On The Mission Readiness Enhancement of Automated Ground Vehicles

***Prof. M. Velardocchia**
Politecnico di Torino –
ITALY

mauro.velardocchia@polito.it

Prof. A. Sorniotti
University of Surrey
UNITED KINGDOM

a.sorniotti@surrey.ac.uk

Keywords: mission readiness, unmanned ground vehicles, vehicle setup, over-the-air control re-calibration.

ABSTRACT

In human driven vehicles, active chassis safety systems have introduced an enhanced control authority over the vehicle dynamics, through specialised actuators allowing, for instance, independent wheel torque control. The paradigm of active safety systems, which restrict the response of the vehicle to make it predictable and intuitive for the average human driver, becomes a rather conservative proposition in the context of automated vehicles, including unmanned ground vehicles (UGVs) for military applications. Previous research on specialised driving techniques used by expert human drivers has demonstrated quantifiable performance benefits from vehicle operation in extreme conditions with high wheel slip and vehicle sideslip angle. This paper provides ideas for novel model predictive vehicle dynamics control concepts for automated vehicles, to fully exploit performance in emergency manoeuvres by pushing the boundaries of current active safety systems. The increased manoeuvrability can enhance the mission readiness of UGVs. Moreover, examples of model based sensitivity analyses of the cornering response to the variation of the main vehicle parameters are provided, which leads to the discussion of over-the-air systems using digital twins to update the vehicle dynamics controller parameters to optimise performance and enhance component durability, as a function of the actual condition of each deployed vehicle.

1.-EXAMPLES OF VEHICLE MODELS AND SENSITIVITY ANALYSES

Introduction and methodology

The evaluation of the dependency of the cornering response on the operating parameters is particularly important to enhance the mission readiness of automated military land vehicles. Since the early design phase, models can simulate the vehicle dynamics response in steady-state and transient conditions, including limit handling (Galvagno et al., 2020). This field of research has been more deeply investigated for human driven than for automated vehicles. The dynamic performance is strongly influenced by the inertia, stiffness and damping properties of chassis and powertrain components, e.g., tyres, suspensions, transmission, engine, and electric motors (Mavros, 2008). Similarly to manned vehicles, unmanned ground vehicles (UGVs) can benefit from chassis control systems, which are nowadays typically implemented through model based methodologies, in which the model should be as simple as possible, yet sufficiently accurate to describe the dynamics of interest.

This section summarises recent investigation results on the comparison of vehicle dynamics models at different levels of complexity (Mosconi et al., 2020; Galvagno et al., 2020, 2021), namely four single track (ST) models, very frequently used for model based control implementations, and a high-fidelity multibody (MB) model, used as a reference. The first ST model, referred to as Model 1, is a conventional linear bicycle model with constant parameters. The second ST model (Model 2) introduces tyre dynamics through a first order relaxation model of the lateral axle force. In addition to the features of Model 2, the third ST model (Model 3) includes the nonlinearity of the lateral axle force characteristics, in the form of variable cornering stiffness, while the fourth ST model (Model 4) also considers the roll dynamics of the sprung mass, under the assumption of constant horizontal roll axis position, see Galvagno et al. (2020) for the details.

The main model input is the steering wheel angle δ; the main outputs are the sideslip angle β at the centre of gravity (COG), lateral acceleration a_y, and yaw rate $\dot{\psi}$. The quasi-steady-state response is analysed through the ramp steer manoeuvre, with a slow steering wheel ramp applied at constant vehicle speed, which permits to generate the understeer and sideslip angle characteristics as functions of lateral acceleration. The transient analysis uses sine sweep steering manoeuvres at constant vehicle speed, to obtain the frequency response functions (FRFs) of the model outputs. The study in Galvagno et al. (2021) discusses the variation of the equivalent parameters and maps of the ST models as a function of modified operating conditions of the reference MB model.

For a case study vehicle, Figure 1 shows the understeer gradient K_{US} as a function of a_y for the different models during a ramp steer manoeuvre, while Figure 2 compares the magnitude and delay of the a_y/δ FRFs during the sine sweep steering test. The introduction of the relaxation length (Model 2), variable cornering stiffness (Model 3) and roll dynamics (Model 4) progressively makes the ST model response characteristics closer to those of the MB model, which is confirmed by the model correlation index in Galvagno et al. (2021).

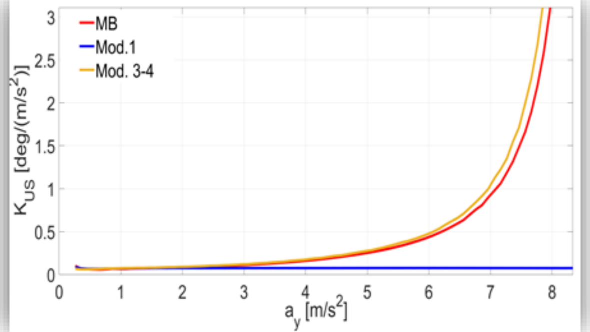


Figure 1: Comparison of the understeer gradients obtained through the considered models

