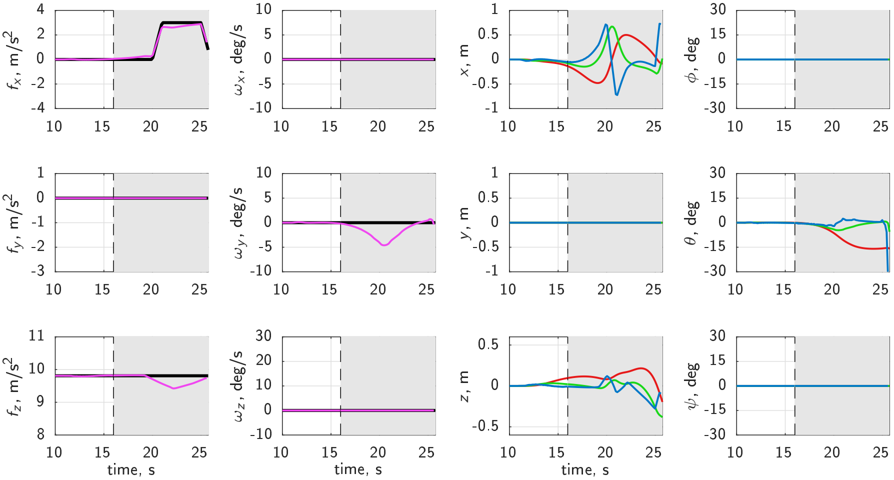

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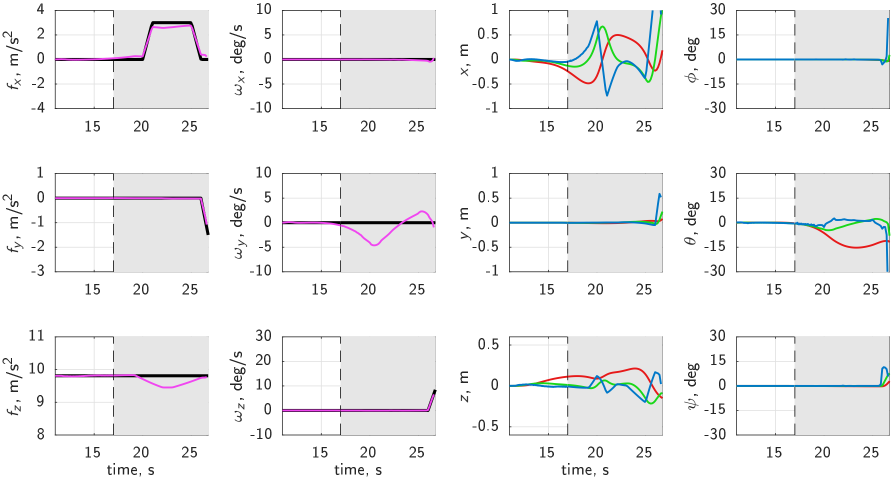

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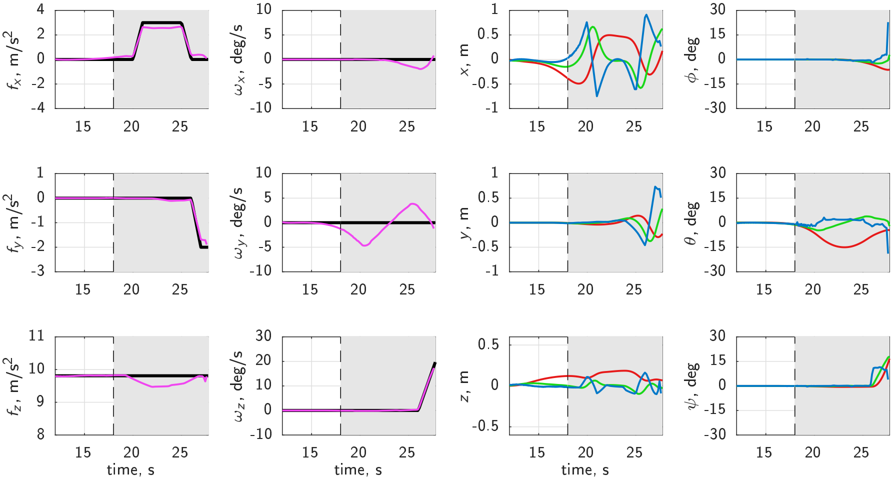

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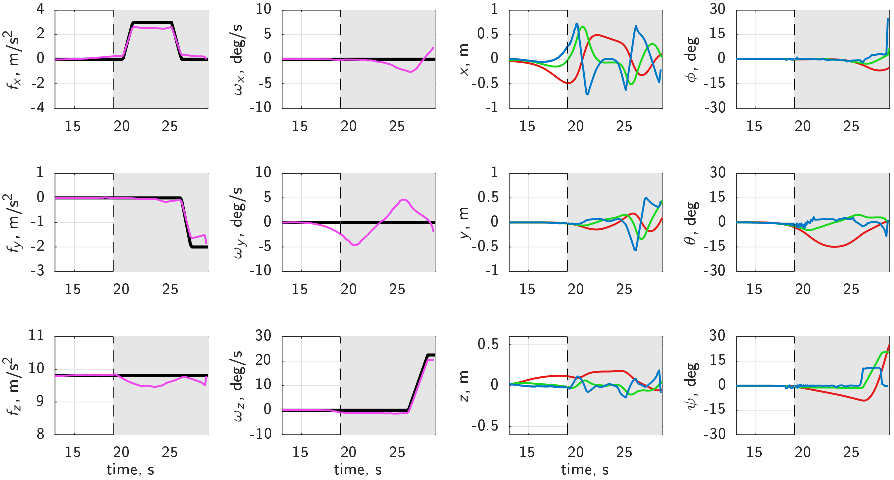

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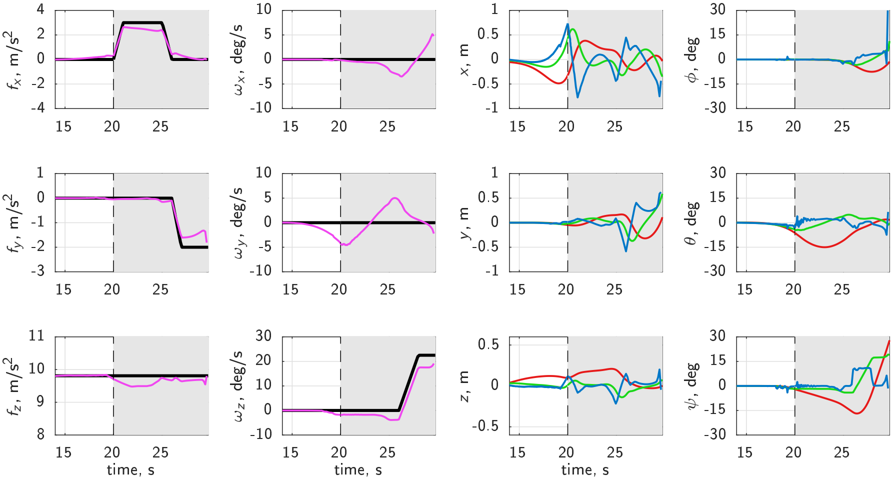

