Needs for Physical Models and Related Methods for Development of Automated Road Vehicles

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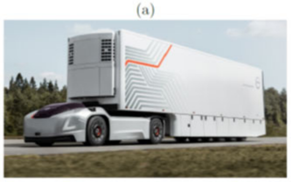
Automated Driving

(a)



(b)

Figure 1.: Driverless concepts: Volvo Vera (a) and 360c Concept (b) Volvo Trucks and Volvo Car Group, respectively)

Figure 2.: Volvo external steering [22]

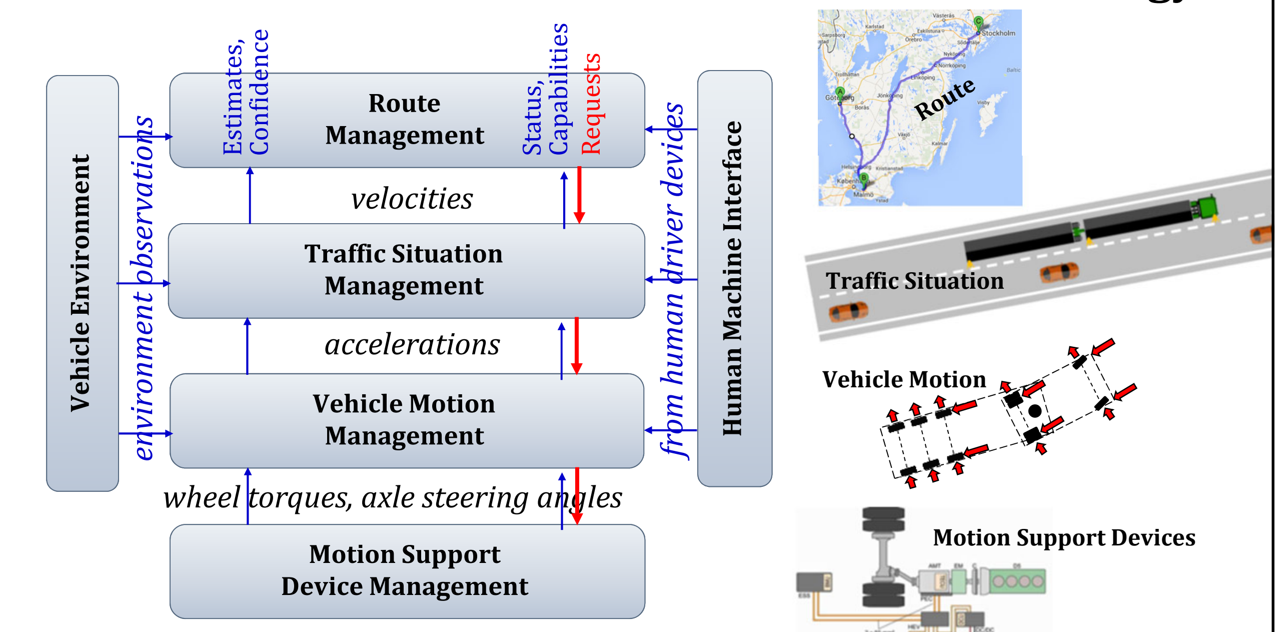
Reference: [Matthijs Klomp, et al, 2019]

SAE J3016

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	the *driving mode*-specific execution by a driver ... sistance system of either steering or accelerati... ion using information about the drivi... with the expectation that the *hu*... rform all remaining aspects of the *dynamic d... ing task* ACC **or** LKA	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and accelerati... deceleration using information about th... environment and with the exp... *uman driver* perform all remaining a... *the dynamic driving task* ACC **and** LKA	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	**High Automation**	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* ...t respond appropriately to a *request to in*... Fig 1 a)	System	System	**System**	Some driving modes
5	**Full Automation**	the full-time p...formance by an au... *iving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver* Fig 1 b)	System	System	System	**All driving modes**

