Proportional-Integral State-Feedback Controller Optimization for a Full-Car Active Suspension Setup using a Genetic Algorithm

Michiel Haemers[1,2,3], Stijn Derammelaere[3], Clara-Mihaela Ionescu[1], Kurt Stockman[1,2], Jasper De Viaene[1,2,3], Florian Verbelen[1,2]

(E-mail: Michiel.Haemers@UGent.be)
[1] *Department of Electrical Energy, Mechanical Constructions and Systems, Ghent University, Belgium*
[2] *Flanders Make, the strategic research centre for the manufacturing industry, Belgium*
[3] *Department of Electromechanics, Op3Mech, University of Antwerp, Belgium*

Abstract: The use of active car suspensions to maximize driver comfort has been of growing interest in the last decades. Various active car suspension control technologies have been developed. In this work, an optimal control for a full-car electromechanical active suspension is presented. Therefore, a scaled-down lab setup model of this full-car active suspension is established, capable of emulating a car driving over a road surface with a much simpler approach in comparison with a classical full-car setup. A kinematic analysis is performed to assure system behaviour which matches typical full-car dynamics. A state-space model is deducted, in order to accurately simulate the behaviour of a car driving over an actual road profile, in agreement with the ISO 8608 norm. The active suspension control makes use of a Multiple-Input-Multiple-Output (MIMO) state-feedback controller with proportional and integral actions. The optimal controller tuning parameters are determined using a Genetic Algorithm, with respect to actuator constraints and without the need of any further manual fine-tuning.

Keywords: Active vehicle suspension, Proportional plus integral controllers, Genetic Algorithm, Full-car model, Constraint satisfaction problems

1. INTRODUCTION

For everyday use passenger cars, an optimal ride comfort is the suspension system's prominent goal. For further ride comfort improvements, active suspension systems can adjust the system energy to control the vibration of the vehicle body, leading to an augmented ride comfort. In recent years, active suspension control technologies have become an extensive research topic, hence these systems have significant influence on the vehicle's subjective ride comfort impression (Wang et al. (2018)).

With a passive car suspension, the movement of the vehicle body is entirely dependent on the road surface and is described by a simple mass-spring-damper system. On the other hand, fully active suspension systems have the ability to actively control the vertical movement of the vehicle body, relative to the wheels. This is achieved by applying an independent force on the suspension and can be accomplished hydraulically or electrically.

In this work, an optimal control for a full-car electromechanical active suspension is presented. For this purpose, an active car suspension lab setup representing a full-car suspension system was built, based on the widely available theoretical full-car active suspension model (Ahmad (2014); Darus (2008)). This new approach allows to accurately simulate a driving car without the need of two degrees of freedom for every wheel, but instead only uses one fixed base and one moveable platform supported by six active rods, leading to a more convenient setup. Kinematic and dynamic analysis have been performed in order to assure system behaviour which matches typical full-car dynamics.

According to the ISO 2631 norm, the driver comfort is quantified by the acceleration levels in the three principal axes of translation (vertical, longitudinal and lateral) (Strandemar (2005)). As the active car suspension lab setup kinematically doesn't allow for longitudinal and lateral movement, the control objective is to minimize the vertical accelerations in Z-axis, and thus maximizing the driver comfort.

For simplification purposes, a full-car active suspension model is often reduced to a half-car or even a quarter-car model, meaning only one actively controlled spring-damper wheel system is examined. This results in less degrees of freedom and an overall simpler structure, but occurring subsystem interactions are neglected. Many control optimisation techniques have been carried out in order to obtain an adequate control for both full-car, half-car and quarter-car active suspension models. Kruczek and Stribrsky (2004), for example, found an appropriate H_∞ control technique for a quarter-car model. A reduced-order H_∞ controller for a full-car model was established by Wang et al. (2007).

Next to robust control, model-based predictive control (MPC) was studied to manage active car suspensions. A hybrid model predictive control for a semi-active half-car model was constructed by Canale et al. (2006). Very recently, a full-car semi-active model-predictive control approach was formed by Nguyen et al. (2016).

Also Proportional-Integral-Derivative (PID) control techniques have been used for active car suspensions. Priyandoko et al. (2009) designed a PI-controller for a quarter-car model. Later, Mouleeswaran (2012) and Ekoru and Pedro (2013) constructed a PID-controller for a quarter-car and a non-linear half-car model, respectively. Even more recently, Moradi and Fekih (2014) composed an adaptive PID-control approach for full-car suspension system simulations, subject to actuator faults.