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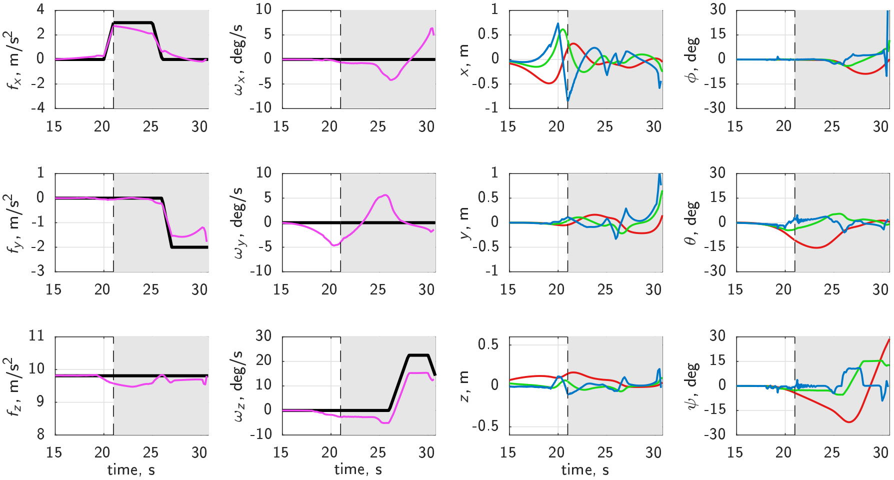

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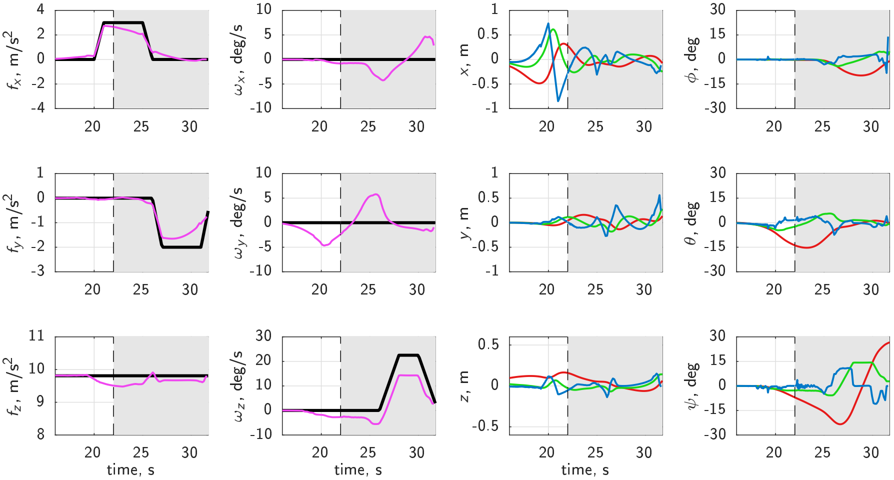

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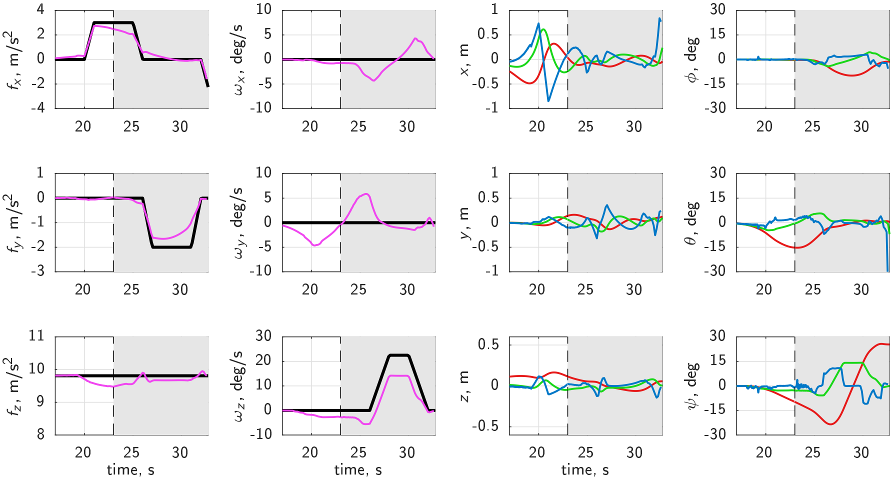

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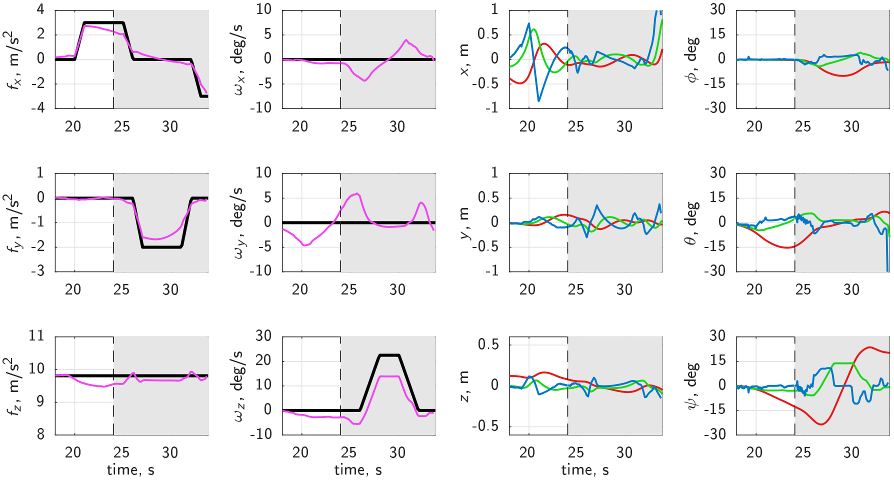

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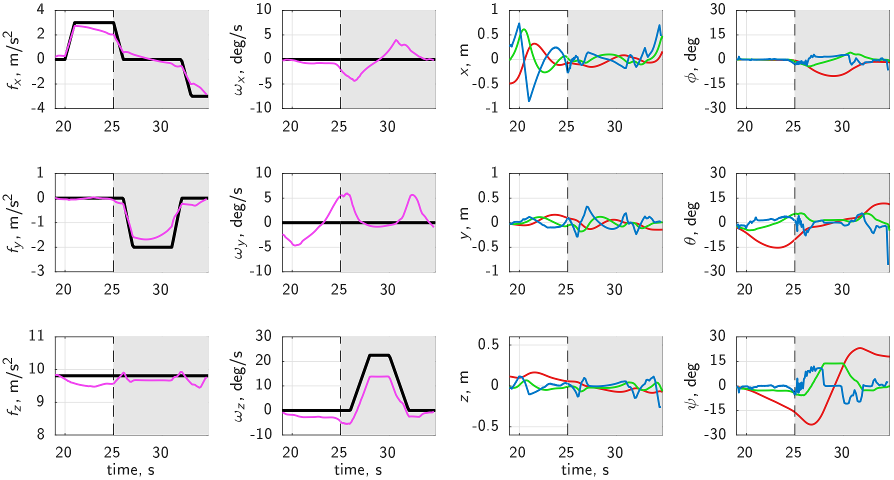