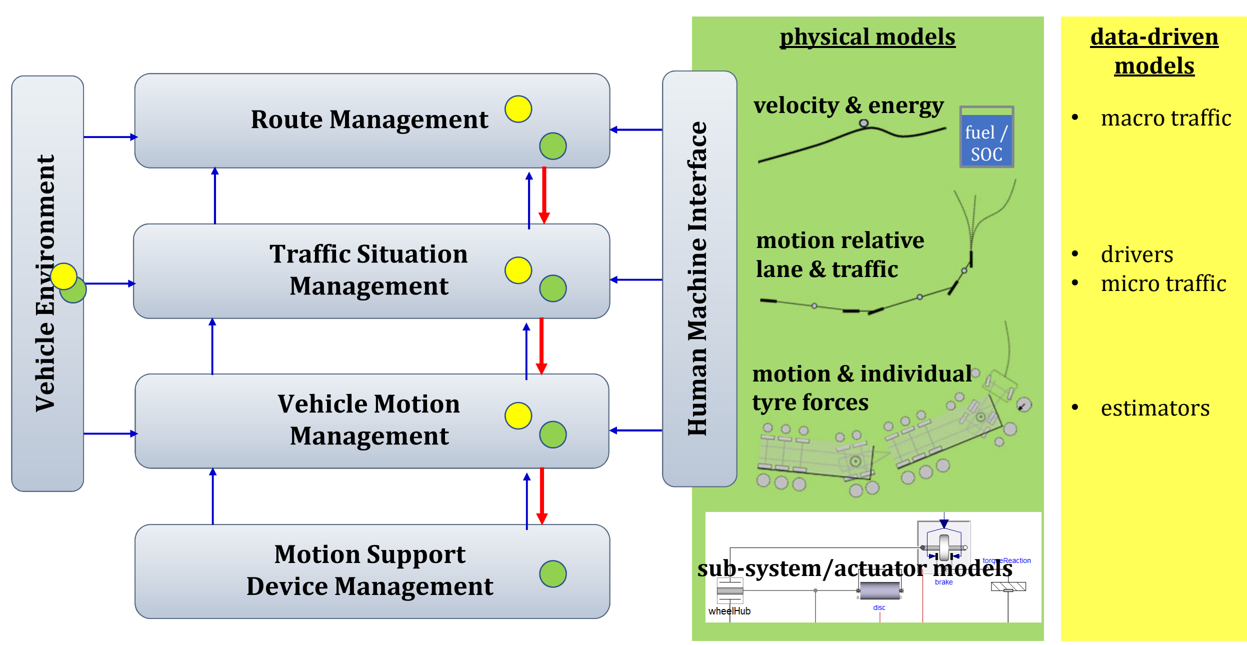
Reference: [SAE, 2014]

"*Function Architecture*" for vehicle motion & energy

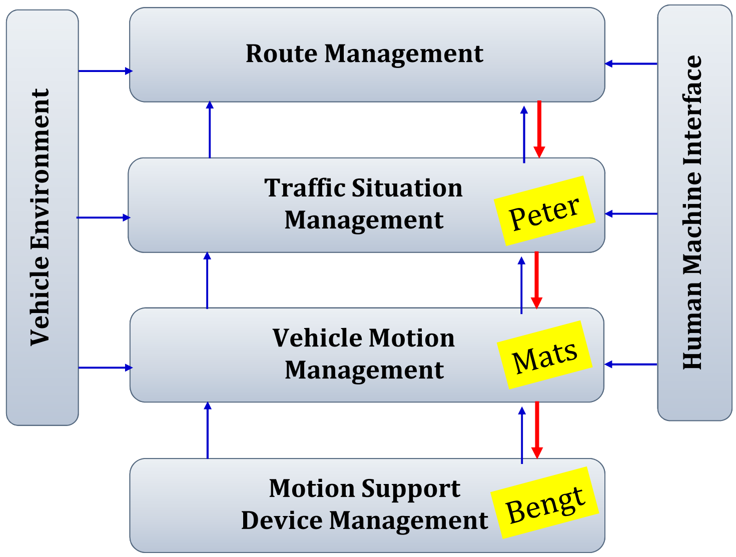


Reference: [Nilsson, 2017]

