OPTIMISED INTELLIGENT TILT CONTROLLER SCHEME USING GENETIC ALGORITHMS

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Abstract:
This paper presents work on a fuzzy control design for improving the performance of tilting trains with local-per vehicle control, i.e. without employing precedence control. An optimisation procedure using Genetic Algorithms was employed to determine both the best fuzzy output membership function and best PID controller parameters. The objective function for the GA procedure was based on a performance index combining the system response on curved and straight track. Simulation results illustrate the effectiveness of the scheme compared to the conventional nulling-tilt approach.

Keywords: tilt control, fuzzy control, genetic algorithms, intelligent control, tilting trains

1. INTRODUCTION

High-speed trains effectively reduce journey times and the way to achieve this is either to develop new infrastructure that maximizes train speeds or to use existing infrastructure with tilting train vehicles. The former solution can prove rather expensive and usually incorporates issues related to the surrounding environment. The latter solution follows a rather straightforward concept, i.e. by leaning the vehicle body inwards on curved sections of the track to reduce the lateral acceleration of passengers thereby enabling higher vehicle speeds.

Early tilt systems used local feedback control from a lateral accelerometer mounted on the body of the vehicle. However, it proved difficult to achieve fast response on curve transitions without suffering a substantial ride quality degradation on straight track. Current tilting train technology utilise 'precedence' tilt control strategies (Goodall, 1999). In this scheme a bogie-mounted accelerometer is used to develop a tilt command signal by measuring the curving acceleration on a non-tilting part of the vehicle. However, because the accelerometer also measures higher frequency movements associated with lateral track irregularities, it is necessary to filter the signal. This filtering action (time delay) creates a detrimental performance on the transition from the straight track to the curve section. The usual solution is to use the accelerometer signal from the vehicle in front to provide “precedence”, carefully designed so that the delay introduced by the filter compensates for the preview time corresponding to a vehicle length.

Recent work on local-per-vehicle nulling-type tilt control using modern control approaches has been reported (Zolotas, 2002). This paper presents an extension of the fuzzy-correction control scheme introduced in (Zamzuri *et al.*, 2005) using a GA-tuning approach. The overall objective being to optimise the output membership function and controller parameters via a performance index

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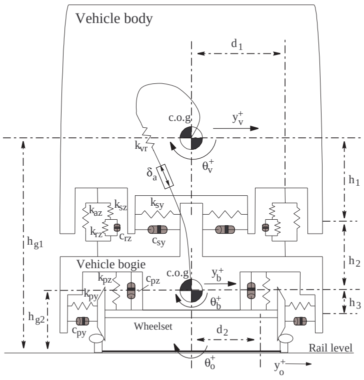

Fig. 1. End-view of the vehicle model

combining both the curved-track and straight-track response of the vehicle.

2. VEHICLE MODELING

The mathematical model used for analysis and control design is based upon the end-view of a railway vehicle, to incorporate both the lateral and roll degrees of freedom for both the body and the bogie structures. A pair of air-springs represents the secondary suspension, while the primary suspension is modelled via pairs of parallel spring/damper combinations. The stiffness/damping of an anti-roll bar connected between the body and the bogie is also included. Active tilting is provided by using an 'active anti-roll bar' (Pearson *et al.*, 1998), see Figure 1. Note that the system is highly complex and characterised by a significant coupling between the lateral and roll motion, and the dynamic modes which result are often referred to as the "sway modes". Details on the mathematical description can be found in (Zolotas and Goodall, 2000).

3. PERFORMANCE ASSESSMENT

Two main design criteria are concerned with tilting trains: (i) providing a fast response on curved track (deterministic criterion), (ii) maintain a good ride quality in response to track irregularities on straight track (stochastic criterion). The paper employs the performance assessment approach proposed in (Zolotas *et al.*, 2000).

