# Automotive drive by wire controller design by multi-objective techniques

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**Abstract**

The presence of flexibility in automotive drivelines, coupled with nonlinear elements such as gear lash leads to the presence of an undesirable oscillatory acceleration response to step changes in throttle input. This oscillation is generally low frequency (approximately 2–5 kHz) and can be of sufficient amplitude to cause driver discomfort and subjective disappointment with the driveability of the vehicle. A pole placement controller is developed for a "drive-by-wire" (electronically operated throttle) system, with the objective of reducing or eliminating the oscillatory response. The results of an existing factorial study are used to calculate the required number of poles. Due to the inherent nonlinearities present in the system and the various constraints which must be applied to the controller design, the polynomial values for the pole placement controller are selected by the application of multi-objective optimisation. The controller is shown to achieve excellent performance and robustness to parameter variations and operating conditions.

*Keywords:* Pole placement; Drive by wire; Multi-objective optimisation; Automotive; Driveability

## 1. Introduction

This paper describes the development of a longitudinal oscillation controller via a low-cost electronic throttle actuator and microcontroller. A feasibility study had been carried out on a vehicle fitted with the electronic throttle system (Stewart & Fleming, 2001, 2002) to confirm the performance potential of such a system. Drive by wire applications for the replacement of the conventional cable link between the throttle pedal and the throttle body are now the focus of development by many major automotive manufacturers. Direct fitting of a stepper or permanent magnet servo motor to the spindle of the throttle butterfly plate allows electronic throttle pedal (fitted with a potentiometer) control via a microcontroller or DSP. High-performance current control algorithms can be implemented around the throttle actuator (Stewart & Kadirkamanathan, 2001) to facilitate a fast acting mechanical response. Other control systems have been designed (Rossi, Tilli, & Tonielli, 2000) to ensure fast and accurate tracking of the pedal demand signal, and have been shown to possess robust operational characteristics. Currently, electronic throttle control and variable valve timing are the most powerful tools in the pursuit of "driveability" (the difference between the driver's perceived required performance and the actual performance of the vehicle), (Azzoni, Moro, Ponti, & Rizzoni, 1998; Stefanopolou, Cook, & Grizzle, 1995). A torque controller is designed and implemented in this paper to shape the vehicle response to the first torsional mode of the driveline. The initial requirement is to damp the oscillations generated by throttle "tip-in" (step throttle input). The control system acts as a dynamic mapping between the accelerator pedal and the throttle butterfly angle, allowing the amount of torque developed by the engine to be closely controlled to improve the driveability of the vehicle. The design problem in this case is multivariable, being described by a five component objective function:

- minimise rise time,
- minimise overshoot,

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- minimise settling time,
- minimise steady-state error,
- minimise delay.

Control analysis and design for this automotive system is complicated by a various factors. There are a number of nonlinearities present, such as backlash in the gearbox, a tyre model which varies nonlinearly with load, and a nonlinear clutch response. Also, a significant time varying lag is present between throttle actuation and torque production due to manifold fill delay. Finally, a nonlinear engine torque-speed mapping exists (Kienke & Nielsen, 2000). It has been found (Stewart & Fleming, 2001), that a set of throttle angle trajectories exist which successfully suppress the vehicle longitudinal acceleration oscillations. The application of the response surface methodology derived a second-order approximation surface of the acceleration response in order to design a simple feedforward controller. In this manner, it was verified that the oscillatory response can be adequately controlled by electronic throttle, however a closed-loop control system was still to be designed. Experimental open-loop data was available from a test car which was fitted with a data acquisition system including a longitudinal axis accelerometer. A V6 engined saloon vehicle was loaned for the purpose of analysis, design and testing. A systematic excitation of the driveline was made experimentally on the vehicle by performing step demands in all gears at discrete points throughout the effective engine speed range of the vehicle, allowing the validation of a dynamic model which had been developed in *Matlab and Simulink*. A representative experimental response is shown in Fig. 1. Particular note should be taken of the time delay between step demand acceleration response. Open-loop study (Stewart & Fleming, 2001) indicates that the control action necessary to reduce the oscillation has a time period similar to the response lag, rendering the delay a significant one. Also the under-damped acceleration profile which can lead to driver dissatisfaction with the perceived smoothness of the overall vehicle response.