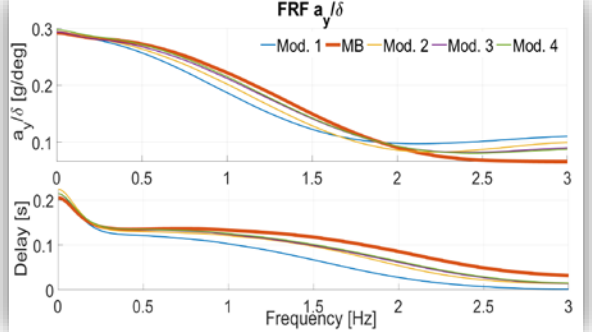


Figure 2: Comparison of the lateral acceleration FRFs obtained through the considered models

Parameter sensitivity analysis

The operating parameters associated with a specific mission can determine important variations of the vehicle dynamics response. Such effect is normally neglected in human driven vehicles, given the significant adaptation capability of human drivers. However, vehicle parameter variations could be very influential on the response of automated vehicles at the limit of handling, given the model based nature of state-of-the-art path tracking and vehicle dynamics controllers. Hence, future active chassis control systems should be automatically re-calibrated to adapt to the varying vehicle parameters. The following paragraphs include some examples of the influence of typical parameters on the cornering response.

Vehicle speed

In Galvagno et al. (2021), the vehicle handling performance was simulated at 90 and 130 km/h. The lateral axle force characteristics, roll stiffness and roll damping coefficient are not affected by the variation of vehicle speed.

For the specific vehicle, the steering ratio is higher for small steering wheel angles, which has an impact on the cornering response at different speeds. The equivalent relaxation lengths of the front and rear axles of the ST models were estimated for 90 km/h, through the comparison of the high-fidelity tyre dynamics of the MB model (red markers) with the constant relaxation length model of the ST formulations, see Figure 3. Figure 4 shows the effect of the vehicle speed on the a_y/δ FRF, and highlights the good match between the ST and MB models at 130 km/h.

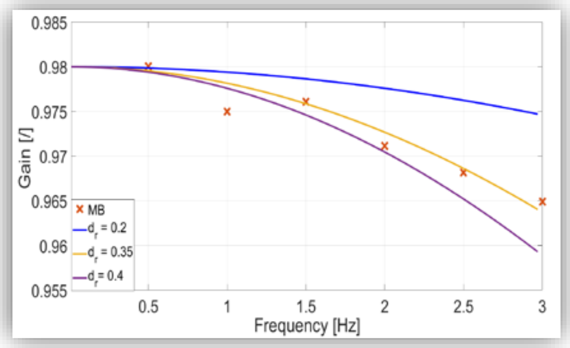


Figure 3: Relaxation length identification for the rear axle

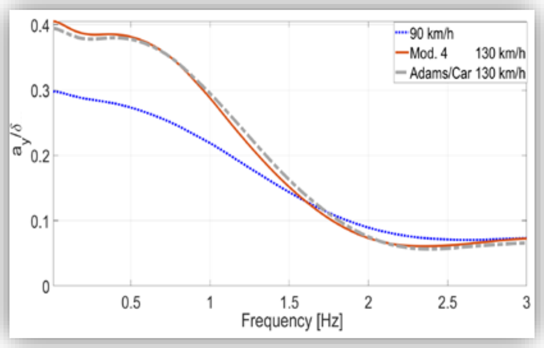


Figure 4: Effect of the vehicle speed on the FRF of lateral acceleration

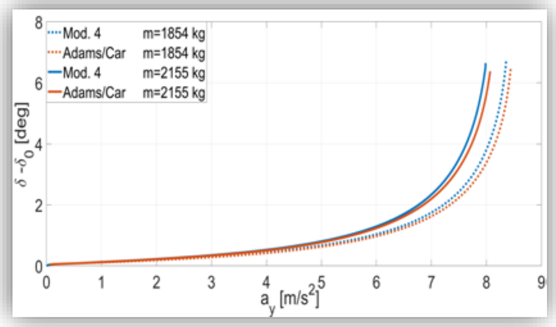


Figure 5: Effect of vehicle mass on the steady-state vehicle response (δ_0 is the kinematic steering angle)

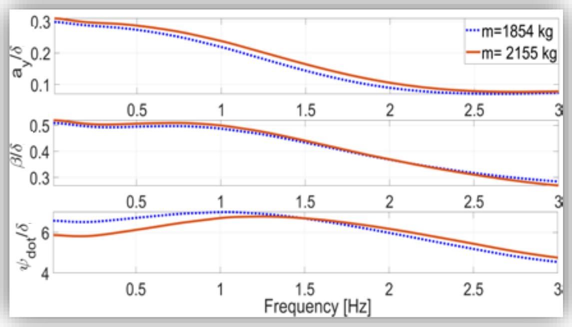


Figure 6: Effect of vehicle mass on the FRFs of lateral acceleration, sideslip angle, and yaw rate for a steering input

Vehicle mass

Vehicle mass has a significant impact on the cornering response, which is confirmed by the understeer characteristics in Figure 5, for two values of vehicle mass. The steady-state and transient axle characteristics of the ST models were derived from the response of the MB model for the corresponding mass. The 16% increase in vehicle mass, without changing the COG position, increases understeer, and reduces the maximum lateral acceleration. In the sweep steering test in Figure 6, the increased vehicle mass determines a significant reduction of the magnitude of the yaw rate response in the low frequency range.