Models for vehicle motion and energy control design

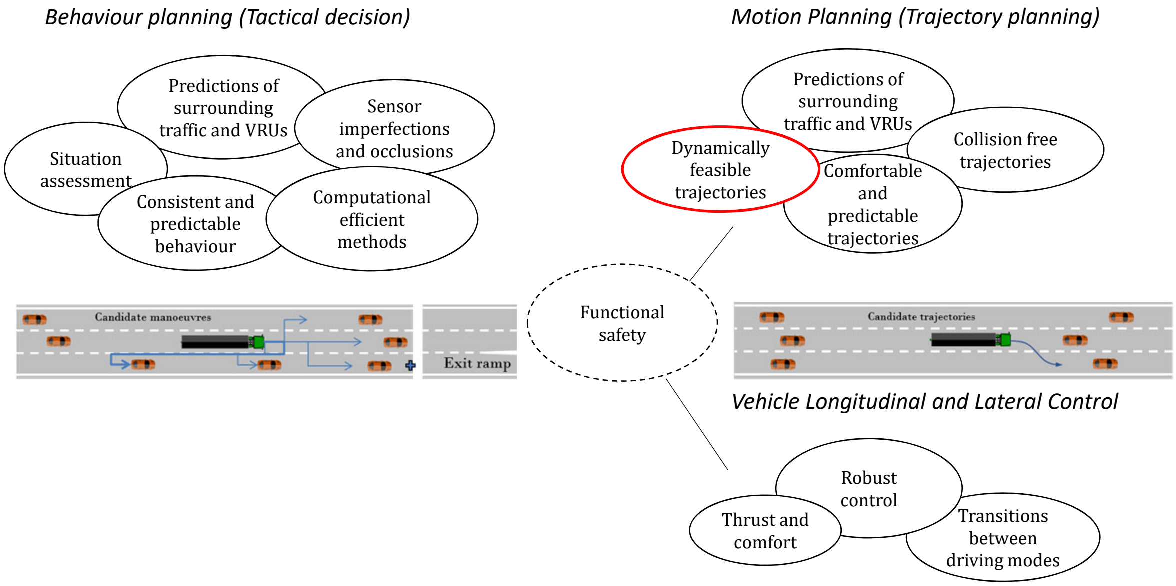


Next speakers



Traffic Situation Management,
Dynamically Feasible Trajectories,
Peter Nilsson, Volvo Trucks

Examples of challenges for TSM

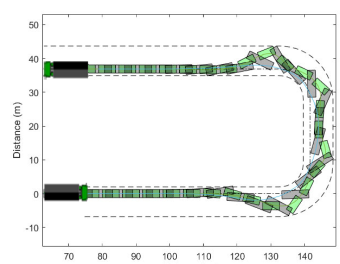


Trajectory planning

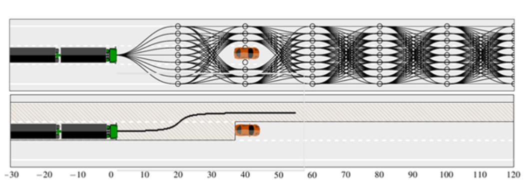
"Trajectory planning is a generalization of path planning, involved with planning the state evolution in time while satisfying given constraints on the states and actuation"

Commonly used methods:

- Numerical optimization (e.g. MPC)
- Graph search (e.g. A*)
- Neural network (e.g. Nvidia PilotNet)
- ...



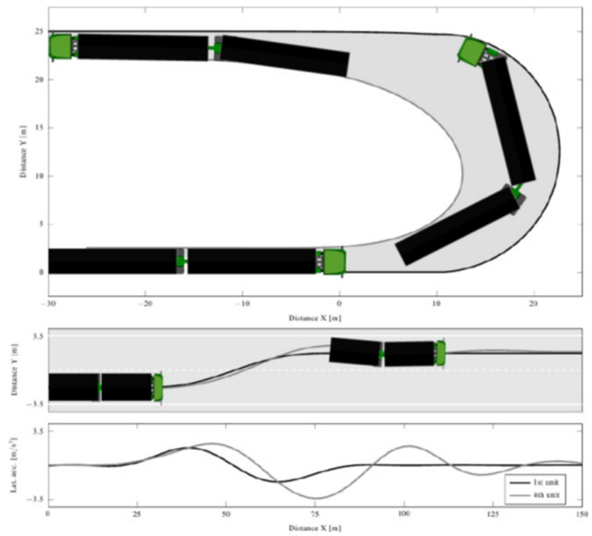
Trajectory planning example:
left curve, tractor semi-trailer



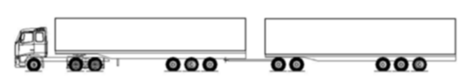
Heavy duty combination vehicles

Example of motion constraints:

- Position of first unit
- Position of trailer units (off-tracking)
- Roll-over threshold (rearward amplification)
- ...

