ACTIVE STEERING ENHANCED ESP FOR COMMERCIAL VEHICLES

László Palkovics

KNORRE-BREMSE, Hungary

It is an actual (and timeless) problem, to develop active safety of vehicles. A possible option is to enhance the electronic stability program with active steering. In case of commercial vehicles the payload is a very important factor: it could heavily change the vehicle's behavior. A commercial vehicle's active steering logic which should be more accurate than the brake based ESP logic should be capable to handle this (and of course many other) problem.

1. ESP situations

The typical ESP situations could be easily typical accident situations. A lot of statistics are investigating what is the connection between these groups. One of the most promising statistics is made by the NHTSA (National Highway and Traffic Safety Administration, USA) [1]. They say that, an SUV (Sport Utility Vehicle) category vehicle's accident chance is decreased with 67 %, if ESP (Electronic Stability Program) is integrated into the vehicle. In case of commercial vehicles, the typical accidents and they reasons are the followings:

– Rollover – high COG

– Sliding out of the road – low friction coefficient or high speed

– Jack-knifing – trailer's hurrying

– Sliding out – the loss of the rear lateral forces

– Oscillation – bad load distribution

– Sleeping – tiredness

Two fundamental things have to be noticed about this list: the first one is the payload. An empty Iveco Eurocargo ML120E21P's mass is 4 tons, and the load distribution on the axles is 70:30. In a laden state the mass will be 12 tons, and the distribution is 29:71. Another fundament is the low frequency of the active steering capable situations. Both the heavier mass (relative to the passenger cars), and the increased inertia of the steering mechanism (relative to the braking mechanism) are causing that, the potential active steering situations are the low frequency behavior cases. Imagine a highway exit: a tightening curve, which not requires sudden steering maneuvers, in contrast with a double lane change. In the latter case the main aim is the fastest reachable intervention. The steering system probably is not the best intervention unit in this case. It is too slow and an accurate intervention is not possible if the lateral wheel slips are heavily changing. So, in different cases the frequencies of the necessary interventions are not the same. This reason and the necessary measured and calculated signal stability (the tire's lateral gripping will be unstable during braking [2]) result that a steering intervention has two fundamental working conditions:

– Low frequency accurate steering intervention, without braking intervention

– High frequency approximate steering intervention, with brake intervention

For these two cases, two different control strategies are necessary. In the first case, very high steering control accuracy can be achieved; in the second case this can not be made. In the first case an accurate and robust controller is needed, in the second case a simple but effective controller is needed.

2. Possible control strategies

Several cases were investigated with simplified simulations, to figure out, which control technology is the best for the low frequency steering based vehicle stability control. Most of these simulations were made with a simple bicycle model, and the aim of the control was to ensure yaw stability. The investigated interventions were:

– Braking intervention only.

– Steering intervention at the front axle.

– Steering intervention at the rear axle.

– Combination of these.

And four control strategies were tested:

– PID control

– Neuro-Fuzzy logic control

– LQ control

– H_∞ method

Our aim was to select empirical and theoretical control strategies: the PID and Fuzzy solutions could be used without any information about the controlled system. With some empirical tuning, or observing the inputs and outputs of the controlled "black box", an enough accurate controller could be made. In case of LQ and H_∞ method, the controller is made with the exact knowing of the controlled system architecture, and the resulted control matrix is depending on some weight parameters. In these cases Riccati equations are used [3] to find out, which is the best solution.

Every control technology stabilized the vehicle, but there were special requirements for the simulations, which resulted in differences between the technologies:

– The size and rate of the control signals were limited.
– The control signals were delayed, and transfer functions were used as actuator simulators.

– The controller's design parameters were significantly inaccurate.

– The measured signals were disturbed like a real EBS sensor's signal [4] (based on real vehicle measurements).

There were three investigated several vehicle states based on complex vehicle simulation results – empty, semi laden and laden state. The controllers were designed and tuned for the semi-laden state with new tires. The worn tire cases were also investigated: simulations were made with worn tires only on the first axle, only on the rear axle and on every axle. Our aim with these defined states was to estimate the tendencies of the developed controller's behavior. The control strategy comparison simulations vehicle states were based on the mentioned Iveco Eurocargo truck.