Toe angles

Toe angle is a typically tunable suspension parameter. Figure 7 shows the understeer characteristics at different toe angles, while Figure 8 reports the FRFs generated through Model 4. Front axle toe-out reduces responsiveness, and improves stability ad high speeds.

Anti-roll bar stiffness

The anti-roll bar stiffness has an impact on the handling performance at high lateral accelerations. The increase – by a factor 3 in the considered example – of the rear anti-roll bar stiffness reduces understeer, and varies the β/δ FRF in Figure 9.

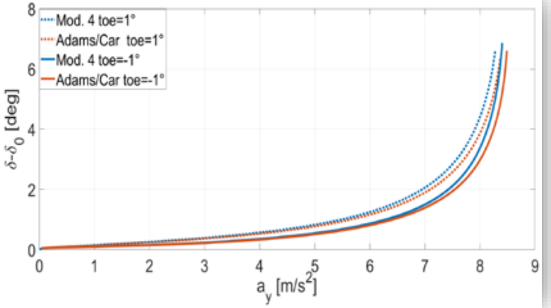


Figure 7: Effect of front axle toe angle on the steady-state vehicle response

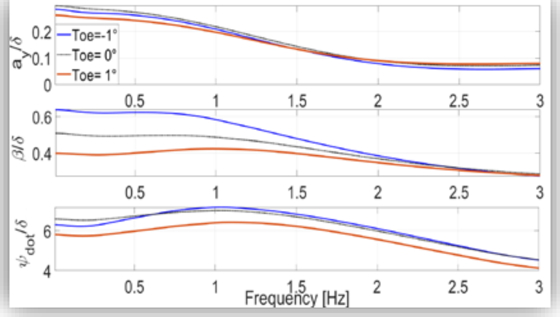


Figure 8: Effect of front axle toe angle on the FRFs

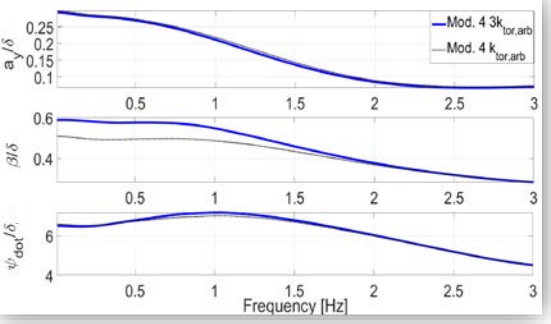


Figure 9: Effect of the rear anti-roll bar stiffness on the FRFs

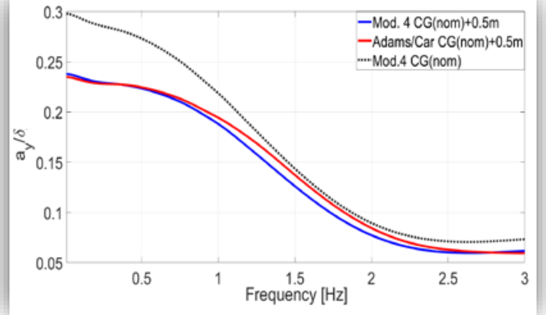


Figure 10: Effect of the longitudinal CoG position on the lateral acceleration FRF

Centre of gravity (COG) position

The longitudinal position of the vehicle COG, for a given value of total mass, can vary as a function of the specific mission. A nonlinear increase of the cornering stiffness occurs on the axle where the weight is moved, while a cornering stiffness reduction occurs on the other one. Figure 10 shows that moving the COG toward the front axle leads to a reduction of the lateral acceleration gain in the low frequency range.

Summary

The correlation between the ST models of different complexity and the MB model permits to rapidly estimate the influence of vehicle setup variations on the vehicle dynamics performance, and supports the re-calibration of the chassis and powertrain controllers, which will be discussed in section 4. Galvagno et al. (2021) indicates that:

- In an ST model, the nonlinearity in the lateral force characteristics, the tyre relaxation formulation, and the roll dynamics determine significant improvements with respect to a conventional two-degree-of-freedom ST model with constant parameters. The main contribution to the steady-state response correlation is provided by the introduction of the nonlinear lateral axle forces, achieving ~70% increase in the correlation index with the MB model. The lateral force nonlinearity also contributes to the accuracy of the FRFs. As expected, the influence of the relaxation length is evident in terms of FRFs and transient performance.
- Model 4 correlates well with the MB model in steady-state and transient conditions, even in presence of variations of vehicle speed, mass, toe angle, anti-roll bar stiffness, and centre of gravity position, and thus represents a good compromise between simplicity and accuracy.

2. VEHICLE STABILITY AND CHASSIS CONTROL: STATE-OF-THE-ART

In the automotive sector, the most widely adopted chassis control actuation systems are represented by stability controllers actuating the individual friction brakes, thus generating a so-called direct yaw moment. This form of vehicle dynamics control, typically active only in emergency scenarios, can be augmented to be continuously operational, in the form of torque-vectoring controllers implemented through controllable differentials or multiple electric powertrains. The benefits of direct yaw moment control can be enhanced by further chassis actuation systems, e.g., based on toe angle control and vertical tyre load control through active steering and suspension systems.