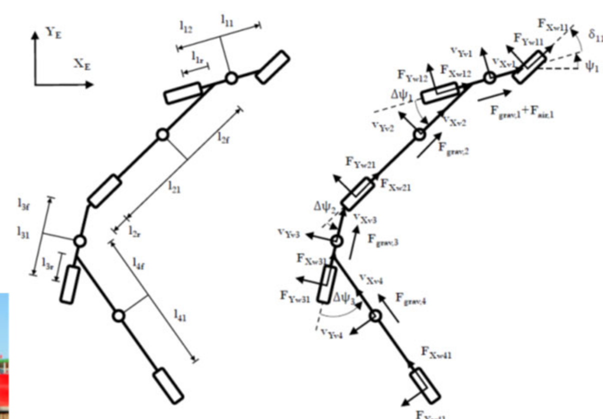


Trajectory planning modelling



Example of modelling:

- One-track models : $\dot{x} = f(x,u,w)$
- Possible states for A-double
  - 1st unit (tractor) : $v_x, v_y, \dot{\psi}_1$
  - 2nd unit (trailer) :$\Delta\psi_1, \Delta\dot{\psi}_1$
  - 3rd unit (dolly) :$\Delta\psi_2, \Delta\dot{\psi}_2$
  - 4th unit (trailer) :$\Delta\psi_3, \Delta\dot{\psi}_3$



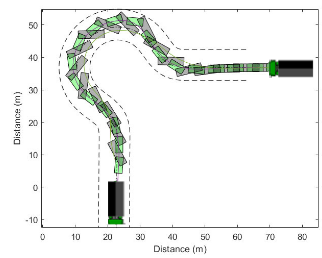
Vehicle variants and trajectory planning challenges

Vehicle variant combinatorics:

- Powertrain : ≈ 10^2 variants
- Chassis : ≈ 10^3 variants
- Vehicle load ≈ 7 - 120t (incl. different heights to CoG)
- Vehicle units : 1-4

Challenge:

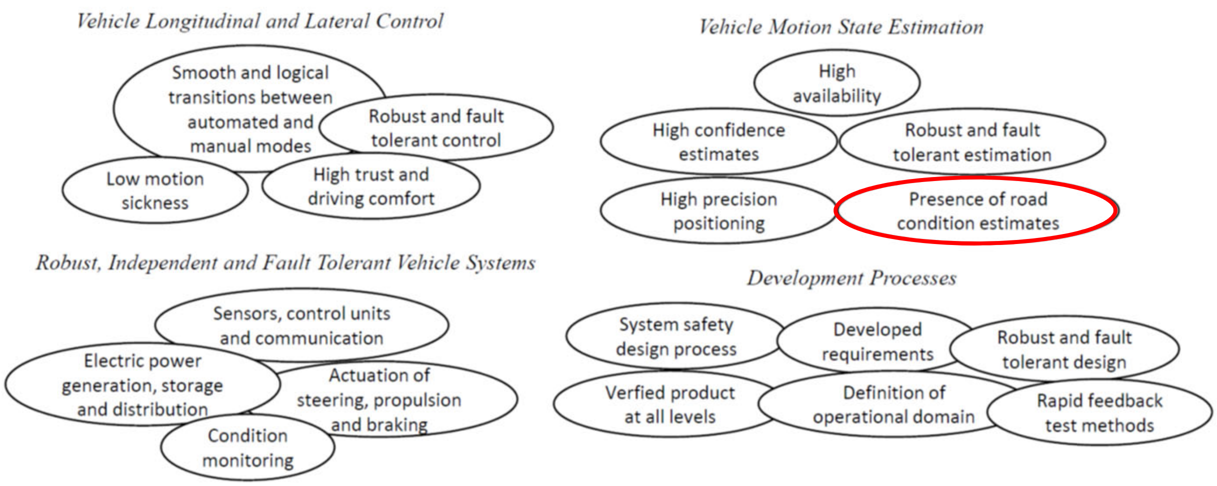
Trajectory planning methodology needs to scalable and robust with respect to variant combinatorics



Trajectory planning example:
Roundabout, tractor semi-trailer

Vehicle Motion Management, Road friction estimation, Mats Jonasson

Challenges for VMM



Reference: [Matthijs Klomp, et al, 2019]

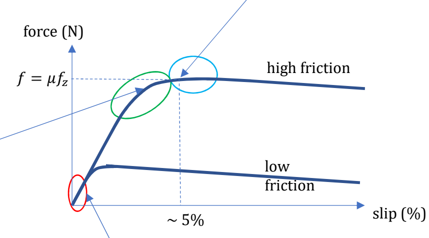
Road condition – road friction

More than 10% of all accidents occur because of slippery conditions*

In the US: yearly approx 500 000 accidents of which 1800 are deadly*

ABS activation, friction can be found $\mu \approx \frac{f}{f_z}$

To estimate friction the tyre must at least be excited to the nonlinear region at "the bend"