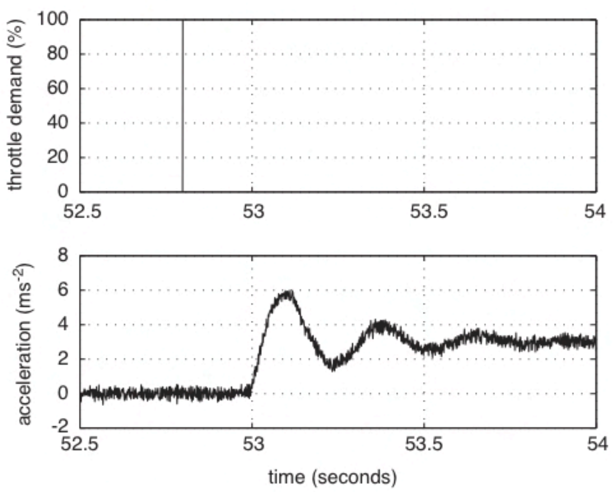


Fig. 1. Vehicle acceleration step response in second gear at 10 ms$^{-1}$.

Cancellation of driveline oscillations has been studied using several methods. Generalised optimal control theory has been applied (Best, 1998), however, the oscillation in the controlled acceleration response was found to be still significant because of the presence of lash nonlinearities. Fuzzy control has been proposed (Willey, 1999), yet stability was found to be a major concern. Pole placement strategies have been used (Richard, Chevrel, de Larminat, & Marguerie, 1999), but acceleration response still remained open to considerable improvement, due to the difficulty of ascertaining the controller polynomial values. This does suggest that progress might be made if the correct controller values could somehow be chosen.

The objectives of the controller design will be to reduce or eliminate both the overshoot and subsequent oscillation of the vehicle acceleration during throttle step demand, while attempting to maintain the open-loop acceleration rise time. The controller design can be best assessed in 2nd gear as this gear demonstrates the worst-case oscillations. The pole placement approach will be further developed by using a multi objective approach to choose the controller polynomial values. There are a number of novel aspects associated with this work. The results of a factorial experimental study are analysed and an approximation derived, to determine the number of poles which it is necessary to place to achieve successful control. A closed-loop controller with performance which fulfills a demanding cost function has been designed, which compares favorably with previous designs described in the literature. A method of varying the system parameters such as lash and loading has been introduced during the iterative design process to derive a robust controller.

## 2. Pole-placement design

The objective of the pole-placement design method is to design a closed-loop system with specified poles and thus the required dynamic response. The measured variable for feedback considered here is provided by a longitudinal accelerometer, as the manufacturer concerned will make such a sensor available in production should the derivation of acceleration from the velocity signal prove inaccurate or too noisy. The resulting characteristic equation will determine the features of the system, such as rise time, overshoot and settling time. The system model and its linear controller can be expressed, respectively, as

$$A(s)y(s) = B(s)u(s), \tag{1}$$

$$S(s)u(s) = T(s)u_c(s) - R(s)y(s), \tag{2}$$

where $A(s)$ and $B(s)$ are polynomials in the Laplace domain and $u(s)$ is the control variable. $S(s)$, $R(s)$ and $T(s)$ are the error, feedback and feedforward controller polynomials in the complex domain. The controller has input $u_c(s)$, which is the command signal and $y(s)$, is the measured output of the plant. Three constraints are associated with the model: the degree of $B(s)$ is less than the degree of $A(s)$, there are no common factors between polynomials $A(s)$ and $B(s)$, and $A(s)$ is a monic polynomial. From Eqs. (1) and (2), the characteristic equation of the closed-loop system will be

$$F(s) = A(s)S(s) + B(s)R(s). \tag{3}$$

The objective of the pole placement design is to find polynomials $S(s)$ and $R(s)$ that satisfy Eq. (3) for specified $A(s)$, $B(s)$ and $F(s)$. Eq. (3) is known as the *Diophantine equation* and can be solved if the polynomials do not have common factors and the system is proper (Astrom & Wittenmark, 1997). The Diophantine equation can be solved using a linear matrix. By expanding both sides of Eq. (3) and equating equal powers of the complex variable $s$, the equation can be expressed in a set of linear equations,

$$\begin{vmatrix} a_0 & 0 & 0 & \dots & 0 & b_0 & 0 & 0 & \dots & 0 \\ a_1 & a_0 & 0 & \dots & 0 & b_1 & b_0 & 0 & \dots & 0 \\ a_2 & a_1 & a_0 & \dots & 0 & b_2 & b_1 & b_0 & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \vdots & \vdots & \dots & \vdots \\ a_N & a_{N-1} & a_{N-2} & \dots & a_0 & b_N & b_{N-1} & b_{N-2} & \dots & b_0 \\ 0 & a_N & a_{N-1} & \dots & a_1 & 0 & b_N & b_{N-1} & \dots & b_1 \\ 0 & 0 & a_N & \dots & a_2 & 0 & 0 & b_N & \dots & b_2 \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \vdots & \vdots & \dots & \vdots \\ 0 & 0 & 0 & \dots & a_N & 0 & 0 & 0 & 0 & b_N \end{vmatrix} * \begin{vmatrix} x_0 \\ x_1 \\ . \\ \vdots \\ x_{Nx} \\ y_0 \\ . \\ \vdots \\ y_{Ny} \end{vmatrix} = \begin{vmatrix} c_0 \\ c_1 \\ . \\ \vdots \\ c_x \\ . \\ . \\ \vdots \\ c_{Nc} \end{vmatrix}, \tag{4}$$