The state-of-the-art of vehicle stability and chassis control for road and off-road vehicles is based on model predictive control implementations, in which a prediction model, also called internal model, is used to predict the future behaviour of the system and calculate an optimal control action, which minimises a cost function J while meeting a given set of equality and inequality constraints. The internal model can be linear or nonlinear. If the model is linear, the linearisation can be carried out at each time step, around the current operating condition of the vehicle, to obtain a so-called linear time-varying model predictive controller. Given the recent progress in the available control hardware and computationally efficient solvers for real-time deployment of model predictive controllers, many recent implementations from the automotive research sector involve forms of nonlinear model predictive control, i.e., in which the internal model is expressed in nonlinear form, i.e., $\boldsymbol{x}(k+1) = f_d(\boldsymbol{x}(k), \boldsymbol{u}(k))$, where $\boldsymbol{x}$ is the state vector, f_d is the nonlinear function expressing the model formulations, $\boldsymbol{u}$ is the control input vector, and k indicates the discretization step.

A typical optimal control problem formulation for model predictive control is defined in discrete time as:

$$\begin{gathered}\min_{\boldsymbol{u}} J(\boldsymbol{x}(0), \boldsymbol{u}(\cdot)) \coloneqq \ell_N(\boldsymbol{x}(N)) + \sum_{k=0}^{N-1} \ell(\boldsymbol{x}(k), \boldsymbol{u}(k)) \\ \text{s.t.} \\ \boldsymbol{x}(0) = \boldsymbol{x_{in}} \\ \boldsymbol{x}(k+1) = f_d(\boldsymbol{x}(k), \boldsymbol{u}(k)) \\ \underline{\boldsymbol{x}} \le \boldsymbol{x}(k) \le \overline{\boldsymbol{x}}\end{gathered} \tag{1}$$

$$\underline{\boldsymbol{x}} \leq \boldsymbol{x}(N) \leq \overline{\boldsymbol{x}}$$
$$\underline{\boldsymbol{u}} \leq \boldsymbol{u}(k) \leq \overline{\boldsymbol{u}}$$
$$\boldsymbol{u}(\cdot) : [0, N-1]$$

where $\ell_N(\boldsymbol{x}(N))$ is the terminal cost; N is the number of steps of the prediction horizon H_P, here supposed to be equal to the control horizon H_c, i.e., $H_c = H_p = N\ T_s$, with T_s being the discretization time; $\boldsymbol{x_{in}}$ is the initial value of the state vector; $\underline{\boldsymbol{x}}$ and $\overline{\boldsymbol{x}}$ are the lower and upper limits for $\boldsymbol{x}$; $\underline{\boldsymbol{u}}$ and $\overline{\boldsymbol{u}}$ are the lower and upper limits for $\boldsymbol{u}$; and $\ell(\boldsymbol{x}(k), \boldsymbol{u}(k))$ is the stage cost function associated to each time step.

The optimal control problem in (1) can be solved online, i.e., on the control hardware of the considered vehicle, which corresponds to a so-called implicit solution of the model predictive control problem. The bottleneck of the implicit methods is represented by the typically significant computational requirements. Moreover, as the solution is generated online, the resulting stability properties cannot be formally evaluated a-priori. Alternatively, the optimal control problem can be solved offline, for the defined range of system states and parameters, which generates the so-called explicit solution (Grancharova et al., 2012), which is then stored in the flash memory of the vehicle control unit. The benefits of the explicit method are: a) a major reduction of the online computational requirements, as the on-board implementation reduces to a function evaluation; and b) the possibility of assessing the stability properties of the explicit solution before deploying the controller on the vehicle. The drawback is represented by the significant memory requirements associated with the explicit solution, which increase with the number of system states, parameters and control moves.

Examples of explicit and implicit nonlinear model predictive control implementations for vehicle stability control are reported in Metzler et al. (2020) and Parra et al. (2021a). In general, the main benefit of model predictive control for vehicle stability control – with respect to more conventional control formulations – is the capability of considering: a) multiple objectives within the cost function, e.g., yaw rate tracking performance, energy efficiency and actuation effort; and b) constraints, e.g., in terms of sideslip angle and individual tyre slip angles.

The current vehicle stability control paradigm based on tracking a reference yaw rate, while constraining slip angles and slip ratios, is expected to remain the same in the first generation of fully automated vehicles, in which the automated driving system will normally keep the vehicle well within the limits of handling, and the stability controller will intervene in emergency conditions to limit the yaw and sideslip dynamics. Industry leaders in automated driving technology, like Waymo in the US, BMW and VW in Europe and Baidu in China, implement automated driving algorithms restricted by driver assist systems such as the anti-lock braking system (ABS) and the electronic stability program (ESP) (Waymo 2018, Baidu et al., 2019).

3. FROM HUMAN-DRIVEN TO UNMANNED VEHICLES – CONTROL SOLUTIONS FOR INCREASED MANOEUVRABILITY

Based on the experience of the authors, this section proposes ideas for enhancing the current generation of vehicle stability and chassis control systems, which could be beneficial to the mission readiness of UGVs:

- **Pre-emptive vehicle stability controllers**, i.e., based on algorithms accounting for the expected future trajectory of the vehicle, and the information from the localisation system. One of the main drawbacks of the state-of-the-art stability controllers is that they are not fully benefitting from the model based prediction, as in the available implementations the steering angle and the reference yaw rate are kept constant along the prediction horizon, which means that only very short prediction horizons are meaningful, as the driver or automated driving system will be modifying the steering angle, without this being accounted for by the stability controller. Pre-emptive model predictive vehicle stability controllers, preliminarily described in the proof-of-concept study in Parra et al. (2021b), would include the computation of realistic steering angle and reference yaw rate profiles, to be used for obtaining the optimal control input along the prediction horizon.