Definitions:

Low friction	$0 < \mu \leq 0.4$
Mid friction	$0.4 < \mu \leq 0.7$
High friction	$0.7 < \mu$

Most driving take place here, not possible to distinguish between low or high friction

* Reference: [IVSS Road Friction Estimation Part II]
* Reference: [US Department of Transportation – Federal Highway Administration
** Reference: [Wallman. Tema vintermodell – olycksrisker vid olika vinterväglag]

Confusion matrix of road friction

Assumed friction ↓ / True friction →	Low (snow)	High (dry asphalt)
Low (snow)	Vehicle speed can be adapted to friction	• False slippery warnings • AD Vehicle will drive unacceptably slow (not transport efficient)
High (dry asphalt)	• AD Vehicle will drive too fast (not safe) • High frequency of accidents	Vehicle speed can be adapted to friction

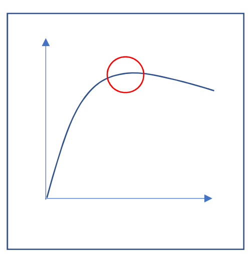
Reference: [Matthijs Klomp, et al, 2019]

Methods for road friction estimation

Optical measurement device

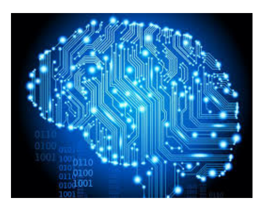
- Contactless
- Requires a map from texture to friction

Model-based estimator



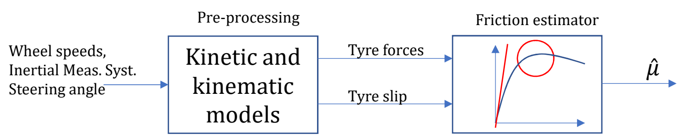
- Use the tyre as the sensor
- Requires knowledge about tyre physics

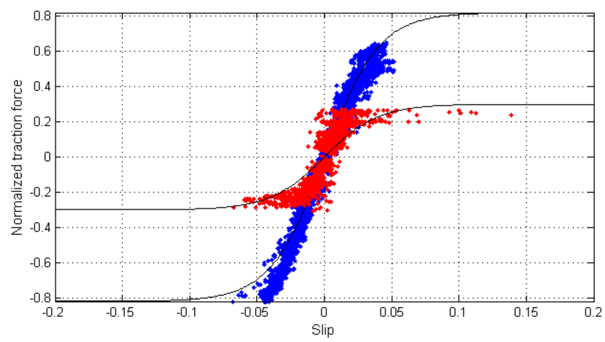
Machine learning estimator



- Use features without knowledge of physics
- Requires training

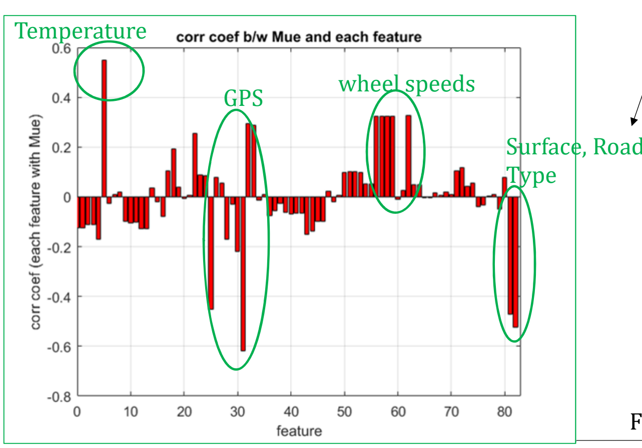
State-of-the art model-based estimator





Features and correlation to friction

Correlation to true friction



Surface & road type are not available in the sensor suite -> important to use a new sensor e.g. a camera

Temperature, GPS, vehicle speed, surface and road type are important features for friction estimation

Features 1…86

* Reference[Roychowdhury, et al, 2018]