Satisfactory PID-settings can be determined in various ways, from manually (mostly based on experience) to tuning via Ziegler-Nichols (Ziegler and Nichols (1942)), relay-feedback methods (Hornsey (2012)) or even through software-dependent auto-tuning procedures. With the ever increasing growth of available computational power in the last decades, new possibilities have emerged to achieve optimal PID-settings in ways that used to be too time-consuming. Therefore, derivative-free iterative optimizing algorithms have become of interest, sampling a large portion of the design space and converging to an optimal solution, even for noisy and discontinuous objective functions and with the possibility to implement hardware constraints. Examples of the many available optimizing algorithms are DIRECT (or Diving Rectangles), Direct Multisearch (DMS), Simulated Annealing (SA), Genetic Algorithm (GA), Covariance Matrix Adaptation Evolution Strategy (CMA-ES) or Particle Swarm Optimization (PSO) (Gao and Porandla (2005); Custódio et al. (2011); Igel et al. (2007); Reza Bonyadi and Michalewicz (2017)).

Genetic Algorithms (GA) have been successfully used to determine optimal controller settings. Wu et al. (2015) used a GA to define the optimal LQR settings to control an inverted pendulum, while Nagarkar and Vikhe Patil (2016) used the same methodologies for a plane's pitch control and a quarter-car MacPherson strut suspension, respectively. A GA can also be used to optimize H_∞ control, as shown by Du et al. (2003), who investigated a quarter-car model. Moreover, Raju and Reddy (2016) used a GA to optimally tune a fractional-order PID-controller to manage an automatic voltage regulator system. In this work, a GA is used to determine the optimal PI-settings to control a full-car active suspension lab setup model.

The paper is organized as follows. Section 2 describes the full-car active suspension model, from which a novel lab setup model is derived, described in section 3. In section 4, the road profile formation and the applied control technique for this active suspension is presented. Section 5 deals with the Genetic Algorithm and how it is used to define the optimal controller settings. The results and overall conclusion is given in section 6.

2. CONVENTIONAL FULL-CAR ACTIVE SUSPENSION MODEL

The model used for a full-car active suspension system is shown in Fig. 1. The full-car suspension arrangement is represented as a linearised seven degree of freedom (DOF) system. It consists of a single mass m_s representing the car body (or chassis) connected to four wheel masses ($m_{u,fr}$, $m_{u,fl}$,$m_{u,rr}$ and $m_{u,rl}$) at each corner. The vehicle body mass is free to heave (z-translation), pitch (angular displacement θ) and roll (angular displacement φ). The suspensions between vehicle body and wheel masses are modelled as a linear viscous damper in parallel with a spring element, while the tyre elasticities are modelled as simple linear springs without damping. An active car suspension is equipped with the ability to impose a force on the wheel masses relative to the vehicle body mass, modelled as the forces f. For simplicity, all pitch and roll angles are assumed to be small (Ikenaga et al. (2000)). Regular mid-size passenger car parameters can be found in Darus (2008). The accompanying motion equations can be found in Ahmad (2014). From these motion equations, a dynamic state-space representation can be extracted.

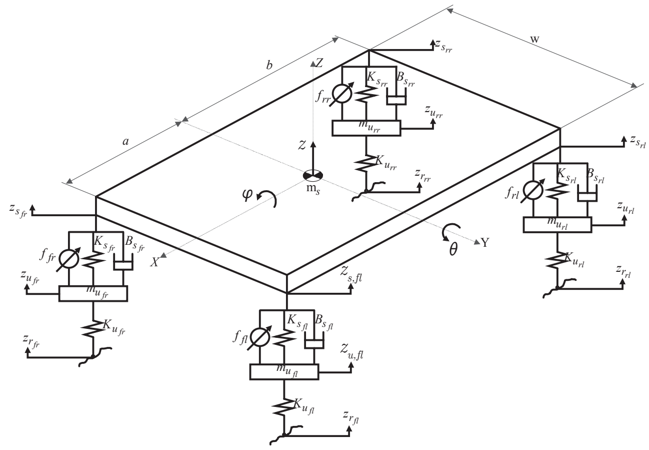

Fig. 1. Full-car active suspension model

3. FULL-CAR ACTIVE SUSPENSION LAB SETUP MODEL

Building a full-car setup based solely on the aforementioned full-car model would be very hard, as vehicle body mass and wheel masses have a lot of degrees of freedom and also the base plates at every wheel corner should be able to have a displacement disturbance. A novel active car suspension lab setup was built in order to successfully emulate a full-car active suspension. The model for this lab setup can be seen in Fig. 2. At every corner of the conventional full-car model's central mass, there is a quarter-car model with two degrees of freedom. In order to reduce the complexity of this full-car suspension model to make it more suitable for a lab setup, the parts representing the wheel masses are substituted by a one degree of freedom design consisting of a spring, damper and force actuator in parallel.