For example, when appropriate before the entry of a corner, the knowledge of the current position of the ego vehicle, together with the information on the expected path ahead, is used in Parra et al. (2021b) to pre-emptively reduce the speed to a level that allows safe negotiation of the turn. The philosophy remains the one of the stability control paradigm, e.g., the pre-emptive braking action is applied only as a last resort and at the minimum intensity level to ensure safe operation along the expected trajectory, within a specified tolerance with respect to the limit of handling. In the same scenario, a conventional stability controller would allow excessively high entry speeds, yielding a rising yaw rate error and sideslip angle, which will then prompt braking and direct yaw moment control to try to stabilise the vehicle. Because of the physical constraints of tyre-road friction, the delayed stabilising effect could be insufficient to keep the vehicle along its expected path. The consequences, shown in Parra et al. (2021b) and in preliminary experiments at the University of Surrey are that: a) the maximum entry speed (i.e., the critical speed) in obstacle avoidance tests can significantly increase (Figure 11); and b) long prediction horizons will truly benefit system performance.

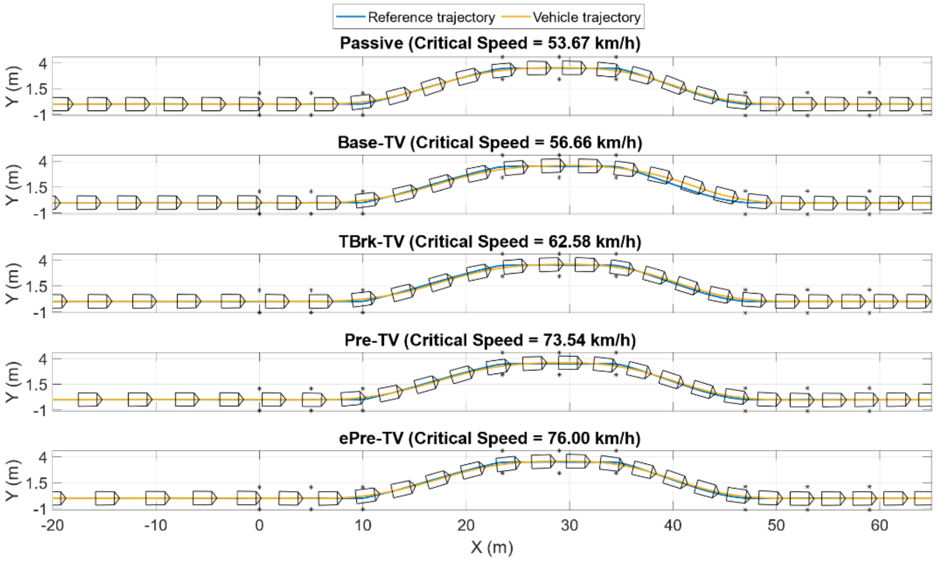


Figure 11: Trajectories along obstacle avoidance tests in high tyre-road friction conditions, carried out from the critical speed for the respective vehicle configuration (from Parra et al., 2021b). Passive: vehicle without stability controller; Base-TV: vehicle with a non-pre-emptive model predictive stability controller; TBrkTV: vehicle with a non-pre-emptive model predictive stability controller including a trail braking function; Pre-TV: vehicle with a pre-emptive model predictive vehicle stability controller, with the approximation of considering constant vehicle speed along the prediction horizon in the generation of the reference yaw rate and steering angle profiles; and ePre-TV: vehicle with a pre-emptive model predictive vehicle stability controller, considering variable vehicle speed along the prediction horizon in the generation of the reference yaw rate and steering angle profiles

- **Stability controllers tracking a reference path**. While the current generation of vehicle stability controllers based on direct yaw moment control, e.g., on the actuation of the friction brakes, follows a yaw rate target, the next generation of highly automated vehicles could benefit from using the direct yaw moment to directly track the reference trajectory of the vehicle, in an integrated control structure including steering angle control and direct yaw moment control, as preliminarily demonstrated and assessed in Chatzikomis et al. (2018), see the control blocks in Figure 12. As mentioned in the conclusions of Chatzikomis et al. (2018), “*integrated steering* *and yaw moment controllers can achieve high entry speeds, and thus enhanced vehicle agility, especially if they include a preview component in their formulation, and are tuned for the specific tire-road friction condition. Therefore, the integrated control structures can be recommended for race vehicle applications,…, with at least approximately known friction conditions.*" Undoubtedly, there is significant scope for the implementation of these integrated multi-actuator path tracking controllers for the enhancement of the operational capability of UGVs in extreme scenarios.