Table 1: The used vehicle states

	Empty	Semi laden	Laden
Mass (kg)	4111	8045	11980
Inertia (kgm^2)	13527	27271	27995
Load distribution (%/%)	70/30	36/64	29/71
front/rear μ (-/-)	0,6/0,8	1,0/1,0	0,8/0,6

Both the simulated vehicle and the developed controllers are based on a bicycle model. In Table 1 the used vehicle parameters could be found, the axle distance is 3,69 m. The tire's cornering stiffness parameters were calculated for a linear tire characteristic, but the maximal lateral tire force is limited. The longitudinal velocity is treated as a constant (15 m/s), and longitudinal tire forces are neglected.

Our aim was to ensure real sensor signal quality and operating frequency for the control logic, so a 10ms discrete step time environment was used for the controllers, and a real EBS system's control signals were analyzed. With calculating of variance of the signals and they derivatives a discrete step time random number generator was used as signal disturbance source. This noise was not filtered in our further signal development work, because the sensor signals are already filtered by the sensor units, and probably with further filtering of the signals significant data loss could be reached.

The goal of the control is to ensure yaw rate reference signal following as good as it possible, with low control signal noise ratio. For this an external control torque is used.

2.1. PID strategy

This control technique is the simplest. P means proportional, I means integrator and D means derivative. With the mentioned variables of a controller input, the controller output could be easily calculated from the sum of the parts. The question is the value of the gains. Equations (1)-(6) define the bicycle model's behavior. From these, equation (7) shows an estimated value of the necessary steady state control torque. With neglecting of the steering intervention case, and the vehicle sideslip product's negligible value, (8) shows a default gain value for the PID parts. Table 2 contains the markings for the mentioned equations.

Table 2: The used markings

Mark	Meaning	SI dimension
m	vehicle mass	kg
a_y	lateral acceleration	m/s^2
F_i	lateral force	N
J_z	vertical vehicle inertia	kgm^2
Ψ	yaw angle	rad
t	time	s
l_i	distance from COG	m
M	control torque	Nm
v_y	lateral velocity	m/s
v_x	longitudinal velocity	m/s
β	vehicle sideslip angle	rad
α_i	wheel sideslip angle	rad
δ_i	steered wheel angle	rad
c_i	wheel cornering stiffness	N/rad

$$m \cdot a_y = F_1 + F_2 \tag{1}$$

$$J_z \cdot \frac{d\dot{\psi}}{dt} = F_1 \cdot l_1 - F_2 \cdot l_2 + M \tag{2}$$

$$\begin{aligned} a_y &= \left(\frac{dv_y}{dt} + \frac{d\psi}{dt} \cdot v_x \right) \\ a_y &\approx \left(\frac{d\beta}{dt} + \frac{d\psi}{dt} \right) \cdot v_x \end{aligned} \tag{3}$$

$$\beta \approx \frac{v_y}{v_x} \tag{4}$$

$$F_i = c_i \cdot \alpha_i \tag{5}$$

$$\alpha_i = -\beta + \delta_i + (-1)^i \cdot \frac{l_i}{v_x} \cdot \dot{\psi} \tag{6}$$

$$M = \begin{bmatrix} \beta & \frac{\dot{\psi}}{v_x} & \delta_1 \end{bmatrix} \cdot \begin{bmatrix} c_1 \cdot l_1 - c_2 \cdot l_2 \\ c_1 \cdot l_1^2 + c_2 \cdot l_2^2 \\ -c_1 \cdot l_1 \end{bmatrix} \tag{7}$$

$$M = \frac{\dot{\psi}}{v_x} \cdot \left(c_1 \cdot l_1^2 + c_2 \cdot l_2^2 \right) \tag{8}$$

In our PID controller a proportional and an integrator part were used. For a better reference signal following property with the equation (8) calculated gain values are produced with 2. In case of a 0,05 rad/s difference between the measured and ideal vehicle yaw rates the static control torque is 18560 Nm.

2.2. Neuro-Fuzzy logic

In this solution the controlled system should be "learned" for the controller [5]. For this, we established a learning script. In this script we measured every vehicle states between a ± 10000 Nm control torque and ±0,1rad steering wheel angle range. The measuring step sizes were 2000 Nm and 0,02 rad, every combination of the control torque and steering wheel angles were investigated. The resulted surface is a plane, which is independent from the steering wheel angle, but depends on the yaw rate difference (in case of 0,05 rad/s yaw rate difference the control torque is about 9500Nm). The reference signal following property of this solution also required an integrator part, and the sum of this and the original difference between the ideal and measured yaw rates were multiplied with 2 – like in case of PID controller. So the mentioned static control torque in case of 0,05 rad/s yaw rate difference is also about 19000 Nm.