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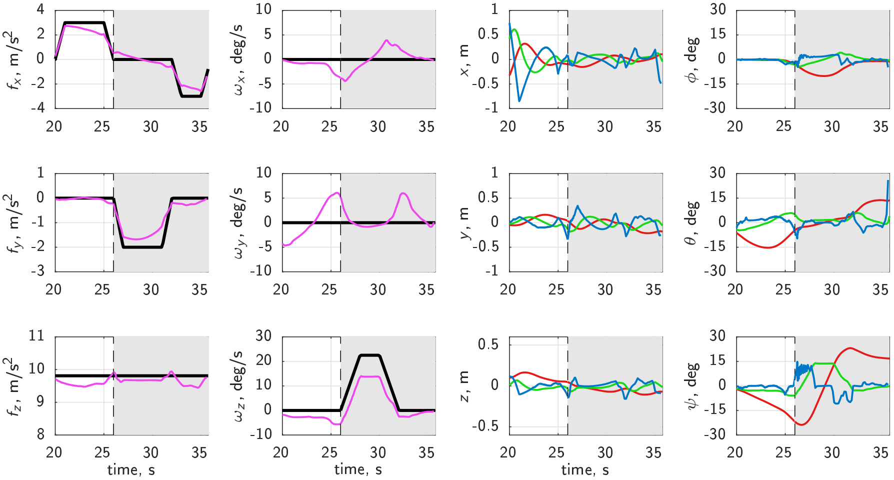

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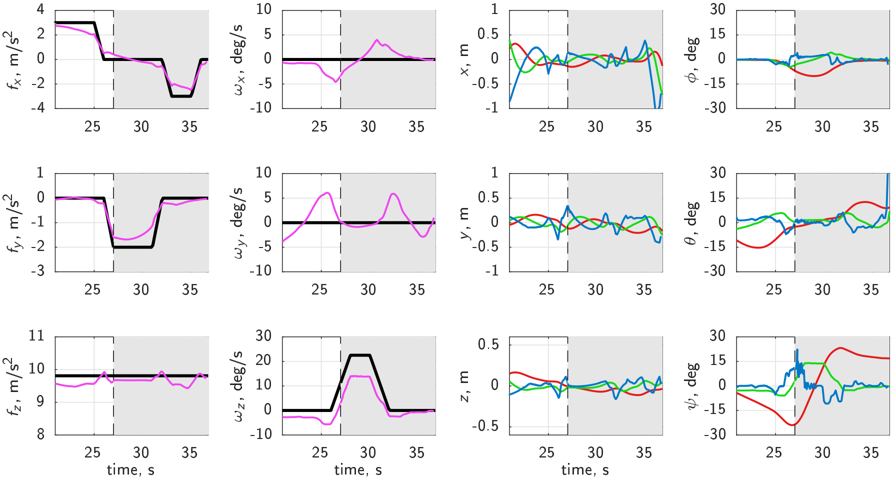

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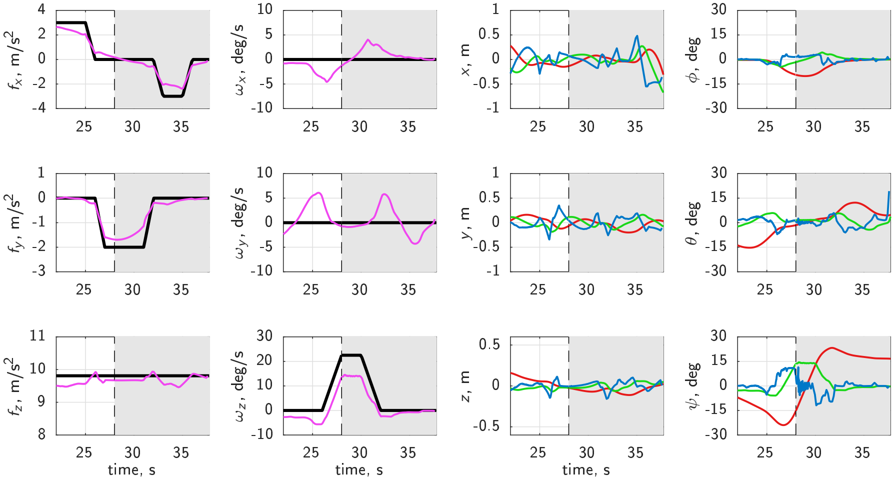

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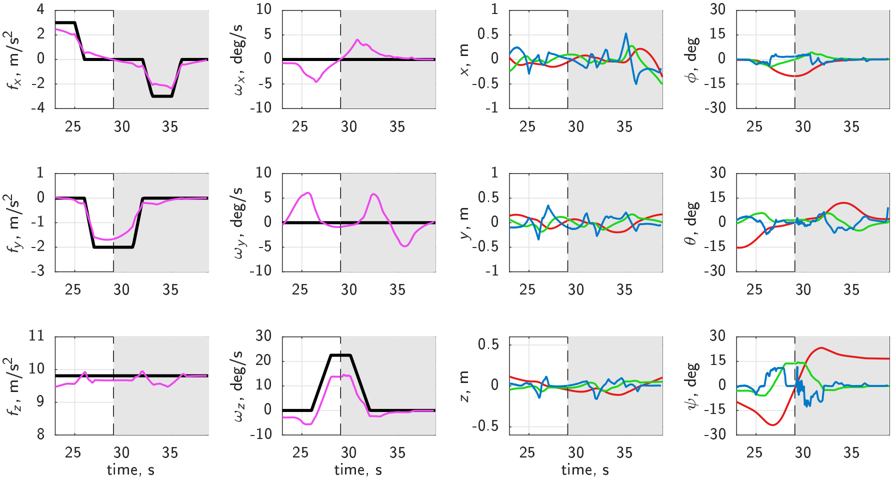

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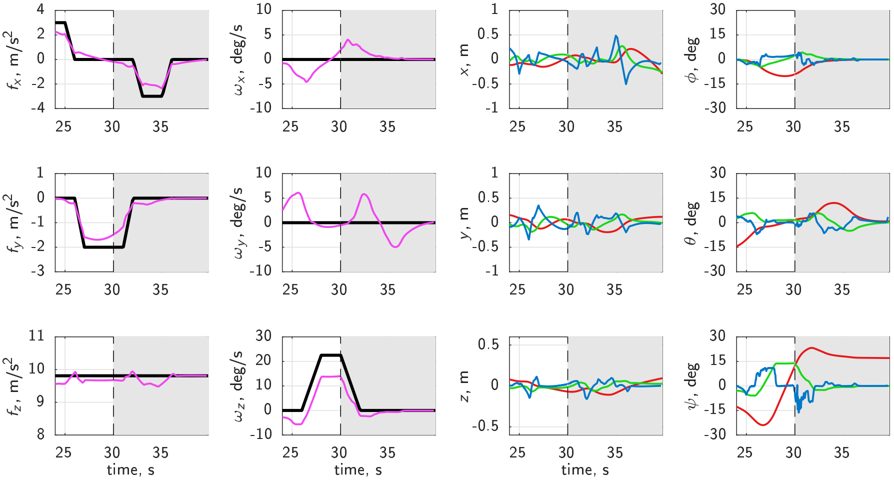