where $N$ denotes the maximum between $n_a$ and $n_b$. Eq. (4) is known as the Sylvester matrix. The number of unknowns is given by the number of coefficients in $S(s)$ and $R(s)$, and is equal to $n_s + n_r + 2$. The number of equations is $n_c + 1$, where $n_s$, $n_r$ and $n_c$ are maximum degrees of $R(s)$ and $F(s)$, respectively. According to Sylvester's theorem, if $A(s)$ and $B(s)$ are coprime, then $S(A, B)$ is non-singular. There is a unique solution for $F(s)$ in Eq. (3) if (Richard, Chevrel, de Larminat, & Marguerie, 1999)

$$\begin{aligned} n_s + n_r + 2 &= n_c + 1 \\ &= \max(n_a + n_s, n_b + n_r) + 1. \end{aligned} \tag{5}$$

Introducing $\alpha$ and $\beta$ as the difference in the relative degree of $B(s)/A(s)$ and $R(s)/S(s)$ respectively gives

$$\alpha = n_b - n_a, \quad \beta = n_s - n_r, \tag{6}$$

where $n_a$ and $n_b$ are the number of coefficients in $A(s)$ and $B(s)$, respectively. The objective is now to find an expression for $n_c$. Using Eqs. (5) and (6), leads to two cases for its calculation, which depend on the result of the operator max(). For the first case $n_a + n_s > n_a + n_s - \alpha - \beta$ derives in $\alpha + \beta > 0$. The order of the controllers will then be

$$\begin{aligned} n_s &= n_a + \beta - 1, \\ n_r &= n_a - 1, \\ n_c &= 2n_a + \beta - 1. \end{aligned} \tag{7}$$

For the second case, it is possible to see that if $n_a + n_s < n_a + n_s - \alpha - \beta$, then $\alpha + \beta < 0$, however for design purposes, that possibility will not be explored here, since it implies that $B(s)/A(s)$ and $R(s)/S(s)$ are not proper.

## 3. Multi-objective optimisation of controller design

Two major questions arise with the use of the pole placement design, firstly what is the optimum location of the poles for the characteristic equation of the controller, and secondly how many poles must be placed? Resolving the issue may be a matter of trial and error if the system is complex and there is noise in the feedback signals or (as it is the case of the driveline) there are nonlinearities, such as delays and saturation curves (Richard et al., 1999; Astrom, 1997). Genetic algorithms (GAs) are stochastic optimisation procedures whose search methods model the natural selection and inheritance process. The main principles for the application of GAs are defined in Holland (1975). More recent publications by Goldberg (1989) and Michalewicz (1999) provide a complete examination and introduction to GAs. The underlying principle that supports GAs is the survival of the individuals (potential solutions) according to their fitness (or abilities to solve a particular problem). For each generation, a new set of individuals is created by breeding the best individuals from previous generations. This process results in the evolution of whole populations in which individuals are better suited to their environment than the individuals that they are created from. The fact that the GAs operate in parallel over a given population makes it possible to evaluate multiple objectives for each of the individuals. This approach is called multi-objective genetic algorithm (MOGA) and is required in many applications where competing objectives are to be optimised. The result of optimising such problems is usually a set of equally valid, nondominated solutions. The union of all those points is known as the Pareto-optimal set. In MOGA, several steps are required: ranking to estimate performance of the population; selection to obtain a population for each generation; and mating to produce new individuals. Fitness sharing and mating restriction techniques can be used to improve the results (Chipperfield, Fleming, & Polheim; Zalzala & Fleming, 1997). The results of an optimisation can be viewed and analysed with a trade-off plot, which shows the competition of the different objectives.

The system response can be approximated as a third-order time-varying model in terms of velocity, whose damping ratio varies as a function of selected gear and road speed. Road surface conditions and vehicle loading are also important factors, but will be assumed to be constant for the moment. The experimentally elicited open-loop response surface for a V6 saloon car, in terms of damping factor for a second-order fit to acceleration response (Stewart & Fleming, 2001, 2002) is shown in Fig. 2. The polynomials $B(s)$ and $A(s)$ can be obtained. For example, at 15 mph in 2nd gear;

$$\frac{v(s)}{u(s)} = \frac{B(s)}{A(s)} = \frac{1615.7}{s^3 + 4.3s^2 + 521.8s}. \tag{8}$$