2.3. LQ regulation

In case of LQR, state observer should be used. In our case equation (9) shows the vehicle model's state space realization's state vector, input vector, and output vector – see Table 3. As it can be seen, the state vector differs from the measureable output vector, so an observer was used [6] to estimate the state vector from the measurements.

$$x = \begin{bmatrix} \beta \\ \dot{\psi} \end{bmatrix} \quad u = \begin{bmatrix} \delta_1 \\ M \end{bmatrix} \quad y = \begin{bmatrix} a_y \\ \dot{\psi} \end{bmatrix} \tag{9}$$

In case of LQ regulators two weight matrices is necessary. The first on is weighting the control signal, the second one is weighting the controlled signals. Equation (10) shows our weights for the control torque (R), and for the lateral acceleration and yaw rate outputs (Q). Equation (11) shows the observer matrix, and equation (12) is the resulted controller.

Table 3: The used LQR and H_∞ markings

Mark	Meaning
x	state space state vector
u	state space input vector
y	state space output vector
R	control signal weight
Q	output weight
L	state observer matrix
K	LQR control vector
w_{in_d1}	“disturbing” steering wheel angle weight
w_{out_ay}	lateral acceleration difference output weight
w_{out_wz}	yaw rate difference output weight
W_{out_M}	control torque output weight
w_{ref_ay}	reference lateral acceleration weight
w_{ref_wz}	reference yaw rate weight
K.a	controller’s state space’s A matrix
K.b	controller’s state space’s B matrix
K.c	controller’s state space’s C matrix
K.d	controller’s state space’s D matrix

$$R = \frac{1}{10000^2} \quad Q = \begin{bmatrix} \frac{1}{0{,}05^2} & 0 \\ 0 & \frac{1}{0{,}01^2} \end{bmatrix} \tag{10}$$

$$L = \begin{bmatrix} -1 & 0 \\ 0 & 100 \end{bmatrix} \tag{11}$$

$$K = \begin{bmatrix} -1864{,}08 & 696777 \end{bmatrix} \tag{12}$$

This controller provides an optimal balance between the control signal and controlled system outputs with respect of the mentioned weights. It does not guarantee the robustness of the closed loop system, like the PID or Neuro-Fuzzy. Equation (13) shows the static control torque for the 0,05rad/s yaw rate difference – the lateral acceleration difference's value is calculated from the Ackermann geometry. As it can be seen, it is comparable with the first two cases. Another important thing is that the LQ regulation method estimates only a proportional gain value for the system states – it is simply a PID controller's P part, which is optimized in some mathematical ways. So for the good reference signal following property also an integrator part should be used with the same gain.

2.4. H_∞ strategy

It is the "newest" control technology. The fundamental idea is the investigation of the closed loop's (the controlled system with the controller) highest singular value in case of unit excitations at every frequency. The goal is to reach the lowest singular value (the lowest H∞ norm) at every frequency [7]. For this weight gains are necessary again. These gains should be integrated into the system's state space realization. Equations (14)-(19) show the used gains – Table 3. The difference output means the difference between the reference signal and the measured signal.

$$w_{in\_d1} = tf\left(\frac{0{,}05}{0{,}3s+1}\right) \tag{14}$$

$$w_{out\_ay} = \frac{1}{6} \tag{15}$$

$$w_{out\_wz} = \frac{1}{0{,}4} \tag{16}$$

$$w_{out\_M} = \frac{1}{100000} \tag{17}$$

$$w_{ref\_ay} = 3 \tag{18}$$

$$w_{ref\_wz} = 0{,}2 \tag{19}$$

$$K.a = [-134{,}7] \tag{20}$$

$$K.b = [214{,}4 \quad 4847] \tag{21}$$

$$K.c = [3579] \tag{22}$$

$$K.d = [564{,}9 \quad 107] \tag{23}$$

$$M = \left(K.d - K.c \cdot K.a^{-1} \cdot K.b\right) \cdot \begin{bmatrix} 0{,}05 \cdot 15 \\ 0{,}05 \end{bmatrix}$$

$$M = 11139Nm \tag{24}$$

The resulted controller is shown by (20)-(23) equations in state space realization, and the static control torque is calculated in (24).