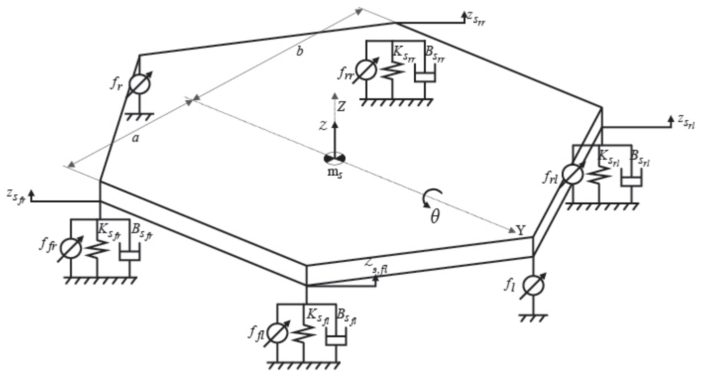

Fig. 2. Full-car active suspension lab model

As a result, the lab setup can be labelled as a parallel robot, extensively studied by Liu and Wang (2014), Merlet (2006) and Ben-Horin (1999). A kinematic study was performed to guarantee that the lab setup will have enough degrees of freedom to accurately emulate an active car suspension. The lower side of the spring, damper and actuator rod cannot translate. This has as an effect that when the central mass is pitching along the Y-axis, the spring, damper and actuator rod should be able to tilt from its initial vertical position. That is why these rods are attached to the base plate and the central mass m_s with ball couplings, providing rotational ability and fixed relative translation. An extra pair of support is provided at the side of the central mass, keeping the central mass from tipping over undesirably. In addition, these rods at the side of the central mass are also fitted with an actuator, so an extra possible location for disturbance injection is provided. This leads to six actuator rods in total, which are set up in a hexagon. Consequently, the central mass is able to translate along the Z-axis and pitch along the Y-axis, which is sufficient for emulating a car driving over a straight road.

Additionally, the lab setup model will not have the same dimensions as a regular passenger car. If, for example, the lab setup dimensions will be half of regular a passenger car dimensions and the lab setup needs to have the same dynamics, its weight will not be half, but $2^3 = 8$ times smaller. This implies that the appropriate scaling laws will have to be taken into account, as can be further inspected in Ghosh (2011). For the downsizing of the full-car model to a lab setup model, a geometrical scaling of two is used. Table 1 depicts the correct downsizing of typical passenger car parameters, next to the lab setup parameters. It shows that the lab setup is appropriate to approach the same overall dynamics as a typical mid-size passenger car.

Table 1. Downscaling typical passenger car parameters to lab setup parameters with a geometrical scaling factor equal to two

	Downsized value from a typical passenger car	Lab setup parameter
Mass inertia (I_{yy})	$4000/2^5 = 125$	104.45 $[kgm^2]$
Suspension stiffness (K_s)	$23000/2 = 11500$	13000 $[N/m]$
Damping coefficient (B_s)	$6000/2^2 = 1500$	1800$[Ns/m]$
Dimension front-rear ($a+b$)	$2.5/2 = 1.25$	1.03 $[m]$
Body mass (m_s)	$1400/2^3 = 175$	58.26$[kg]$

The motion equations to compose the dynamic linear time-invariant (LTI) model can be seen in equations 1 and 2. From these, a state-space representation can be deduced.

$$\begin{aligned} m_s\ddot{z} = &-m_s g - (K_{fr} + K_{fl} + K_{rr} + K_{rl})\, z... \\ &- (B_{fr} + B_{fl} + B_{rr} + B_{rl})\, \dot{z}... \\ &+ (a\,(K_{fr} + K_{fl}) - b\,(K_{rl} + K_{rr}))\, \theta... \\ &+ (a\,(B_{fr} + B_{fl}) - b\,(B_{rr} + B_{rl}))\, \dot{\theta}... \\ &+ f_{fl} + f_{fr} + f_{rl} + f_{rr} + f_r + f_l \end{aligned} \quad (1)$$

$$\begin{aligned} I_{yy}\ddot{\theta} = &(a\,(K_{fr} + K_{fl}) - b\,(K_{rl} + K_{rr}))\, z... \\ &+ (a\,(B_{fr} + B_{rl}) - b\,(B_{rr} + B_{rl}))\, \dot{z}... \\ &- \left(a^2\,(K_{fr} + K_{fl}) + b^2\,(K_{rr} + K_{rl})\right) \theta... \\ &- \left(a^2\,(B_{fr} + B_{fl}) + b^2\,(B_{rr} + B_{rl})\right) \dot{\theta}... \\ -a\,(f_{fl} + f_{fr}) &+ b\,(f_{rl} + f_{rr}) + \left(\frac{b-a}{2}\right) f_l + \left(\frac{b-a}{2}\right) f_r \end{aligned} \quad (2)$$