- **Stability controllers for vehicle operation beyond the limits of handling.** The state-of-the-art vehicle stability controllers intervene during emergency manoeuvring by restricting the response of the vehicle within a stable regime of low wheel slip and vehicle sideslip angle – i.e., operating conditions that are predictable and more easily controllable. The driver or automated driving system maintains the responsibility of providing the necessary actions to avoid an accident, relieved from the challenge of controlling the vehicle in unstable and non-intuitive operating conditions. However, this approach does not always make use of the true capabilities of a vehicle. Previous research on specialised driving techniques used by expert human (race) drivers has demonstrated quantifiable performance benefits from vehicle operation in extreme conditions with high wheel slip and vehicle sideslip angle. For example, trail braking and power-oversteer techniques are used to achieve higher speed in tight (low radius) corners (Velenis et al., 2008, 2011). The paradigm of active safety systems, which restrict the response of the vehicle to make it predictable and intuitive for the average human driver, becomes a rather conservative proposition in the context of automated vehicles, which could benefit from the implementation of extreme driving techniques in emergency scenarios.

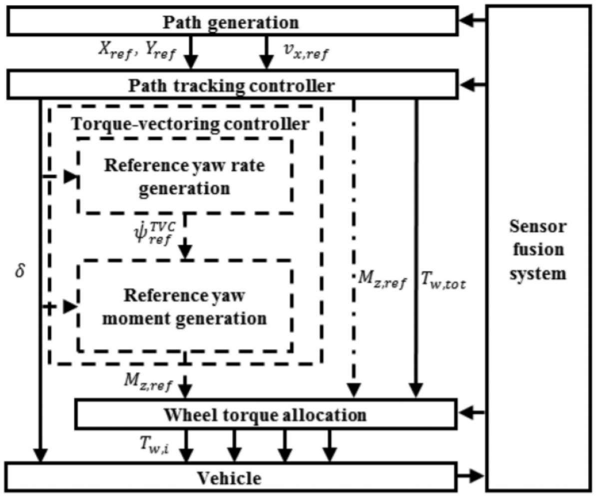
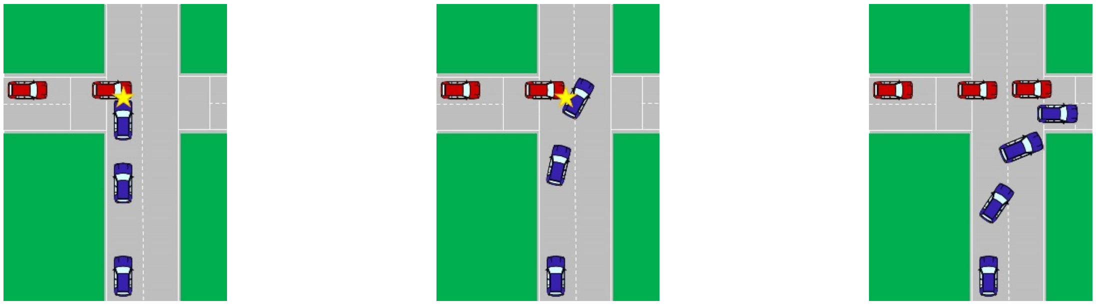


Figure 12: Block diagram of the path tracking and stability control structures compared in Chatzikomis et al. (2018), see the original paper for the nomenclature

For example, to understand the new paradigm, consider the case of an impending crash between two vehicles at an intersection (Figure 13). In Figure 13(a) the blue vehicle attempts to avoid the collision solely by braking. Even with the intervention of the ABS, which minimises the braking distance under most road conditions, the collision may not be avoided. In Figure 13(b) the blue vehicle attempts to avoid the accident by turning and braking. The conventional stability control intervention prevents the vehicle from developing high sideslip angles and excessive levels of understeer or oversteer, but does not guarantee collision avoidance. One way for the blue vehicle to avoid the collision may be to perform a manoeuvre that significantly reduces the turning radius (Figure 13(c)), by mimicking specialised techniques developed by race drivers (e.g., rally drivers), involving extreme operating conditions.



(a) (b) (c)

Figure 13: (a) Emergency braking supported by ABS; (b) Braking and cornering supported by a state-of-the-art vehicle stability controller; (c) Execution of extreme handling manoeuvre (proposed novel solution)

4. OVER-THE-AIR CONTROLLER RE-CALIBRATION DURING VEHICLE USE

Based on their pre-deployment calibration, vehicle dynamics controllers have an optimal tuning for a set of nominal vehicle parameters, typical of the condition of when the vehicle is delivered to the final users. However, during the lifetime of the vehicle, the hardware characteristics will change depending on the mission, the installed tyres, or with the progressive wear of the driveline, suspension and braking system components. Therefore, the performance of a pre-set controller will not be optimal with respect to the actual plant. Hence, future intelligent vehicles are expected to have the capability of detecting the vehicle conditions, and apply over-the-air (OTA) modifications to the control system calibration. OTA control re-calibration could also be adopted for health monitoring purposes, e.g., to prevent hardware failures through conservative control. For example, if significant wear is estimated in the drivetrain, the control system could be re-tuned to extend durability by reducing the torque transients and powertrain responsiveness. In case of suspension component wear, the controller could be updated to ensure vehicle safety while penalising extreme braking or cornering behaviour. In case of wear of a specific system or component on a vehicle with redundant actuators, the re-calibration algorithm could impose a re-distribution of the control action among the available actuators, e.g., brake-by-wire system and electric motors, while ensuring unaltered vehicle response in most conditions. The re-calibration would include modification of the reference cornering response, e.g., in terms of reference yaw rate and sideslip angle constraints, according to the identified tyre parameters and suspension compliance properties. The outcome will be the design of individual-vehicle-centred controllers, enhancing performance, maintenance and durability.