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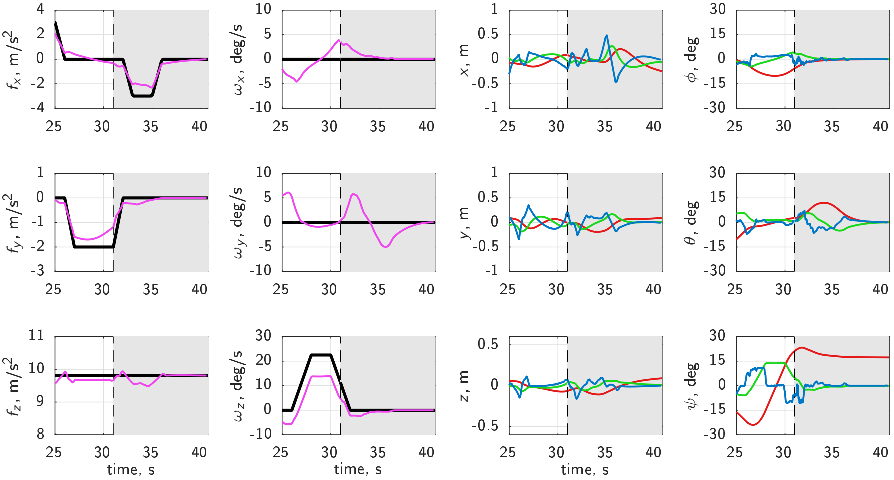

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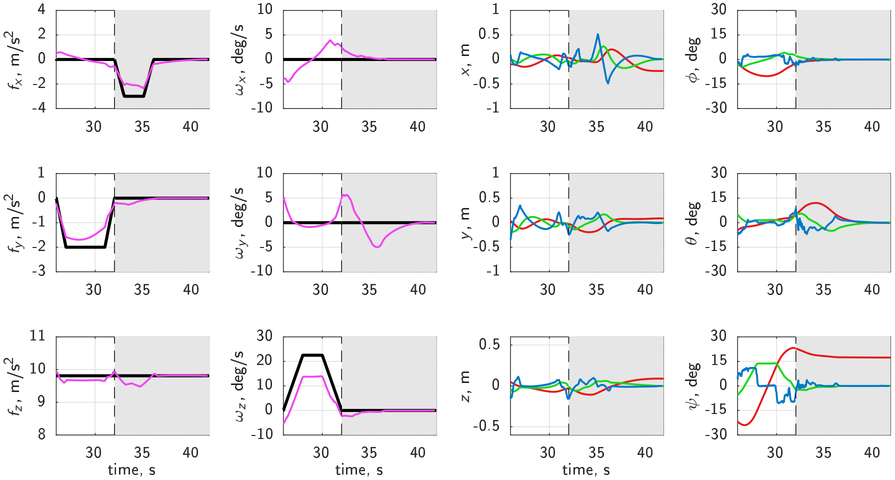

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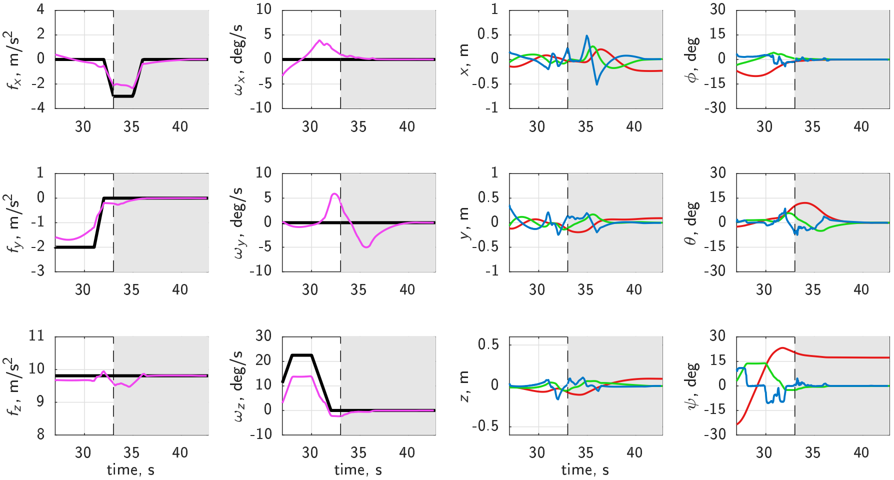

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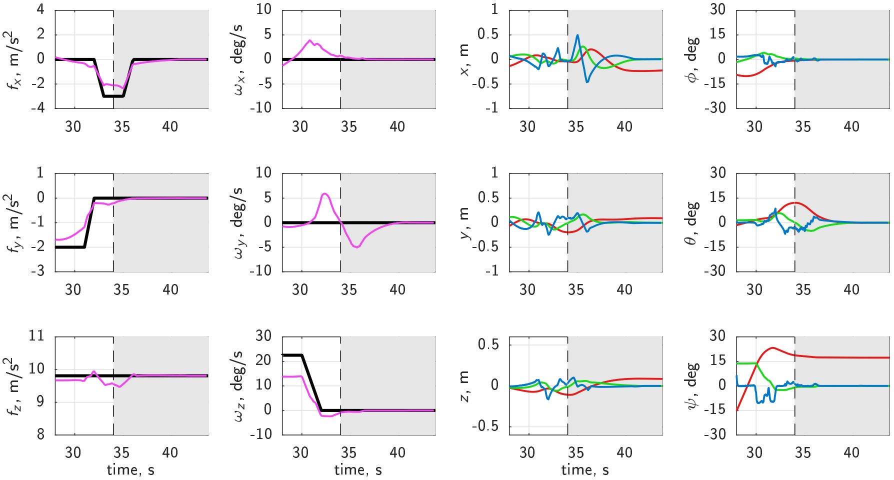

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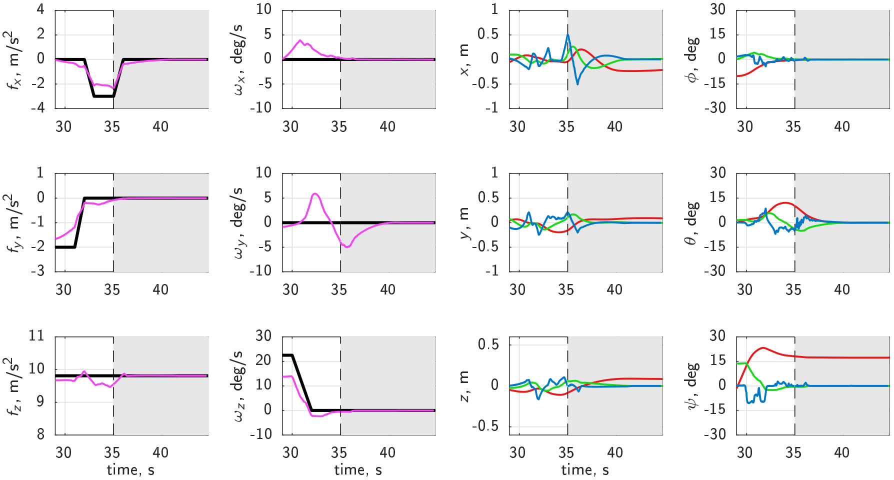