The full-car active suspension lab model has four system states, being central mass heave position (z), heave velocity ($\dot{z}$), pitch angular displacement (θ) and pitch angular velocity ($\dot{\theta}$). Five inputs are available, being actuator force on for every wheel rod (front-rear f_{fr}, front-left f_{fl}, rear-right f_{rr} and rear-left f_{rl}) and gravitational acceleration g.

4. ACTIVE SUSPENSION CONTROL

To accurately mimic a driving car, a relevant road profile needs to be formed. According to the ISO 8608 norm, a road profile can be mathematically composed, based on the assumption that a given road has equal statistical properties everywhere along a section to be classified. That is: the road surface is a combination of a large number of longer and shorter periodic bumps with different amplitudes. Another input parameter for the road profile formulation is the road roughness factor, varying from 1 to 8 with 1 being a high quality (smooth) road surface like an asphalt layer. On the other hand, a road roughness factor of 8 represents a very poor road quality, as in roadway layers consisting of cobblestones or similar material (Tyan et al. (2009); Agostinacchio et al. (2014)).

The lab setup model does not allow to impose the road profile as displacement disturbances, because the lower sides of the rods are fixed on the base plate with ball couplings (as mentioned in section 3). Instead, the lab setup only allows to make use of actuator force disturbances. Therefore, the road profile displacement for every wheel needs to be translated into a corresponding force acting between the base plate and the central vehicle mass. This is shown graphically in Fig. 3. As a result, the top side of Fig. 4 depicts a road profile encountered by a vehicle driving with a velocity of 72 km/h for 20 seconds and a road roughness factor of 5. The bottom side of Fig. 4 illustrates the corresponding disturbance force. There will also be a time delay for these force disturbances between the front and the rear wheels, depending on the vehicle speed. These actuator force disturbances are appointed as d_{fr}, d_{fl}, d_{rr} and d_{rl} for front-right, front-left, rear-right and rear-left wheel respectively. The extra available actuators at the supporting rods at the side of the setup are not being used in this case.

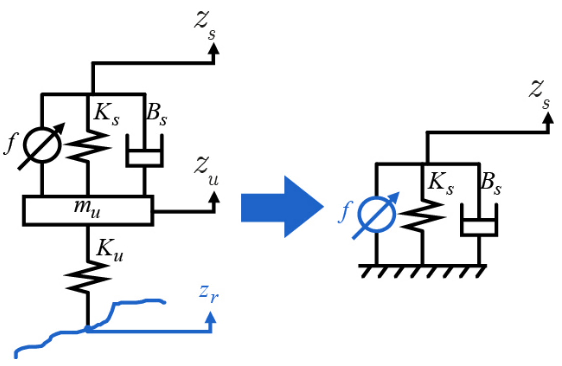

Fig. 3. Road profile conversion from quarter-car displacement disturbance to lab-setup force disturbance