The assessment of the *curve transition* is based upon the idea of "ideal tilting", i.e. where the tilt action follows the specified tilt compensation in an ideal manner according to the maximum tilt angle and cant deficiency compensation factor. Deviations from the "ideal tilting" response quantifies the *additional* dynamic effects which are caused by the suspension/controller dynamics on the transitions to and from the curves, and provides an objective measure which can be used to compare different strategies (see Appendix A). Note that the calculation of P_{CT} factors is also included in this stage.

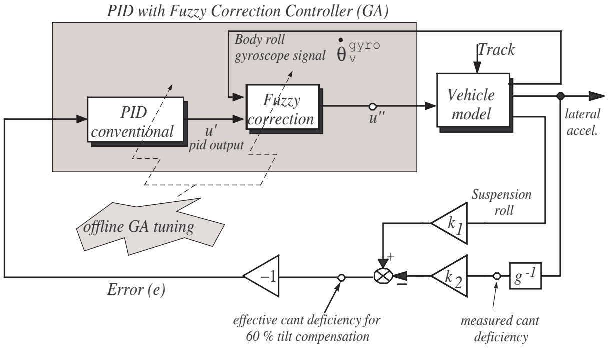

Fig. 2. PID with Fuzzy Correction (with offline GA optimisation)

For the straight track case the 'rule-of-thumb' which is currently followed by designers *is to allow the degradation of the lateral ride quality of the tilting train by no more than a specified margin compared with the non-tilting vehicle, a typical value being* 7.5%. It is essential, for assessing the tilt controller performance, this comparison to be made at the higher (tilting) speed.

4. FUZZY CONTROL DESIGN

The control design objective is to provide a fast response on curved track while minimizing track irregularities on straight track segments. The control approach followed in this paper involves the design of a conventional PID controller to give a fast curve transition performance and then a fuzzy correction mechanism which improves stability (minimise overshoots and prevent critical oscillations) in the overall system. The PID controller is driven by the effective cant deficiency signal and thus guarantees the appropriate tilt compensation on steady curve (i.e. 60% in this case). Moreover, the output signal from the PID is fed to the fuzzy correction block to further accommodate for curve transition and straight track performance. The body roll rate is the additional decision making variable input to the fuzzy correction block. The control scheme can be seen in Figure 2.

The design of the controller can be divided into three stages :

1. conventional PID to give fast response on curve track
2. fuzzy correction aimed at minimizing straight track irregularities and preventing large overshoot and oscillations on the curved track
3. further tuning if necessary (the GA-tuning approach is discussed in the next section)

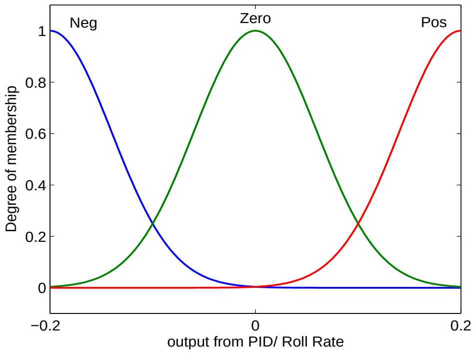

Fig. 3. output from PID (u') and Roll gyro ($\dot{\theta}_v^{gyro}$)

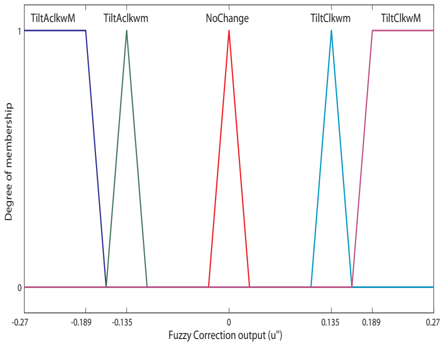

Fig. 4. Output controller u"

In the first instance the PID can be tuned using the well known Ziegler-Nichols method (Astrom and Hagglund, 1995). The parameters are chosen to give a fast response on curved track subject to guaranteeing stability.

For the fuzzy correction mechanism, both inputs shown in Figure 3 consist of three equally distributed gaussian Membership Functions with 50% overlap for each signal. Figure 4 shows the fuzzy correction output *u"* consisting of trapezoidal and triangle membership functions. Furthermore, the *Center of Area* (COA) defuzzification procedure with well known max-min inference method was used.