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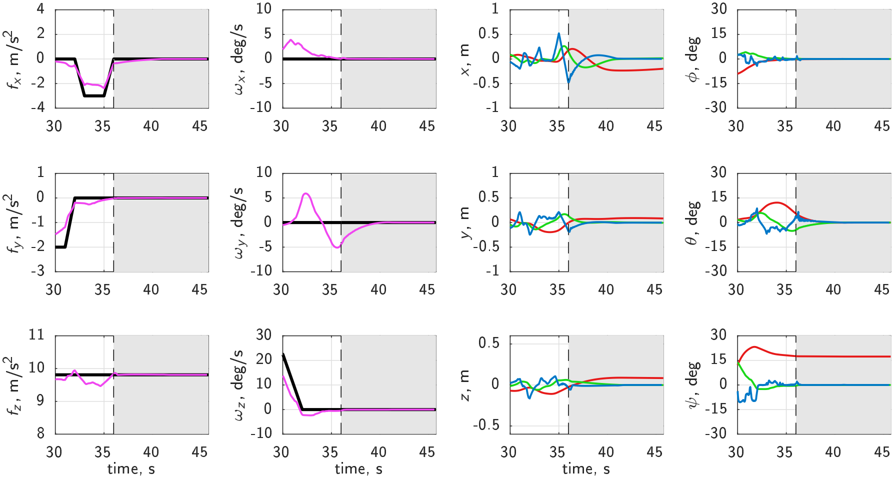

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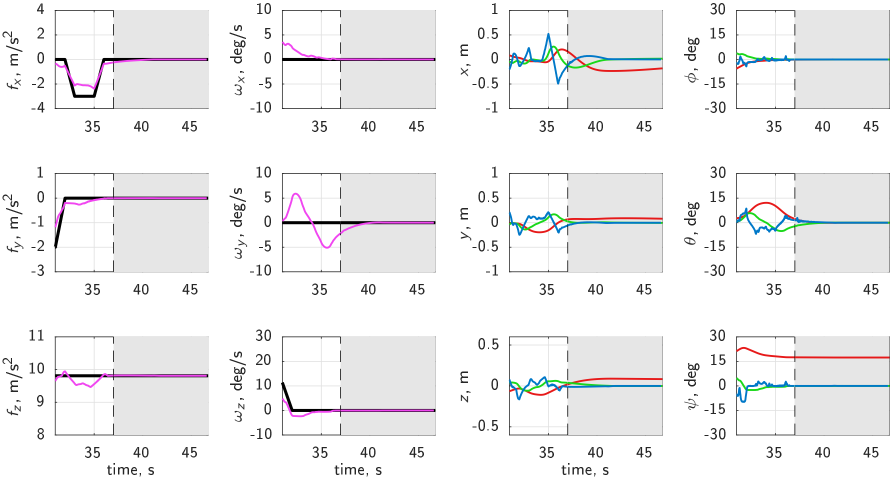

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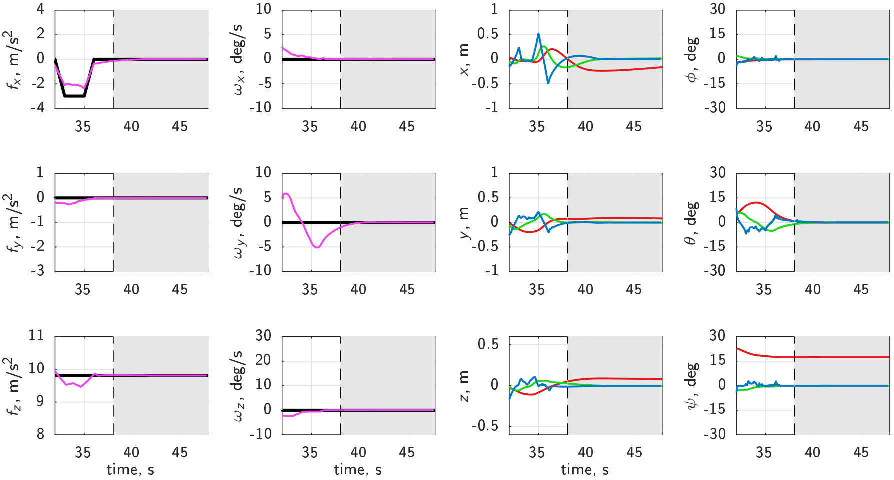

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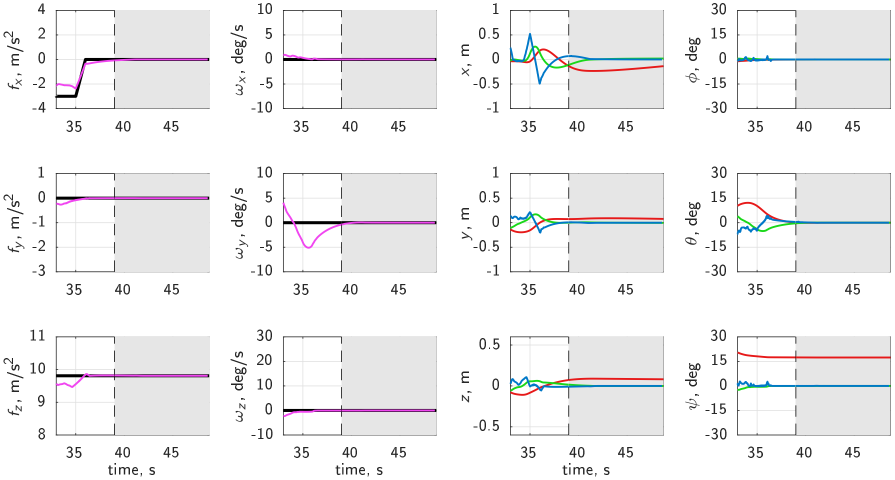

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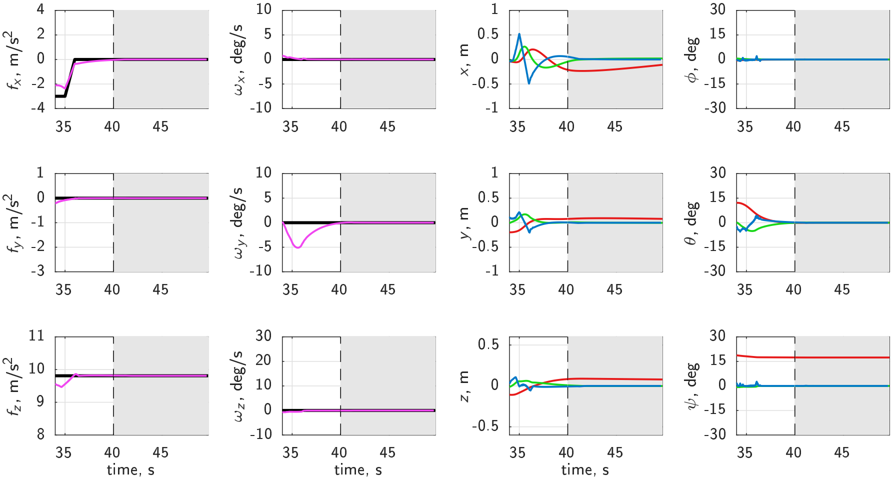

Objectives of this work

1. How to predict? *Develop a simple prediction method.*

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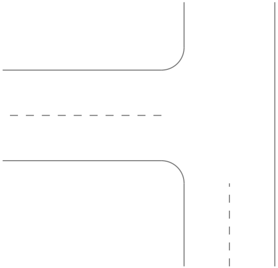
$$\frac{1}{N}\sum_{k=0}^{N}\underbrace{\|\mathbf{y}(\mathbf{x}_k,\mathbf{u}_k)-\hat{\mathbf{y}}_k\|^2_{W_\mathbf{y}}}_{\substack{\text{input tracking}\\ \text{``inertial signals'' term}}}+\underbrace{\|\mathbf{x}_k-\hat{\mathbf{x}}\|^2_{W_\mathbf{x}}}_{\substack{\text{state tracking}\\ \text{``washout'' term}}}+\underbrace{\|\mathbf{u}_k\|^2_{W_\mathbf{u}}}_{\substack{\text{input tracking}\\ \text{``aggressiveness'' term}}} \tag{5}$$