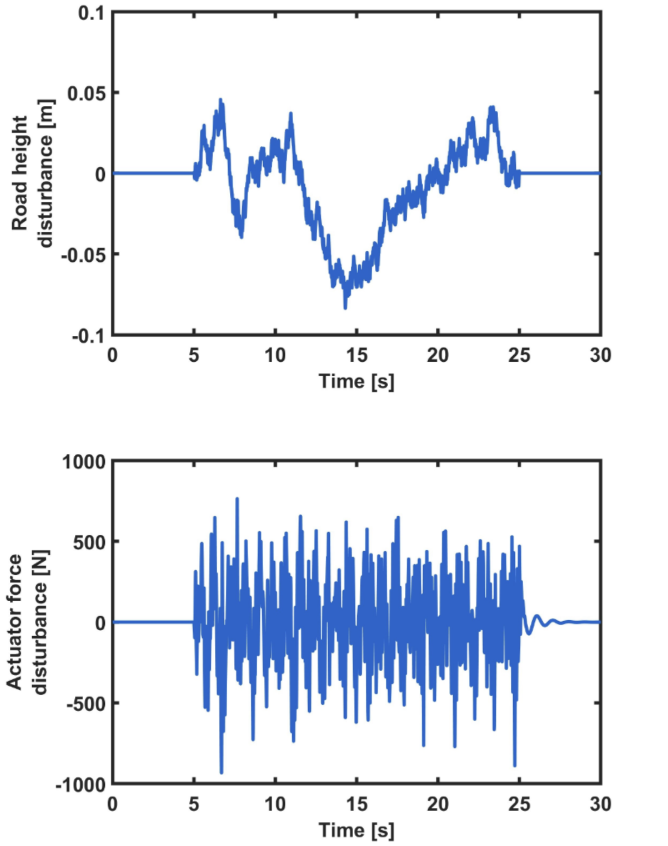

Fig. 4. Result of the road profile conversion from full-car displacement disturbance to lab setup force disturbance

As stated in section 3, a state-space representation is used to model the full-car active suspension lab setup. The applied control loop for this model can be seen in Fig. 5. There are two sets of inputs: u_1 and u_2 to minimize the objective function, which is to minimize accelerations in Z-direction. The first input matrix u_1 being the force control input for each actuator of the active suspension. The second input matrix u_2 consists of the aforementioned force disturbance inputs d_{fr}, d_{fl}, d_{rr} and d_{rl} and gravitational acceleration g. These disturbance inputs are predefined by the road profile to simulate (and vary in time), but are not part of any control loop.

Next to the state feedback matrix K_0, an integral feedback matrix K_i is used in order to implement integral action, assuring the system to achieve the reference value during operation. The K_0 and K_i can be seen as the P and I elements of a PI-controller, respectively. There are four states $(z, \dot{z}, \theta, \dot{\theta})$ and four control inputs $(f_{fr}, f_{fl}, f_{rr}, f_{rl})$, so control feedback matrix K_0 has dimensions $[4 \times 4]$, resulting in a Multiple-In-Multiple-Out (MIMO) controller. There are two reference values (for z and θ), so integral feedback matrix K_i has dimensions $[4 \times 2]$. As a consequence, there are 24 feedback gains to be determined. This proves to be a challenging task for which some controller tuning techniques are available to make a first thorough guess, but they often do not make optimal use of the (input) constraints and subsequently need further manual fine-tuning. With the use of a Genetic Algorithm, the optimal feedback gains can be found relatively easy, without further manual adjustments and with respect to (discontinuous) constraints.

5. GENETIC ALGORITHM

Genetic Algorithms (GA) are based on evolutionary processes and Darwin's concept of natural selection. In this selection, only the fittest individuals survive, while the less performing ones are left out. In this context, the objective function is usually referred to as a fitness function, and the process of 'survival of the fittest' implies a maximization procedure. A GA begins by randomly generating, or seeding, an initial population of candidate solutions. Starting with the initial random population, GA then applies a sequence of operations like the design crossover where two individuals from the initial population (parents) are reproduced to get two new individuals (children) or mutation where one individual from the initial population is slightly changed to get a new individual. Next, the worst designs are left out from the population and good ones are included in the next generation. The above entire process is repeated to further improve the objective function until a stopping criterion is met. Possible stopping criteria are related to e.g. maximum time or maximum number of generations (Gao and Porandla (2005)).

As the driver comfort is maximized for minimal acceleration in Z-axis, the GA's objective function is to minimize the RMS value of the central body's acceleration in Z-axis. Also, (non-)linear constraints can be taken into account by the GA. In this particular case, the actuator controller effort cannot exceed 1000 N, which is rather hard to take into account with conventional methods, but very easy to implement in the GA.

As stated earlier, the Genetic Algorithm used for this application has 24 variables to be optimized, representing the K_0 and K_i feedback matrices. A population size of 30, elite count of 5 and a crossover fraction of 0.5 is used. The algorithm is schematically displayed in Fig. 6.