The linguistic variables for each membership functions represent the condition for each value. For example, the PID output *u'* is represented by the linguistic variables *Neg*, *Zero* and *Pos*. For the body roll gyro input $\dot{\theta}_v^{gyro}$, the linguistic variable are also *Neg*, *Pos* and *zero*, while for the fuzzy correction output *u"* , the linguistic variables represent the tilting direction of the car body as *tilt the car body clockwise maximum* represented by *TiltClkwM*, tilt car body medium anticlockwise represented by *TiltAclkwm* etc. Clockwise and Anticlockwise characterize the direction of tilt based on the curve direction (i.e. inwards and outwards of the curve respectively). Note that the membership function ranges were chosen to represent typical required operating ranges for the current application of tilt. The development of fuzzy rules was based on:

- stabilizing the system:
  if u' is **changing fast** *and the* $\dot{\theta}_v^{gyro}$ *is* **zero** *then* **apply maximum tilt effort u"**
- preventing overshoot and oscillation.
  if u' **changes** *and* $\dot{\theta}_v^{gyro}$ **changes** *then* **maintain medium till effort u"**

Detail on the rules can be further seen in Table 1,

Table 1. PID-Fuzzy Correction Rule Base

$\dot{\theta}_v^{gyro}/u'$	Neg	Zero	Pos
Neg	TiltClkwm	TiltClkwm	TiltClkwM
zero	TiltAclkwM	NoChange	TiltClkwM
Pos	TiltAclkwM	TiltAclkwm	TiltAclkwm

5. GENETIC ALGORITHMS TUNING OPTIMISATION

The main difficulty of the above scheme is primarily the choice of of the membership function profile and also the PID controller parameters. These are based on the experience of the designer and can be time-consuming.

Genetic Algorithms is stochastic search techniques drawing inspiration from the principles of natural evaluation and genetic laws (Holland, 1998) that operate without the knowledge of the task domain and utilize only the fitness of evaluated individuals. In general, there are three basic operators of a GA: (i) reproduction (ii) crossover and (iii) mutation.

In this paper, we utilise eight real-coded GA variables to optimize the PID parameters (K_P, K_D and K_I), and the position and width of the output fuzzy membership functions (see Figure 2 offline GA). The upper and lower limits on the parameters are established based on the control scheme proposed in (Zamzuri *et al.*, 2005). The initial choice of the parameters and the limits clearly reduce the computational time associated.

In this study only the output membership function has been used for the optimisation process. Figure 4 presents the output membership function which consists of three *triangular* membership functions and two *trapezoidal* membership functions located at each end of the fuzzy set (from (Zamzuri *et al.*, 2005)). Figure 5 illustrates the concept of coding the membership functions. The genetic algorithm seeks the optimal profile (based on the position and width of the membership functions), except for the zero position of MF *NoChange* and also the end limits of (*TiltClkwM* , *TiltAclkwM*).

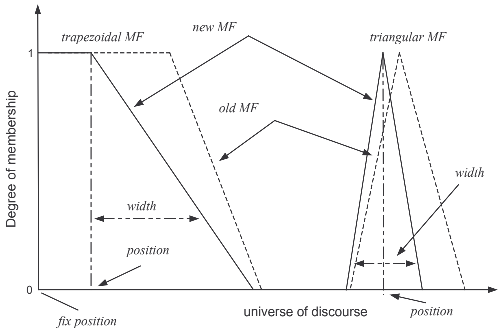

Fig. 5. Tuning of position and width of membership functions

The overall performance index incorporates two terms, i.e. both minimizing the curved track response error from the ideal case (deterministic) and minimizing the influence of straight track irregularities (stochastic). In particular the integral time of absolute error index, (ITAE) (Astrom and Hagglund, 1995), was employed for both terms defined as

$$ITAE = \int_0^t t|\theta_{err}|(t)dt \tag{1}$$

where

$$\theta_{err} = \theta_{ECD_{aktif}} - \theta_{ECD_{passive}} \tag{2}$$

and

$\theta^{(actv)}_{ECD}$ = effective cant deficiency of active system (with control)