In this case, as it can be seen the method results a state space controller, which has its own integrator part. And for this there is no need for state observer, like in case of LQR – the system measureable outputs could be directly connected for the resulted controller. So a good reference signal following property could be achieved. But as it was mentioned, we investigated several load states and tire wear cases, and a realization was resulted with this investigation: a fully laden vehicle with worn tires is the most critical situation for an ESP controller. If we tuned the H_∞ controller to ensure robustness also in this situation, then the other situation's reference signal following property was worse.

2.5. Comparison results

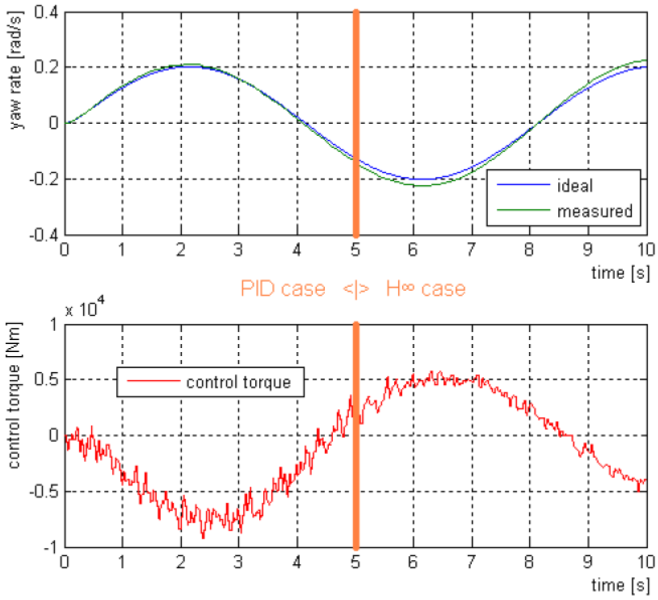

Figure 1: PID vs. H_∞ controlling method

The left of Figure 1 shows the PID control result: good reference signal following result with high control signal noise ratio. The right of Figure 1 shows the H_∞ control results: reduced control signal noise ratio with worse control signal following property. In the figure the upper graphs show the ideal and measured yaw rates of the vehicle. The controllers were developed for a semi laden vehicle state with new tires. Both the presented cases were simulated with a fully laden vehicle, which rear tires are more worn than the first ones – as it was mentioned this is the most critical case. The Neuro-Fuzzy and LQR results are not presented, because they are very similar to the PID case – the resulted static control torques indicated this.

3. Adaptive reference model

To separate the steering and braking interventions, and to ensure a more accurate and smoother steering control, we defined two types of interventions:

1. "continuous intervention"

2. "unexpected intervention"

The differences between the two cases are the sources of the disturbances:

– If the vehicle behavior is influenced only by the average road friction (and the vehicle properties of course), then it is controlled by the "continuous intervention" control logic.

– If the vehicle behavior is influenced by an outer source or a local road friction change, or a braking intervention is active, or he continuous intervention is inaccurate, then it is controlled by the "unexpected intervention" control logic.

The first logic is capable to handle under steered or over steered behavior of the vehicle with high accuracy steering control. The second logic is capable to handle sudden disturbances with fast interventions – even with active steering and individual braking. For "continuous intervention", the average road friction is estimated. Based on (1), (2), and (5) the equation for estimating the cornering stiffness off the wheels is (25). All variables of (25) could be directly measured (with wheel speed, steering wheel angle, yaw rate and lateral acceleration sensors) or estimated with integration from the measured signals, except the mentioned cornering stiffness – c_1 and c_2 –, so these parameters could calculated from (25). The necessary equations are (26) and (27): the "hat" marks in these equations estimated values. The bicycle model's sideslip angles and the cornering stiffness parameters are estimated, because the used mass, inertia and COG distance parameters are also estimated.

$$\begin{bmatrix} a_y \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} \dfrac{\alpha_1}{m} & \dfrac{\alpha_2}{m} \\ \dfrac{\alpha_1 l_1}{J_z} & -\dfrac{\alpha_2 l_2}{J_z} \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{M}{J_z} \end{bmatrix} \tag{25}$$

$$\hat{c}_1 = \frac{\ddot{\psi} \cdot J_z + a_y \cdot m \cdot l_2 - M}{\hat{\alpha}_1 \cdot (l_1 + l_2)} \tag{26}$$

$$\hat{c}_2 = \frac{-\ddot{\psi} \cdot J_z + a_y \cdot m \cdot l_2 + M}{\hat{\alpha}_2 \cdot (l_1 + l_2)} \tag{27}$$

With further processing of the resulted steering stiffness parameters (for example a filtering method is necessary), two behavioral states can be estimated (from these stiffness parameters, vehicle velocity and steering wheel angle):

- the "original trajectory",

- the "ideal trajectory".