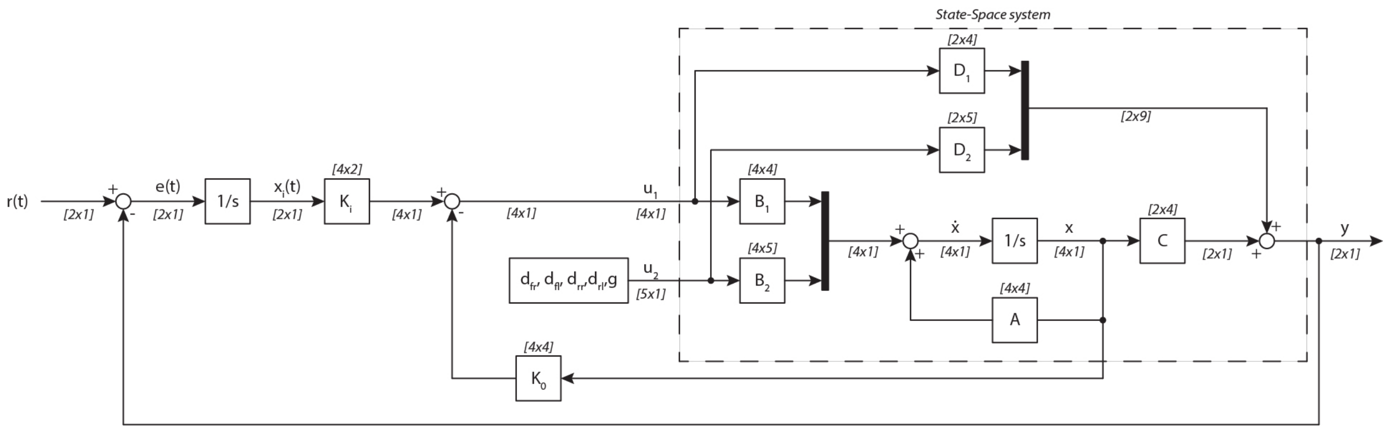

Fig. 5. Control loop for the full-car active suspension lab model

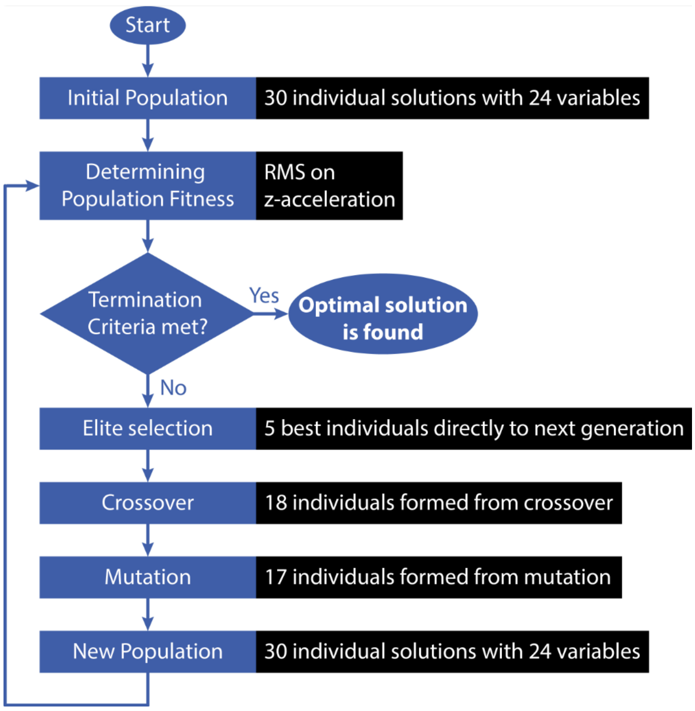

Fig. 6. General Genetic Algorithm scheme (blue) and applied on case (black)

6. RESULTS

After passing through 10 generations and calculating for about 60 minutes, the Genetic Algorithm optimization successfully determined the MIMO-controller's optimal feedback gains K_0 and K_i. The resulting performance of this MIMO-controller is compared to a full-car passive suspension, which is the case for the biggest part of all normal passenger cars.

Fig. 7 shows the comparison between the car body acceleration in Z-axis for passive and active car suspension control. It is very obvious that the vehicle body acceleration is dramatically reduced, resulting in a much more comfortable ride. According to the ISO 2631 norm, the driver comfort is quantified by the RMS value of the acceleration, here changing from 3.8975 for passive control to 0.0530 in the case of the active control with MIMO-

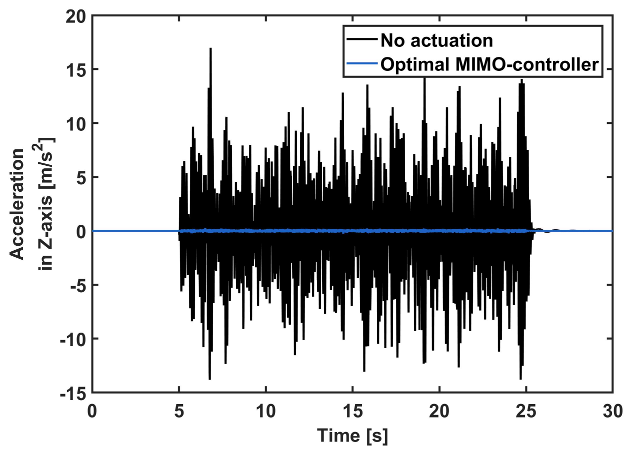

Fig. 7. Comparison between acceleration for passive car suspension and active car suspension with optimal controller settings