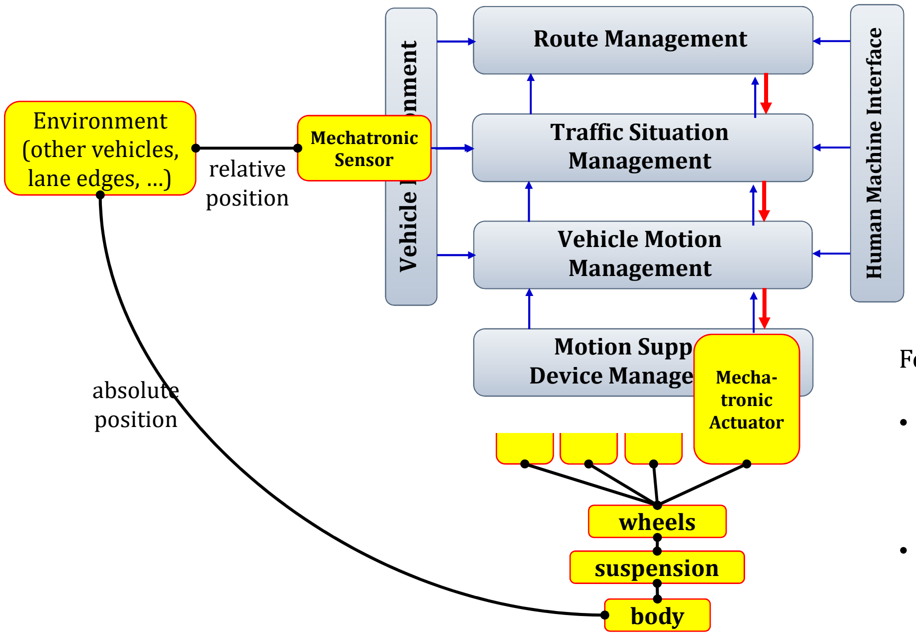
Challenges road friction estimation

- General:
  - Difficult to identify friction for normal driving (low friction utilization)
- Model-based:
  - Model uncertainties for different tyres - the physics is hard to model
  - The pre-processing is not accurate enough
- Machine learning:
  - Generalizability of machine learning algorithms to various situations
  - Generalizability would require large testing
  - Training of machine learning algorithms require ground truth – road friction is hard to measure

Reference [Jonasson, et al] 2018

Motion Devices, Virtual Verification, Wheel Model, Bengt Jacobson

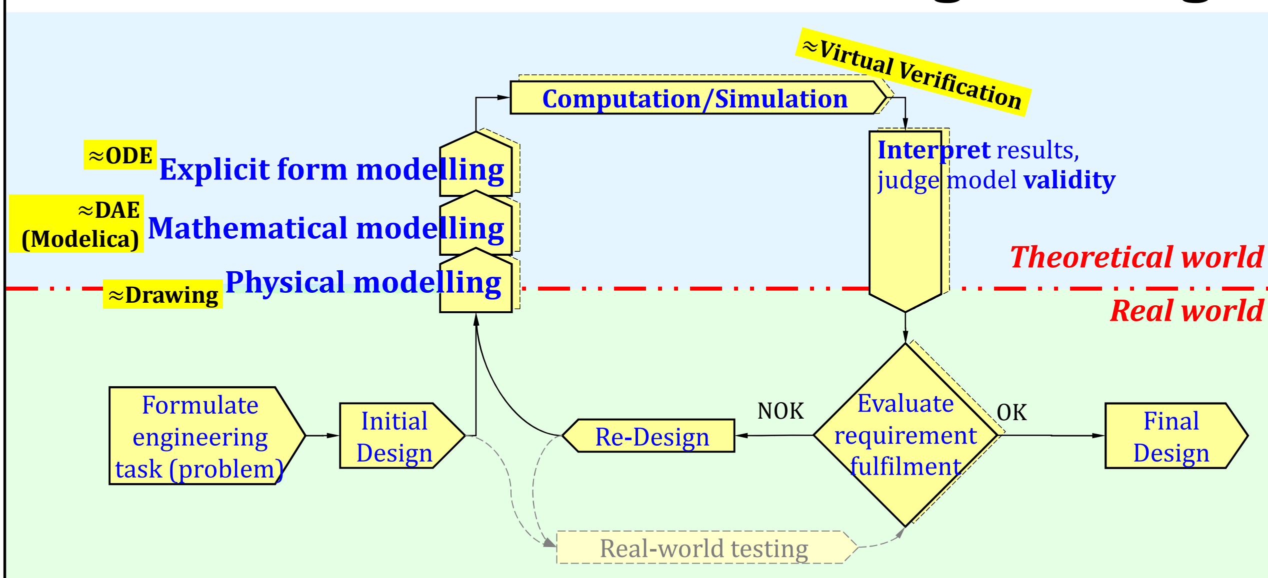
Models for Virtual Verification



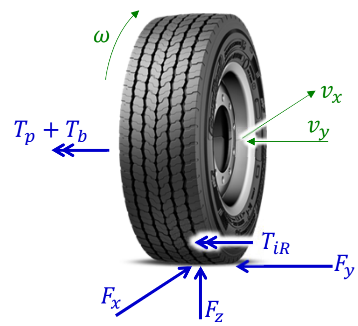
For Virtual Verification:

- Higher **accurate** and larger **validity** range than for control design.
- But **only simulate-able**, no need for linearized, inversion, etc.