Based on the experience of the authors on vehicle control, this section outlines a possible re-calibration routine for the controllers in sections 2 and 3, using vehicle models such as those discussed in section 1. The proposed re-calibration process consists of the following three steps, according to the schematic in Figure 14:

- **Digital-twin-based identification of the vehicle condition**, in terms of level of wear (e.g., the mechanical backlash of the powertrain, or the deterioration of the suspension dampers and bushings) and parameter variations (e.g., in terms of tyre behaviour). This routine uses a simulation model (digital twin) of the vehicle system, which would run offline (i.e., on the cloud) to consider and monitor the individual vehicle condition. The digital twin is updated with a disturbance observer approach, i.e., the update would be based on the difference between the outputs of the current digital twin receiving the OTA inputs, and the outputs of the actual plant. The update mechanism can use least square algorithms, nonlinear filtering techniques, and machine learning, or a combination of the previous techniques.

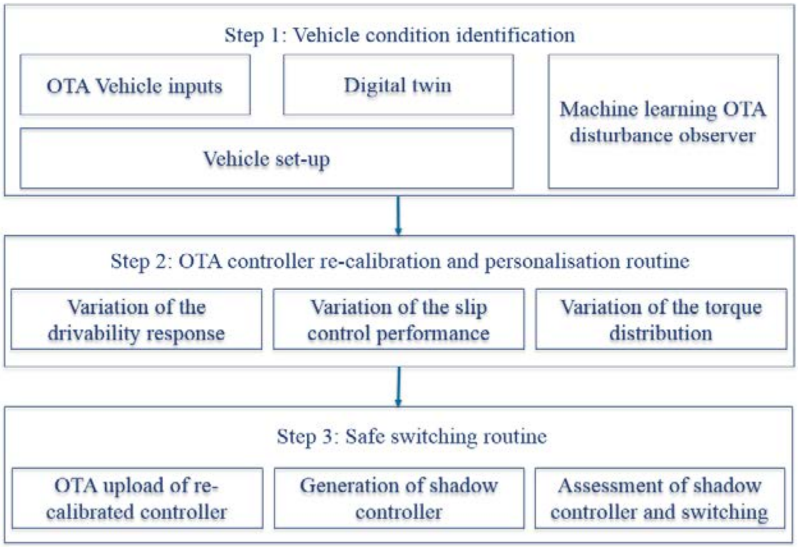


Figure 14: Example of OTA controller re-calibration steps during vehicle use

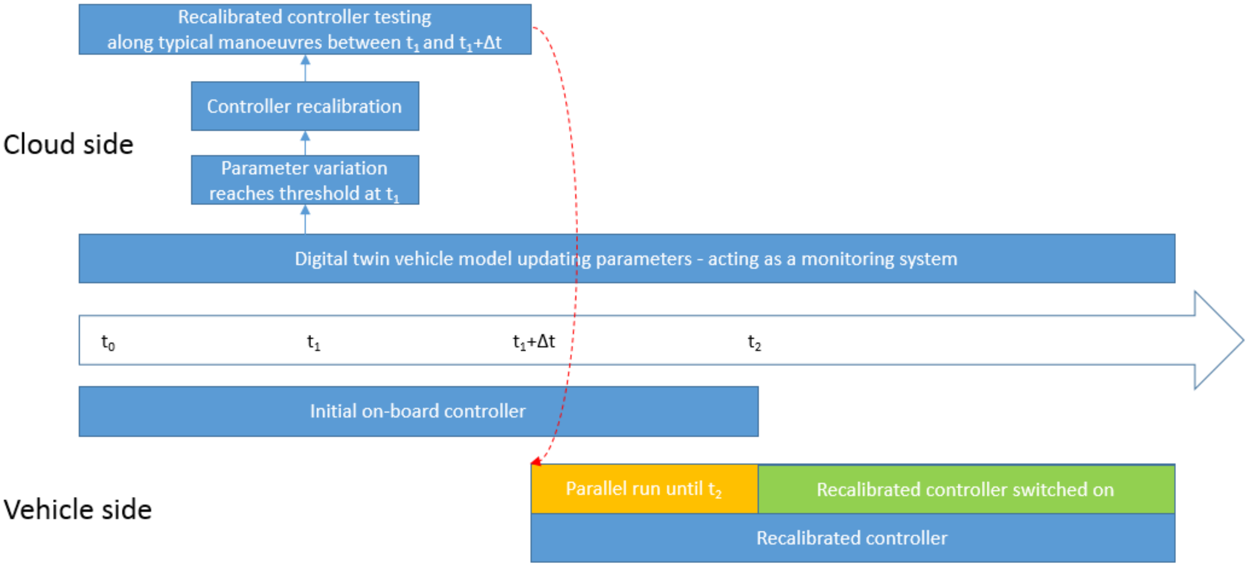


Figure 15: Conceptual schematic of the phases of the OTA update of the vehicle controller

- **OTA controller re-calibration and personalisation routine**, incorporating the information from the vehicle condition identification module, for the intermittent update of the model based controller parameters during vehicle deployment. The timing of controller re-calibration is decided based on the level of identified model parameter variations. The effectiveness of the re-calibrated controller can be tested by using the latest manoeuvres that are available from the cloud data, before the new calibration is deployed from the cloud to the vehicle.