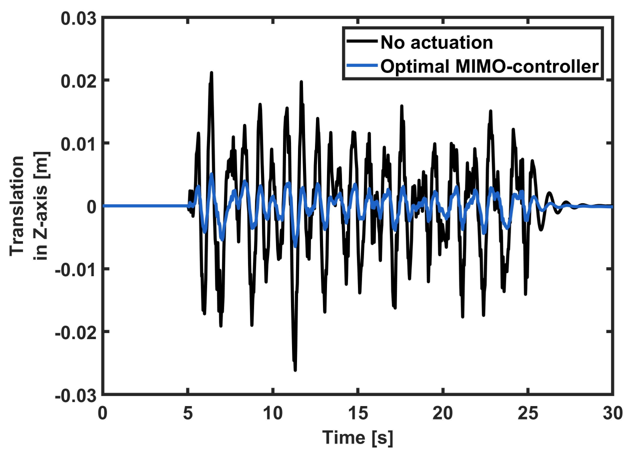

Fig. 8. Comparison between translation for passive car suspension and active car suspension with optimal controller settings

controller. In other words, an tremendous increase in driver comfort is achieved.

Fig. 8 depicts the comparison between the car body translation in Z-axis for passive and active car suspension control. It can clearly be seen that the vehicle body experiences less movement in Z-axis.

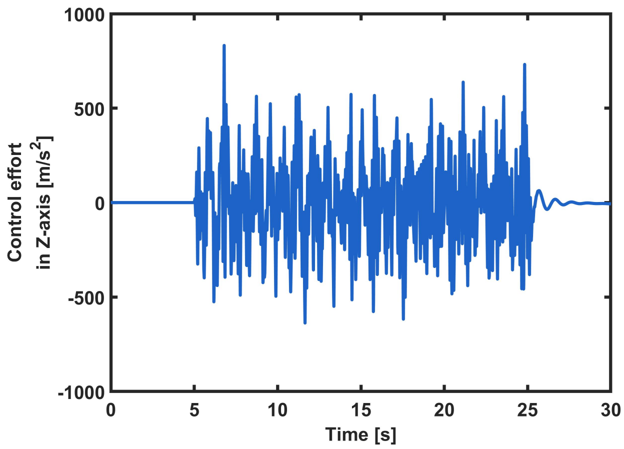

Fig. 9. Front-right actuator control forces for active car suspension with optimal controller settings

In addition, the actuator control force of the front-right actuator is displayed in Fig 9, which verifies that the actuator force does not exceed the constraint of 1000 N, as desired. The applied control forces for the other three actuators have a similar response. Obviously, there are no actuator forces present in the case of a passive car suspension.

7. CONCLUSION

From these results, at can be concluded that a Genetic Algorithm has been successfully applied to find the optimal PI MIMO-controller tuning parameters for an active car suspension lab setup model, with respect to actuator constraints and without the need of further manual fine-tuning. A comment on this methodology is that this only concerns simplified simulations of a lab setup with small sampling times. In an actual setup, there will be e.g. a certain delay between actuator force set-point and actual force, undeniably leading to a system where such low acceleration values are most likely not to be realized.

ACKNOWLEDGEMENTS

This research was partially supported by Flanders Make, the strategic research centre for the manufacturing industry.

REFERENCES

Agostinacchio, M., Ciampa, D., and Olita, S. (2014). The vibrations induced by surface irregularities in road pavements - a Matlab® approach. *European Transport Research Review*, 6(3), 267–275.

Ahmad, A. (2014). Active Suspension Control based on a Full-Vehicle Model. *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, 9(2), 06–18.

Ben-Horin, R. (1999). Kinematics, dynamics and construction of a planar actuated parallel robot.

Canale, M., Milanese, M., and Novara, C. (2006). Semi-active suspension control using "fast" model-predictive techniques. *Ieee Transactions on Control Systems Technology*, 14(6), 1034–1046.

Custódio, A.L., Madeira, J.F.A., Vaz, A.I.F., and Vicente, L.N. (2011). Direct Multisearch for Multiobjective Optimization. *SIAM Journal on Optimization*, 21(3), 1109–1140.