Realtime prediction method



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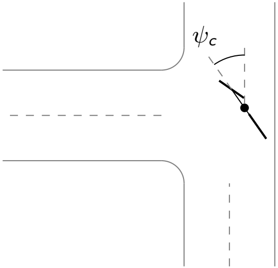

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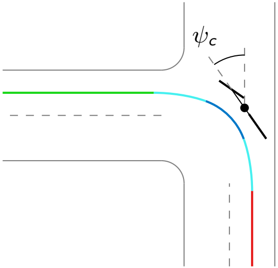

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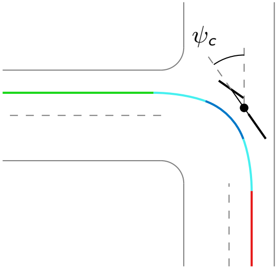

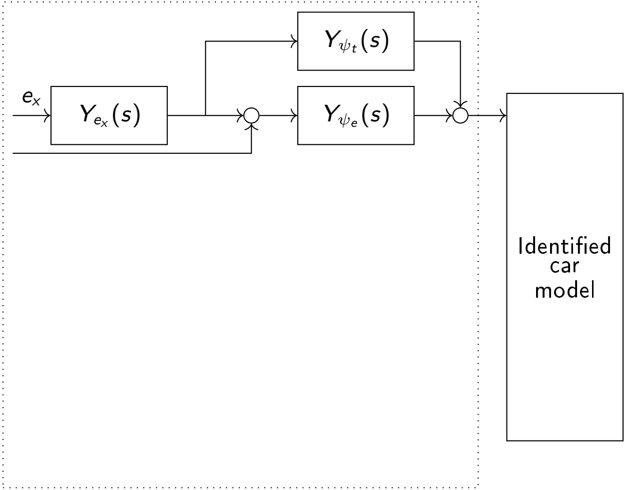

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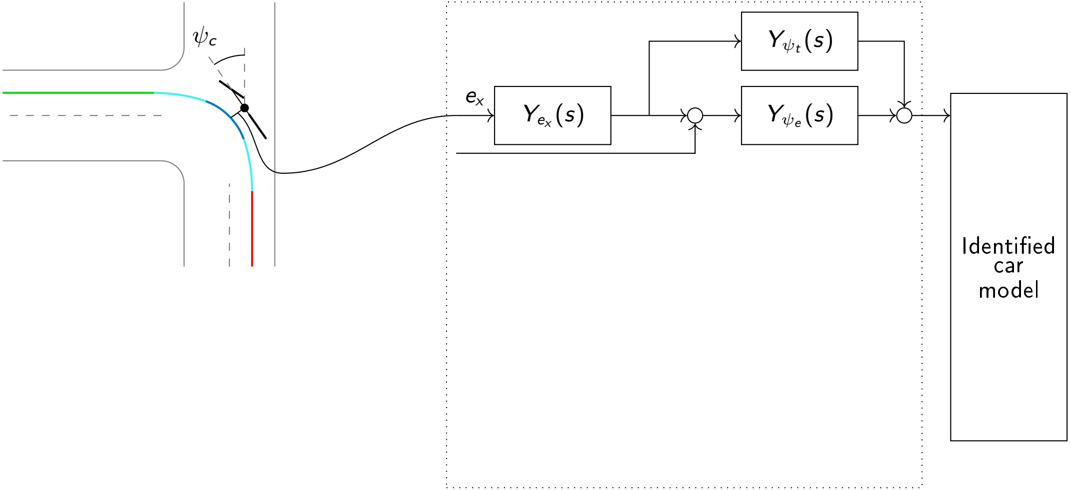

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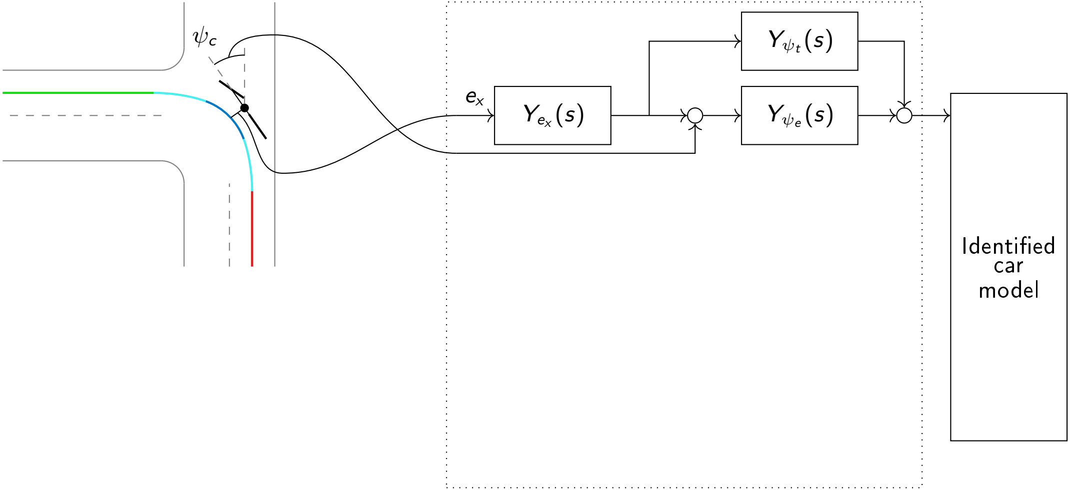

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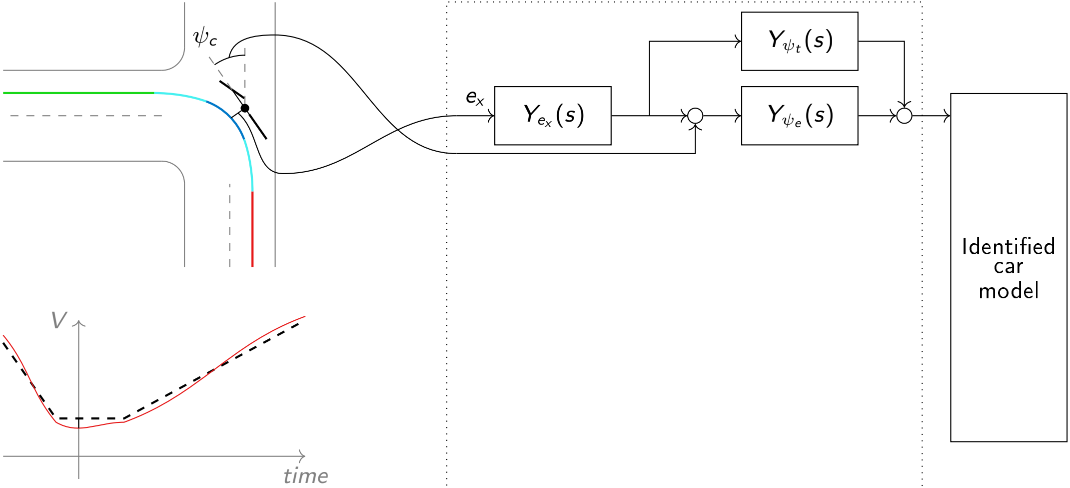