The fundamental idea of these trajectories, is to ensure that, the vehicle's original behavior and ideal behavior will be known always exactly irrespectively of any interventions or disturbances. With the difference of these two trajectories, the continuous control signal could be always calculated (28), (29). The "original trajectory" means, what would be the vehicle's original behavior without any interventions or disturbances. The "ideal trajectory" means, what should be the best vehicle behavior – it can depend on any previously defined condition. In our system, the ideal vehicle behavior is a neutral steered vehicle. A neutral steered vehicle is estimated from the cornering stiffness parameters: depending on the COG position, an ideal proportion of the cornering stiffness parameters could be fixed. With the generation of the ideal cornering stiffness parameters starting from each axle, the better ideal parameters are considered for the ideal virtual vehicle model.

$$M = \frac{\hat{c}_1 \cdot l_1 + \hat{c}_2 \cdot l_2}{2} \cdot (l_1 + l_2) \cdot \frac{d\dot{\psi}}{v_x} \tag{28}$$

$$\delta_1 = \left(l_1 - \frac{\hat{c}_2}{\hat{c}_1} \cdot \frac{l_2^2}{l_1} \right) \cdot \frac{\ddot{\psi}}{v_x} \tag{29}$$

So, the "continuous intervention" is based on two calculated trajectories ("original trajectory" and "ideal trajectory"), and operates with possibly small range steering angles by an adaptive reference model. At the same time, the "unexpected intervention" logic also operates with the "ideal trajectory" (and basically only with steering intervention, which is simply added to the previous steering angle), but it closes the loop with observing the real vehicle state – "real trajectory". The difference of these trajectories is the input of a PID or H∞ controller. The control loop closes with this "real trajectory", because the "continuous intervention" control logic has no feedback from the vehicle's real state – it accepts only friction conditions, wheel speeds and steering wheel angles. The "unexpected intervention" control logic's "real trajectory" input depends on the interventions – the control system's output has influence on the system's input. The braking actuator's working causes worse steering control (the frequently changing longitudinal slip influences the cornering stiffness). That is the reason why during braking intervention, the "unexpected" active steering is operating with the last (before braking) estimated cornering stiffness values, or with a simple PID controller. The "continuous" active steering will be stopped in this case. So, in case of more intervention power is needed the "unexpected intervention" logic's steering signalwill act at the same time with the braking torque.

4. Results

For advanced vehicle simulations we used a complex multi-body environment, it was the SIMPACK software [8] – a fleet of commercial vehicles is built. Figure 2 shows a 4x2 validated MAN TGA tractor's sinus maneuver with active front steering. The yaw rate signal's three cases could be seen: the ideal trajectory with green, which is calculated with a classic reference model. The original trajectory is marked with red; this is estimated with the adaptive reference model. And the real trajectory, which is the blue line – this is one is resulted by the simulation; this is the vehicle's measured "real" behavior. Our aim was to control the vehicle from the red line to green line, and at the same time the two latter lines had not to move. As it can be seen, it is successfully done.