- **Safe switching from the old controller calibration to the OTA re-calibrated controller**. During the re-calibration process, the parameters of the re-calibrated controller are sent OTA to the vehicle. The re-calibrated controller initially runs on-board in parallel with the active controller, i.e., it is implemented as a shadow controller. A routine automatically ascertains whether the outputs of the shadow controller can be deemed safe and provide the expected performance, and if so, the switching to the re-calibrated controller will occur. The sequence of phases of the safe switching routine at the cloud and vehicle levels is reported in Figure 15, where t_1 is the time at which the controller re-calibration is implemented, which is followed by re-calibrated controller testing on the cloud, until $t_1 + \Delta t$. At this time, the re-calibrated controller is deployed on the vehicle, where it runs as a shadow controller until t_2, time at which, if the re-calibration is deemed safe by the specific assessment routine, it will replace the previous setup.

5. CONCLUSIONS

Based on the experience of the authors in vehicle dynamics control, this contribution discussed potential chassis control related ideas to increase manoeuvrability, and thus enhance the mission readiness of automated military land vehicles. The initial section reported an example of model based sensitivity analysis of the cornering response of a case study vehicle, with respect to the variation of its main parameters. Simplified yet accurate vehicle models are at the core of the state-of-the-art vehicle chassis control systems, based on model predictive control, which optimises the system behaviour along a finite prediction horizon. Innovative stability control ideas were proposed for enhancing the manoeuvrability of future automated vehicles, namely: a) pre-emptive vehicle stability controllers; b) stability controllers directly tracking a reference path rather than a reference yaw rate; and c) stability controllers for vehicle operation beyond the limit of handling. Finally, an example of potential over-the-air controller re-calibration routine along the vehicle life span was outlined, using a digital twin, e.g., based on model formulations similar to those discussed in the initial section. In conclusion, the authors believe that there is significant scope for further vehicle dynamics research to increase the mission readiness and to optimise the maintenance of automated military land vehicles.

REFERENCES

[1] Baidu, BMW, VW et. al. “Safety First for Automated Driving (SaFAD),” White Paper, 2019.

[2] C. Chatzikomis, A. Sorniotti, P. Gruber, M. Zanchetta, D. Willans, B. Balcombe, “Comparison of Path Tracking and Torque-Vectoring Controllers for Autonomous Electric Vehicles,” *IEEE Transactions on Intelligent Vehicles*, 3(4):559-570, 2018.

[3] E. Galvagno, M. Galfrè, M. Velardocchia, A. Morello, V. Nosenzo, E. Capitelli, “Experimental-Numerical Correlation of a Multibody Model for Comfort Analysis of a Heavy Truck,” SAE Technical Paper 2020-01-0768, 2020.

[4] E. Galvagno, M. Galfrè, G. Mari, A. Tota, M. Velardocchia, “A methodology for parameter estimation of nonlinear single-track models from multibody full vehicle simulation,” SAE Technical Paper 2021-01-0336, 2021.

[5] A. Grancharova, T.A. Johansen, *Explicit Nonlinear Model Predictive Control, Theory and Applications*, Ed. Springer, 2012.

[6] G. Mavros, “A study on the influences of tyre lags and suspension damping on the instantaneous response of a vehicle,” *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 222(4):485-498, 2008.

[7] M. Metzler, D. Tavernini, P. Gruber, A. Sorniotti, “On Prediction Model Fidelity in Explicit Nonlinear Model Predictive Vehicle Stability Control,” *IEEE Transactions on Control Systems Technology*, 2020 (in press).

[8] L. Mosconi, F. Farroni, A. Sakhnevych, F. Timpone, A. Capobianco, F.S. Gerbino, “Identification of Tire Transient Parameters from Vehicle Onboard Sensors Data,” Advances in Italian Mechanism Science, IFToMM Italy, 2020.

[9] A. Parra, D. Tavernini, P. Gruber, A. Sorniotti, A. Zubizarreta, J. Pérez, “On nonlinear model predictive control for energy-efficient torque-vectoring,” *IEEE Transactions on Vehicular Technology*, 70(1):173-188, 2021a.

[10] A. Parra, D. Tavernini, P. Gruber, A. Sorniotti, A. Zubizarreta, J. Pérez, “On pre-emptive vehicle stability control,” *Vehicle System Dynamics*, 2021b.

[11] E. Velenis, P. Tsiotras, J. Lu, “Optimality Properties and Driver Input Parameterization for Trail-Braking Cornering,” *European Journal of Control*, 14(4):308-320, 2008.

[12] E. Velenis, D. Katzourakis, E. Frazzoli, P. Tsiotras, R. Happee, “Steady-State Drifting Stabilization of RWD Vehicles,” *Control Engineering Practice*, 19(11):1363-1376, 2011.

[13] Waymo, “Waymo Safety Report, On the Road to Fully Self-Driving,” 2018.