$\theta^{(passv)}_{ECD}$ = effective cant deficiency of passive system (no control)

The ITAE index limits large initial overshoots and introduces stricter minimisation as time progresses, thus it is expected to offer an advantage in improving the tilt performance. Moreover, the objective function for the GA tuning procedure is given by

$$f = w_1 \sum_{t=0}^{max(t)} ITAE^{(det)} + w_2 \sum_{t=0}^{max(t)} ITAE^{(stoch)} \tag{3}$$

variables w_1 and w_2 represent the (complementary) weighting factors of the deterministic and stochastic profiles respectively ($w_1 + w_2 = 1$). Note the incorporation of both deterministic track and stochastic track for proper minimisation, and thus proper tilt action improvement.

6. SIMULATIONS

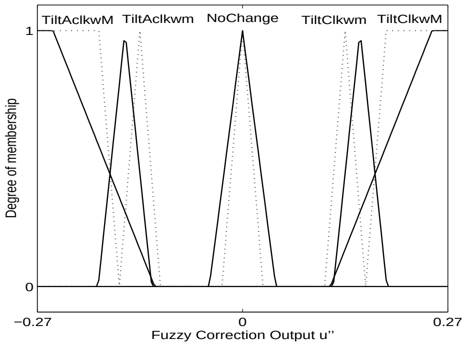

Fig. 6. Output membership function without (dotted) and with GA optimisation (solid)

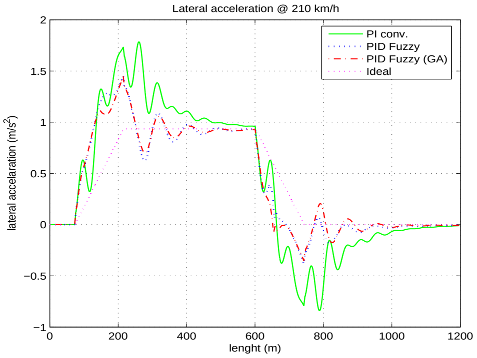

Fig. 7. Body Lateral acceleration

The Genetic Algorithms procedure was simulated for 100 generations on a randomly initialized population of 10 solutions. The GA performance use roulette wheel selection method with probability crossover and mutation rate of 0.9 and 0.125 respectively, and with weighting factors w_1 and w_2 of 0.2 and 0.8 respectively.

The system was simulated at a speed of 210 km/h with 1000 m curved radius and 6^o cant angle (the track profile included 145 m transition length at each end of the curve). For proper comparison, the system was simulated using using three controllers (i) PID with Fuzzy Correction mechanism (manually tuned (Zamzuri *et al.*, 2005)) (ii) The same controller using GA-tuning and (iii) nulling PI conventional controller. Figure 6 shows the optimal output fuzzy membership function for both the manually tuned and GA-tuned schemes. Table 2 presents the PID parameter values using the Ziegler-Nichols tuning method (manual-tuning) and the GA-tuning method.

Table 2. Manual Ziegler-Nichols vs GA tuning for the PID controller

PID params	Ziegler-Nichols	Genetic Alg.
K_P	0.19	0.31
K_I	1.15	1.60
K_D	0.03	0.04

Moreover, Figures 7 and 8 show the time-domain responses of the tilt system for the controller schemes considered in the paper.