...one view of model based engineering



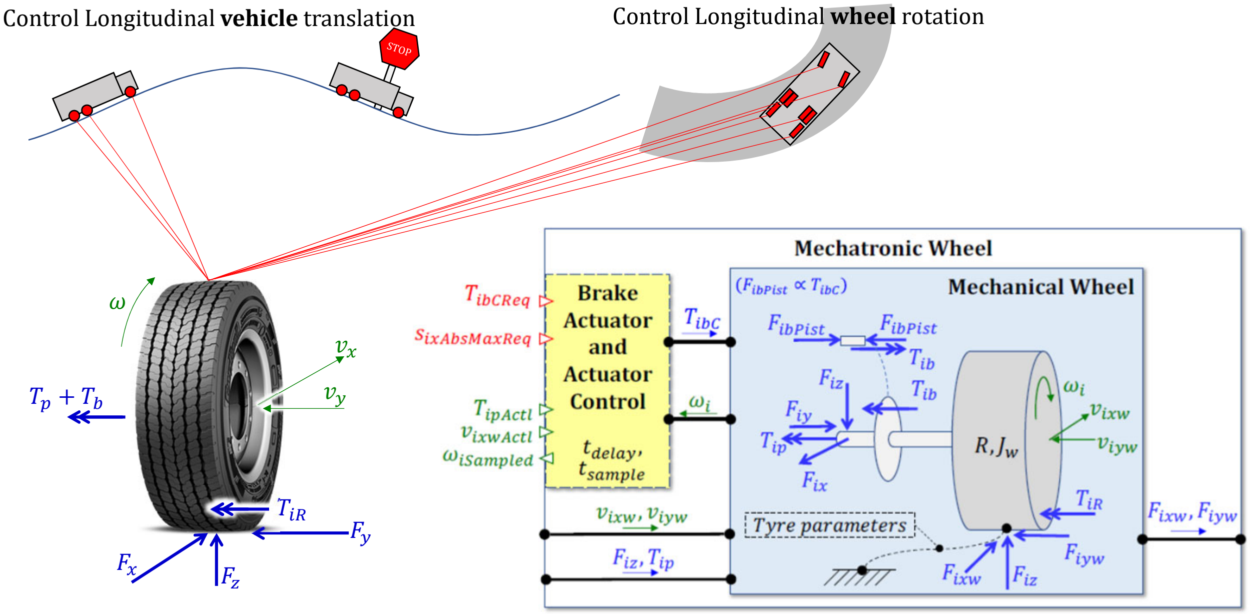
Wheel model as example



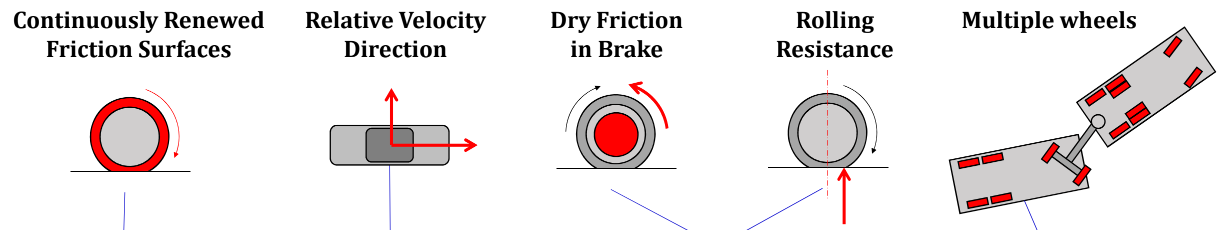
Wheel model use cases

Control Longitudinal **vehicle** translation

Control Longitudinal **wheel** rotation



Wheel model, Mechanical challenges



$$F_x = C_x \cdot s_x; \quad s_x = \frac{R \cdot \omega - v_x}{|R \cdot \omega|};$$