Darus, R. (2008). Modeling and Control of Active Suspension for a Full Car. *University Teknologi Malaysia*, (May).

Du, H., Lam, J., and Sze, K.Y. (2003). Non-fragile output feedback H vehicle suspension control using genetic algorithm. *Engineering Applications of Artificial Intelligence*, 16(7-8), 667–680.

Ekoru, J.E.D. and Pedro, J.O. (2013). Proportional-integral-derivative control of nonlinear half-car electro-hydraulic suspension systems. *Journal of Zhejiang University SCIENCE A*, 14(6), 401–416.

Gao, W. and Porandla, S.K. (2005). Design optimization of a parallel hybrid electric powertrain. *2005 IEEE Vehicle Power and Propulsion Conference*, 6 pp.

Ghosh, A. (2011). *Mechanics Over Micro and Nano Scales.*

Hornsey, S. (2012). A Review of Relay Auto-tuning Methods for the Tuning of PID-type Controllers. *Reinvention: an International Journal of Undergraduate Research*, 5(2).

Igel, C., Hansen, N., and Roth, S. (2007). Covariance Matrix Adaptation for Multi-objective Optimization. *Evolutionary Computation*, 15(1), 1–28.

Ikenaga, S., Lewis, F., Campos, J., and Davis, L. (2000). Active suspension control of ground vehicle based on a full-vehicle model. *Proceedings of the 2000 American Control Conference. ACC*, 6.

Kruczek, A. and Stribrsky, A. (2004). H Control of Automotive Active Suspension With Linearmotor. *IFAC Proceedings Volumes*, 37(14), 365–370.

Liu, X.J. and Wang, J. (2014). *Parallel Kinematics - Type, Kinematics, and Optimal Design.*

Merlet, J.P. (2006). *Parallel Robots*, volume 208.

Moradi, M. and Fekih, A. (2014). Adaptive PID-Sliding-Mode Fault-Tolerant Control Approach for Vehicle Suspension Systems Subject to Actuator Faults. *IEEE Transactions on Vehicular Technology*, 63(3), 1041–1054.

Mouleeswaran, S. (2012). Design and Development of PID Controller-Based Active Suspension System for Automobiles. *PID Controller Design Approaches-Theory, Tuning, and Application to Frontier Areas*, II, 71–98.

Nagarkar, M.P. and Vikhe Patil, G.J. (2016). Multi-objective optimization of LQR control quarter car suspension system using genetic algorithm. *FME Transactions*, 44(2), 187–196.

Nguyen, M., Canale, M., Sename, O., and Dugard, L. (2016). A Model Predictive Control approach for semi-active suspension control problem of a full car. *2016 IEEE 55th Conference on Decision and Control (CDC)*, (Cdc), 721–726.

Priyandoko, G., Mailah, M., and Jamaluddin, H. (2009). Vehicle active suspension system using skyhook adaptive neuro active force control. *Mechanical Systems and Signal Processing*, 23(3), 855–868.

Raju, N.R. and Reddy, P.L. (2016). Optimal Tuning of Fractional Order PID Controller for Automatic Voltage Regulator System through Genetic Algorithm. *International Journal of Engineering and Technology (IJET)*,8(3), 922–927.

Reza Bonyadi, M. and Michalewicz, Z. (2017). Particle Swarm Optimization for Single Objective Continuous Space Problems: A Review. *Evolutionary Computation (MIT)*, 25(1), 1–54.

Strandemar, K. (2005). *On Objective Measures for Ride Comfort Evaluation.*

Tyan, F., Hong, Y.F., Tu, S.H., and Jeng, W.S. (2009). Generation of random road profiles. *Journal of Advanced Engineering*, 4(2), 151–156.

Wang, H., Mustafa, G.I., and Tian, Y. (2018). Model-free fractional-order sliding mode control for an active vehicle suspension system. *Advances in Engineering Software*, 115(August 2017), 452–461.

Wang, J., Zolotas, A., and Wilson, D. (2007). Active suspensions: a reduced-order H control design study. In *IEEE Mediterranean Conference on Control & Automation*, 27-29 June, 1–7.

Wu, B., Liu, C., Song, X., and Wang, X. (2015). Design and implementation of the inverted pendulum optimal controller based on hybrid genetic algorithm. *2015 International Conference on Automation, Mechanical Control and Computational Engineering*, (Amcce), 623–629.

Ziegler, J.G. and Nichols, N.B. (1942). Optimum settings for automatic controllers. *Transactions of the ASME*, 64, 759–768.