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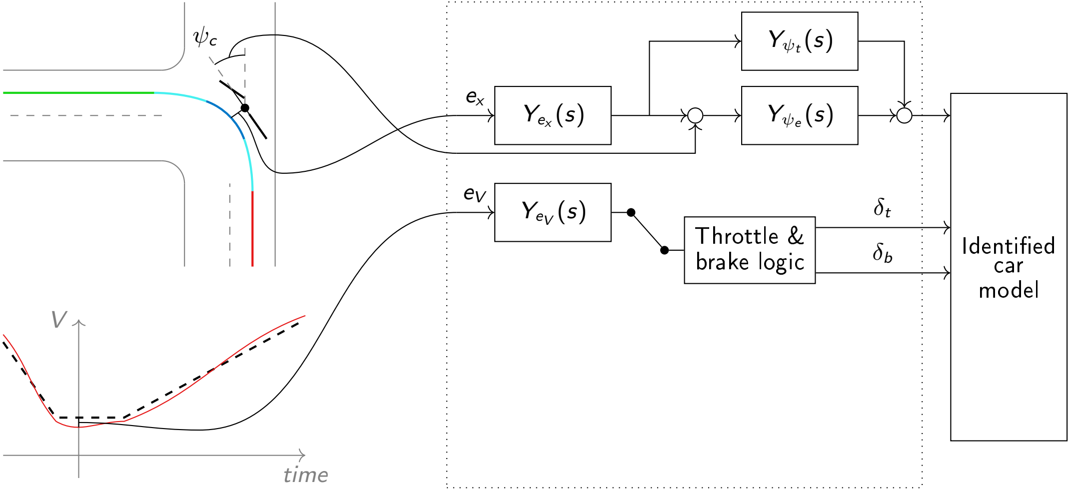

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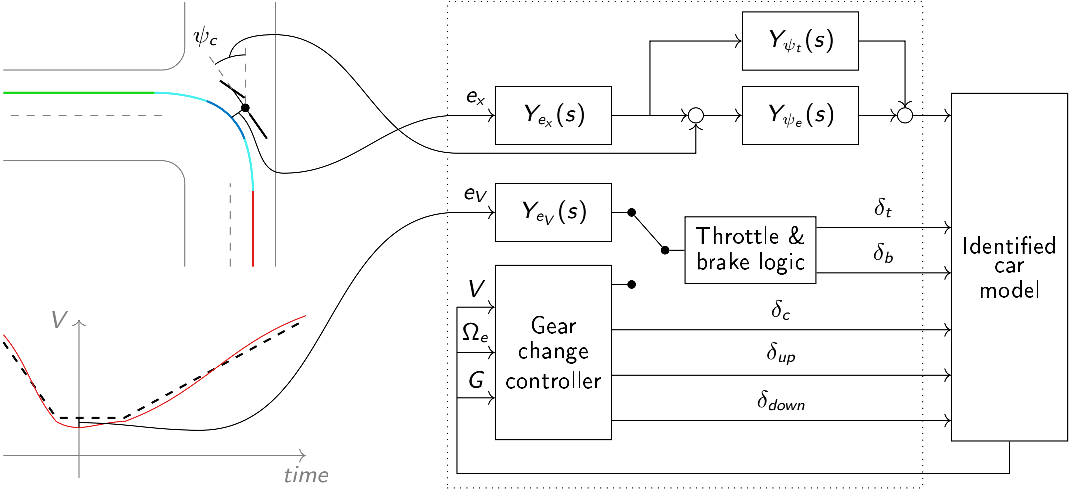

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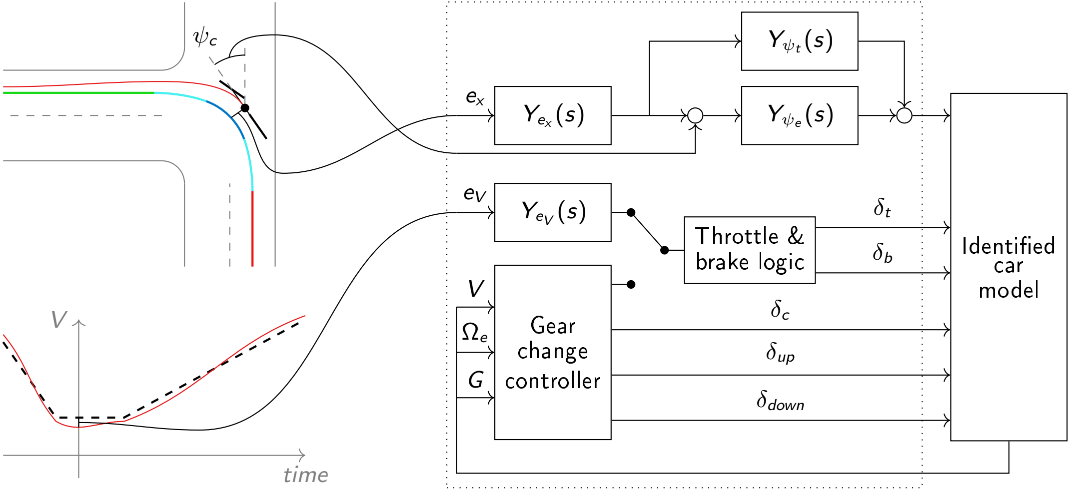
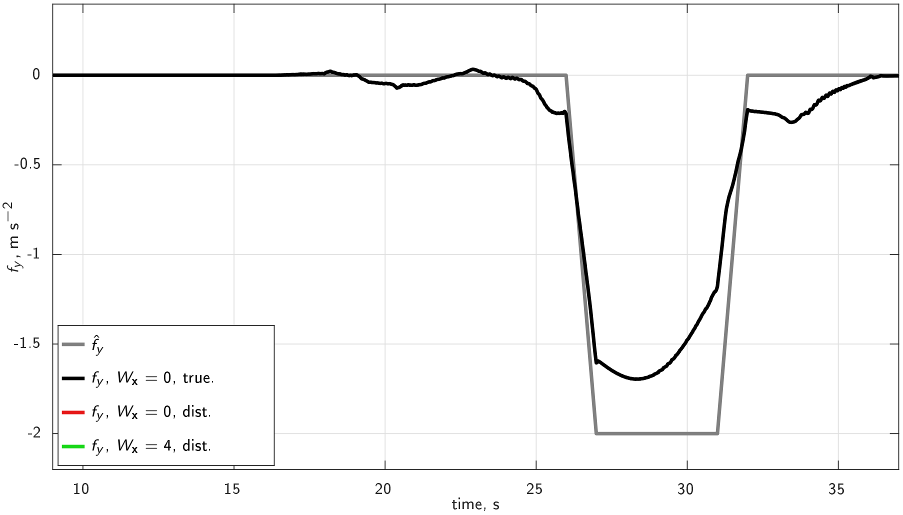