Table 3. Performance assessment results

	Deterministic	PI Conv.	PID-Fuzzy Manual	PID-Fuzzy with GA
Lat. accel.	steady state (%g)	n/a	9.5	9.5
	R.M.S deviation error (%g)	4.60	3.4	3.08
	peak value (%g)	18.20	14.8	14.7
Roll gyro	R.M.S jerk level (rad/s)	0.03	0.03	0.03
	peak value (rad/s)	0.1	0.12	0.11
P_{ct}	peak value level (%g/s)	9.33	9.9	9.72
	standing (% of passengers)	67.80	64.0	62.37
	seated (% of passengers)	21.0	19.0	18.7
	Stochastic			
Ride qual.	active tilt(%g)	0.406	0.40	0.396
	Ride qual. degradation (%)	6.98	5.0	4.3

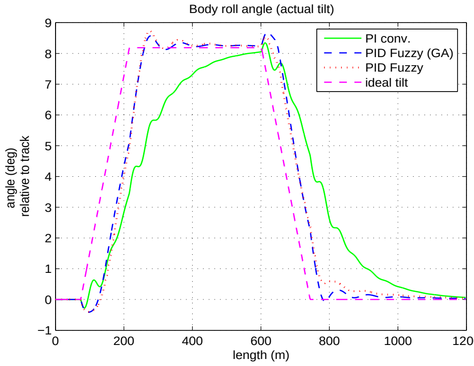

Fig. 8. Body Roll Angle

7. PERFORMANCES ANALYSIS

This section presents the performance assessment, based on the procedure discussed in Section 3, of the discussed fuzzy schemes (PID-Fuzzy manual and PID-Fuzzy with GA tuning) together with a baseline conventional PI nulling controller. The associated results are shown in Table 3. Both PID-fuzzy correction control schemes provide a much better performance compared to the conventional controller. Although the PID-Fuzzy with GA tuning scheme offers a small (but noticeable) improvement compared to the PID-Fuzzy manual, it is easier to design for more accurate results. Note that the straight track ride quality of the non-tilting vehicle at 210 km/h is 0.381%g.

8. CONCLUSION

The paper reveals the potential of using a PID-Fuzzy with GA tuning control solution in a nulling-tilt control framework for improving the performance of local-per-vehicle tilt. Both fuzzy control schemes (manual-tuned and GA-tuned) provided substantial improvement of the tilt performance compared to the conventional nulling controller. The advantage of using the GA-tuned solution is the more straightforward setup of the output membership function and PID controller parameters via the chosen performance index. Future work will investigate on multi-objective Genetic Algorithm (MOGA) solutions for both the membership functions and controller parameters.

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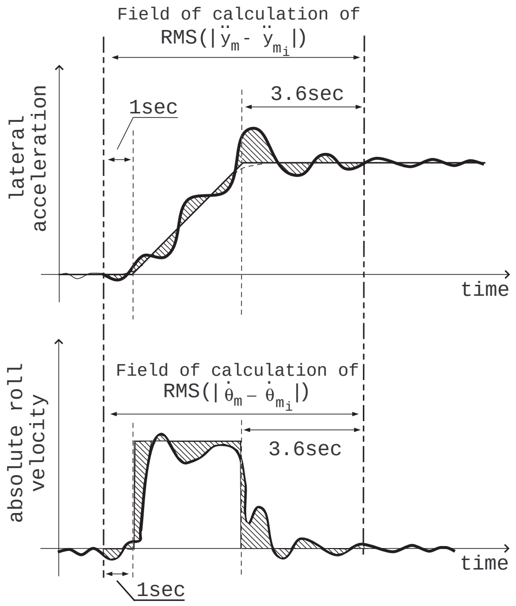

Fig. A.1. "Ideal Tilting"- Calculation of deviation of actual from ideal responses for acceleration and roll velocity

$|\ddot{y}_m - \ddot{y}_{m_i}|$, the deviation of the actual lateral acceleration $\ddot{y}_m$ from the ideal lateral acceleration $\ddot{y}_{m_i}$, in the time interval between 1s before the start of the curve transition and 3.6s after the end of the transition.

$\left|\dot{\theta}_m - \dot{\theta}_{m_i}\right|$, the deviation of the actual absolute roll velocity $\ddot{\theta}_m$ from the ideal absolute roll velocity $\ddot{\theta}_{m_i}$, in the time interval between 1s before the start of the curve transition and 3.6s after the end of the transition.