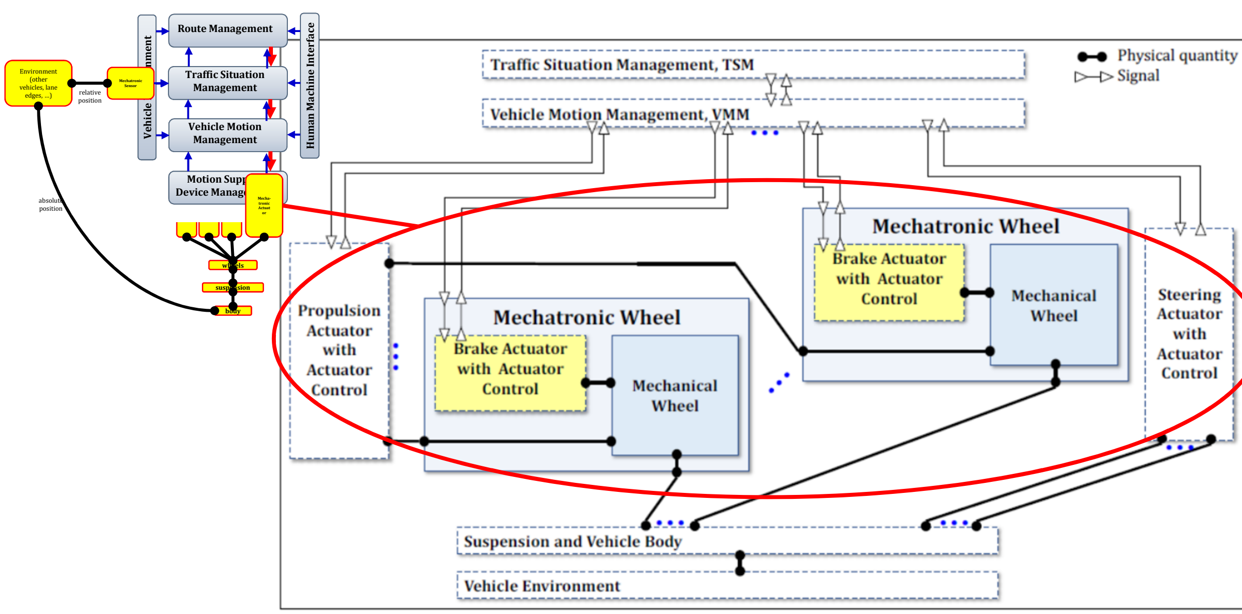
$$J \cdot \dot{\omega} = T - F_x \cdot R - T_R; \quad T_R = -\,\mathrm{sign}(\omega) \cdot (T_{bc} + RRC \cdot R \cdot F_z);$$

$$[F_x, F_y] = \min(C_{xy} \cdot s_{xy}, \mu \cdot F_z) \cdot [\sin(\theta_{Fxy}), -\cos(\theta_{Fxy})];$$

$$s_{xy} = \frac{\sqrt{(R \cdot \omega - v_x)^2 + v_y^2}}{|R \cdot \omega|}; \theta_{Fxy} = arctan2(-v_y, (R_w \cdot \omega - v_x));$$

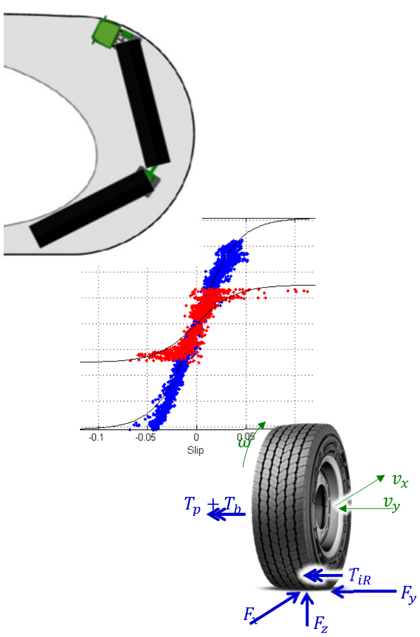
If vehicle standstill and two or more wheels locked: Statically underdetermined

Wheel model in its model context



Conclusions

You have seen:



Automated driving needs modelling in many aspects:

- TSM and VMM needs Physical modelling for "**Control/algorithm design**".
- "**Virtual verification**" drives Physical modelling, incl. exchange of models between organisation.

References

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Thanks for your attention