Prediction inaccuracies



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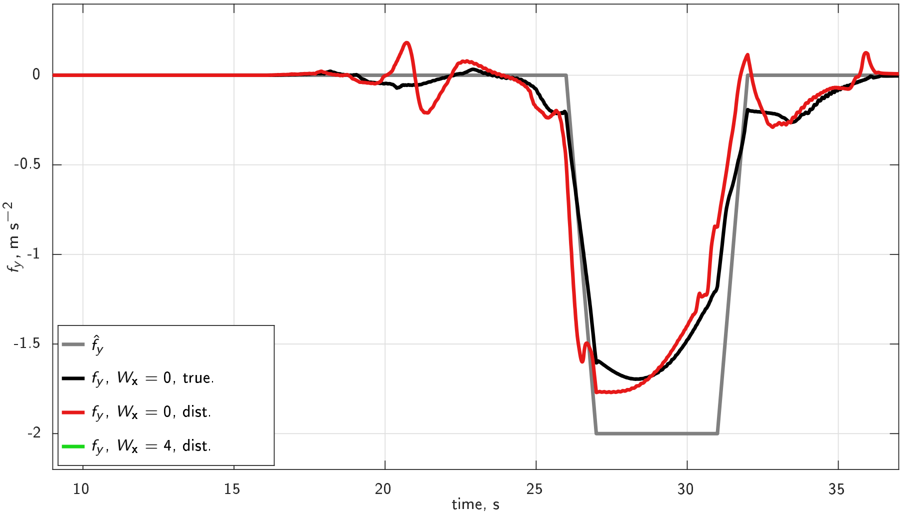

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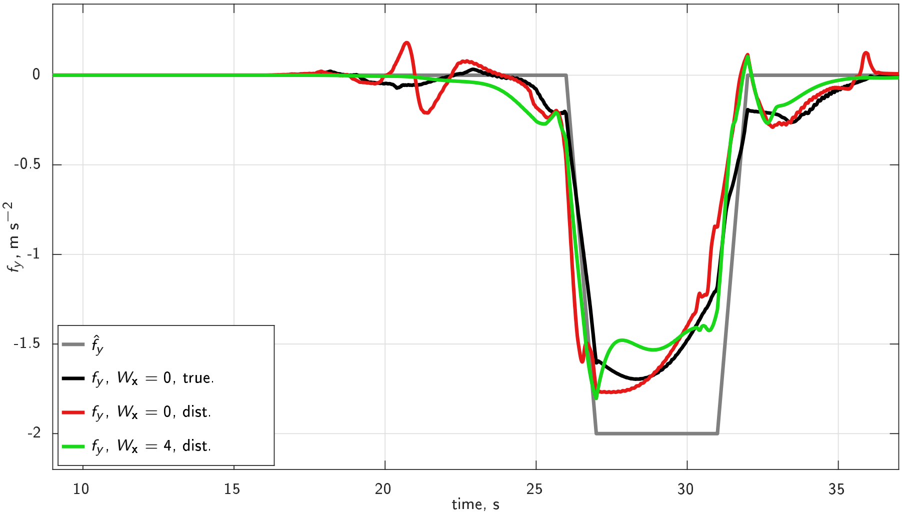

Realtime prediction method

Figure: https://www.youtube.com/watch?v=4OFMcHZ4fQc

Experiment goals

Investigate how the perceived quality of the motion depends on

1. the prediction method (Realtime or True)

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	Prediction	State-error weight		
		$W_\mathsf{x} = \mathrm{diag}([\mathbf{0}\ \mathbf{0}])$	$W_\mathsf{x} = \mathrm{diag}([\mathbf{1}\ \mathbf{0}])$	$W_\mathsf{x} = \mathrm{diag}([\mathbf{4}\ \mathbf{0}])$
Active	*Realtime*	A-R0	A-R1	A-R4
Passive	*Realtime* *True*	P-R0 P-T0	P-R1 P-T1	P-R4 P-T4

Subject task

1. Active: provide verbal feedback (subjective comments)

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2. Passive: rate the Perceived Motion Incongruence (PMI) [Cle17]
   Assign verbal qualifiers: terrible, very bad, bad, somewhat bad, so-so, somewhat good, good, very good, or excellent

Results: verbal feedback

Active part

1. Overall quality of motion between “somewhat good” and “very good”.

Results: verbal feedback

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4. “Accelerations too weak” and “motion too early” in A-R4.

Results: verbal feedback

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Passive part

1. Comments consistent with Active conditions.

Results: verbal feedback

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Passive part

1. Comments consistent with Active conditions.
2. “Unexpected motion before the car started moving” in P-T0 and P-T1.

Perceived Motion Incongruence ratings

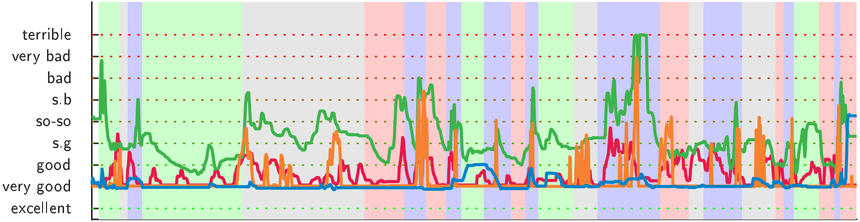
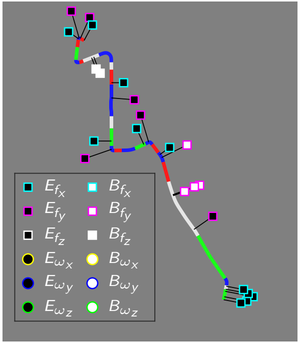
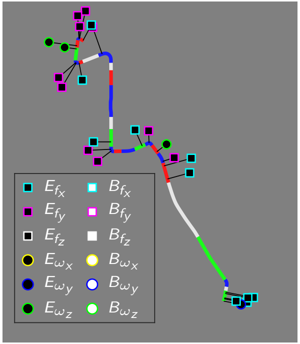


Figure: Maximum value of the two PMI ratings, scaled to the verbal qualifiers assigned to the 'best' and 'worst' PMI ratings. Condition P-R1.

Results: rating peak analysis



(a) P-R0.



(b) P-T0.

Figure: Comparison between Realtime and True prediction for $W_x = \mathrm{diag}([\mathbf{0}\ \mathbf{0}])$.

Rating peak analysis main observations

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3. “Bumps” visible only for Realtime prediction
4. $W_{\mathsf{x}} = \mathrm{diag}([\mathbf{0}\ \mathbf{0}])$ causes “ghost motion”
5. $W_{\mathsf{x}} = \mathrm{diag}([\mathbf{4}\ \mathbf{0}])$ causes too weak lateral cues

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1. Change experimental paradigm

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2. Also predict longitudinal control inputs of the human
3. Kinematic car model is too simplistic, more accurate dynamic car model needed
4. Use output error weights W_y to improve trade-off between different Degrees of Freedom

Conclusions

Despite the limited number of participants, we conclude:

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1. the MPMCA with Realtime prediction was positively evaluated by participants,
2. a non-zero state-error weight in the cost function is a reasonably effective method to prevent motion roughness, and
3. the rating-peak analysis revealed some easy-to-implement improvements to the Realtime prediction method.

Realtime prediction method

Figure: https://www.youtube.com/watch?v=4OFMcHZ4fQc

References

- D. Cleij, J. Venrooij, P. Pretto, D. M. Pool, M. Mulder and H. H. Bülthoff, **Continuous Subjective Rating of Perceived Motion Incongruence During Driving Simulation**, *IEEE Transactions on Human-Machine Systems*, 2017.
- M. Katliar, F. M. Drop, H. Teufel, M. Diehl and H. H. Bülthoff, **Real-Time Nonlinear Model Predictive Control of a Motion Simulator Based on a 8-DOF Serial Robot**, in European Control Conference, 2018.