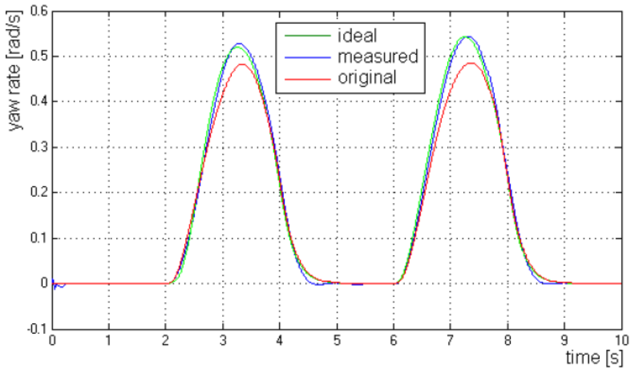

Figure 2: Sinus maneuver with "continuous intervention" control logic

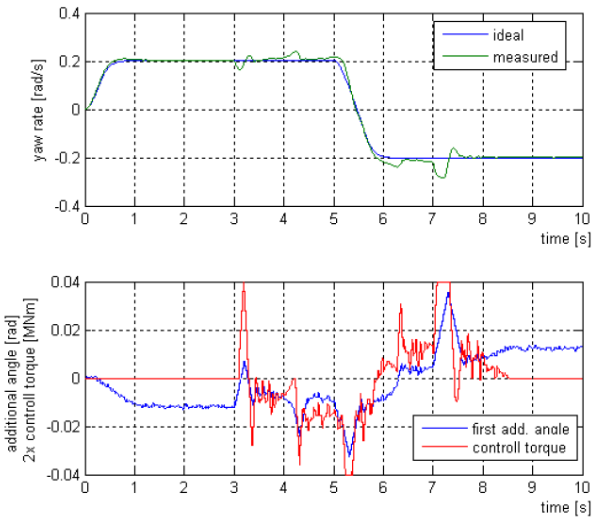

Figure 3: SESP's working in a low-µ zone

Figure 3 shows another simulation which is done with the previously mentioned bicycle model based vehicle model. In the bottom graph the control torques around the vehicle's vertical axle and the additional steering angles could be seen – these angles are the sum of the adaptive reference model's angle (as "continuous intervention") and the H_∞ control's angle (as "unexpected intervention"). The simulated vehicle is also the fully laden over steered Iveco Eurocargo. In the 3rd second the vehicle ran in a low friction zone – which zone's friction coefficient is the half of the previous zone -, and in the 7th second the vehicle ran out of this zone. At the moment of running in, the front axle lost first the grip – the vehicle behaved suddenly under steered. As it can be seen, the steering system was too slow to follow this change, so the braking actuator started to intervene. At the runningout moment in the 7th second, the first axle take the grip first, so the vehicle was suddenly over steered. As you can see, the steering actuator was also too slow, but after a half second, the vehicle state was stabilized, and the braking intervention was blended out slowly.

With the MAN model μ-split braking were also simulated with a real commercial vehicle ABS ECU. An example: during a braking from 80km/h (0,8 and 0,2 were the friction coefficients at the two sides) the biggest yaw rate (Steering ESP) was 0,18rad/s without SESP, and 0,08rad/s with SESP.

5. Conclusion

A commercial vehicle's mass and inertia properties could be significantly changed during the vehicle's daily activity. It is a challenge to follow these changes, and ensure always the best vehicle dynamic control with respect to the vehicle's state. In case of a classic brake based commercial vehicle ESP, accuracy is not the most important viewpoint – the intervention's velocity and the vehicle speed reducing effective of a braking system are the biggest advantages of this system. To ensure a more advanced vehicle dynamic control system level, the next step is the active steering. For this, more accurate control logic is needed.

Our aim is to develop this logic. The comparison of the classic control strategies showed they disadvantage: these systems are only reacting on the difference between the ideal and real states. For the accurate control integrator part and a high gain value proportional part are needed. These are resulting delay in the control loop and high control signal noise ratio. With an adaptive reference model, it is possible to "control together with the vehicle", not to react on the vehicle's behavior. The control signal will be smoother, more accurate and more direct. In the future further investigations will be done: we would like to develop our active steering logic, and we would like to make some vehicle tests. We think that, this adaptive reference model could be capable to control an active servo engine or a rear steered axle. These interaction modes are not so safety critical, like the front axle's active steering or a steer-by-wire conception. So, they are more realizable with a view to economical or technical challenges.

References

1. Insurance Institute for Highway Safety – Status Report vol. 41, No. 5, 2006

2. Hans B. Pacejka: Tyre and Vehicle Dynamics Second Edition, ISBN-10: 0-7506-6918-7, Chapter 1.2

3. Kemin Zhou, John C. Doyle, Keith Glover: Robust and Optimal Control, Cloth, 1996, ISBN 0-13-456567-3

4. Knorr-Bremse GmbH Systeme fur Nutzfarzeuge, Product Documentation Site, http://www.knorr-bremsecvs.com/engb/documentation/Pages/Documentation.aspx

5. The MathWorks, Documentation, Fuzzy Logic Toolbox, http://www.mathworks.com/access/help/desk/help/toolbox/fuzzy/fp715dup12.html

6. Joao P. Hespanha: Undergraduate Lecture Notes On LQG/LQR Controller Design, April 1. 2007, University of California, Santa Barbara

7. Bruce A. Francis: A Course in ∞ Control Theory, Springer Verlag, Berlin, Heidelberg, 1987, ISBN 3-540-17069-3

8. SIMPACK AG, SIMPACK Multi-Body Simulation Software, http://www.simpack.de