As part of the model, a second-order approximation will be added to Eq. (8) to model the delay relating to the manifold fill delay. The resulting polynomials were

$$\frac{B_1(s)}{A_1(s)} = \frac{B(s)P_{num}(s)}{A(s)P_{den}(s)}, \tag{9}$$

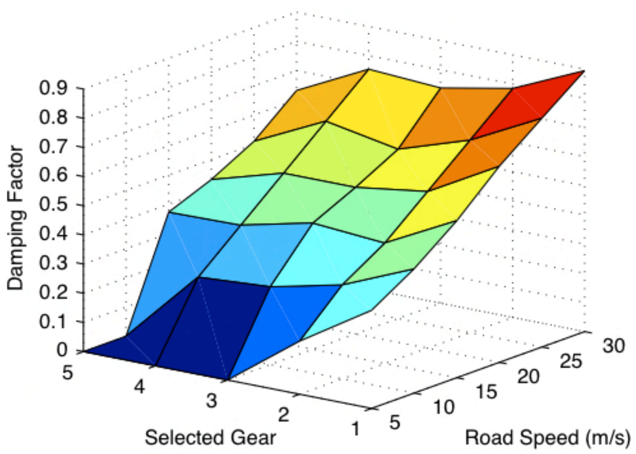


Fig. 2. Experimental vehicle damping ratio response surface.

where $A_1(s)$ and $B_1(s)$ are the new polynomials representing the system and $P_{num}(s)$ and $P_{den}(s)$ are the numerator and denominator, respectively, of the Pade approximation. The order difference in the process polynomials is $\alpha = n_a - n_b = 5 - 2 = 3$, and defining $\beta = 0$, the order of the controllers $S(s)$ and $R(s)$ and the closed-loop characteristic equation $F(s)$ can be found as in Eq. (7). Then, $n_s = 4$, $n_r = 4$ and $n_c = 9$. This leads us to the matter of determining the value of nine roots for the characteristic equation. The lower order approximations have been used to determine a tractable number of poles to place in the controller design. However, now we can apply an experimentally verified high-order non-linear model to enable the MOGA to search for the optimal, robust design.

The use of MOGA in the search for an optimal controller requires first to choose a set of decision variables, e.g. features that will affect the behaviour of the system. A suitable type of coding must be proposed for those variables. The objectives, or variables to assess the system have also to be defined and an objective function must be proposed to evaluate each individual. The controller's performance is evaluated by simulating the model of the system using a step input to the system.

For example in the single objective case, a population $P$ consists of individuals $\mathbf{c}_i$ with $i = 1, \ldots, \mu$, thus

$$P = \{c_1, \ldots, c_i, \ldots, c_\mu\}. \tag{10}$$

The population size in this case was kept constant. Each individual in the population is a potential solution to the optimization problem. The objective function $f(\mathbf{x})$ is a scalar valued function of an $n$ dimensional vector $\mathbf{x}$ which represents a point in real space $\Re^n$. The vector $\mathbf{x}$ is constructed from $n$ variables $x_j$ with $j = 1, \ldots, n$. The variables $x_j$ are known as *genes*, with an individual $\mathbf{c}_i$ consisting of $n$ genes:

$$\mathbf{c}_i = [c_{i1}, \ldots, c_{ij}, \ldots, c_{in}]. \tag{11}$$

The process of optimisation is begun with a random population of individuals followed by a process of calculating the fitness of each individual, which equates to the quality of each individual in terms of the objective function $f(\mathbf{x})$. The average fitness $F_m$ of the population is determined by

$$F_m = \frac{\sum_{i=1}^{\mu} F(\mathbf{C}_i)}{\mu} \tag{12}$$

while the relative fitness $p_i$ of an individual $\mathbf{c}_i$ is calculated by

$$p_i = \frac{F(\mathbf{c}_i)}{\sum_{i=1}^{\mu} F(\mathbf{c}_i)}. \tag{13}$$

In the multiobjective case considered here, each solution has a vector describing its performance across the set of criteria, with the vector then being transformed into a scalar fitness value achieved by ranking the population of solutions relative to each other. Next, the genetic operators *selection*, *crossover and mutation* are applied with the new individuals produced by this process forming the next generation of the population. Selection is performed based upon the fitness value which probabilistically determines how successful each individual will be at propagating its genes to the next generation. The crossover operator involves the exchange of genetic material between parents to create new offspring.

The pole locations will be the decision variables in the MOGA, since those are the unknowns in Eq. (3) and will be used to calculate directly the values of the coefficients for the polynomials $R(s)$, $T(s)$ and $S(s)$. The gain of $T(s)$ will also be included as a decision variable. The coding of the variables was real, since that allows more natural data handling and is more efficient. The objectives set the goals to reach and ensure that every selected individual satisfies the specifications. The performance objectives have already been described, and relate to overshoot, settling time, etc.

A novel Gaussian mutation operator was included in the mutation stage in order to improve the optimisation in the borders of the search space. This operator changes the mutation probability rate of an individual when it is close to the borders of the search space, avoiding a nonuniform statistical process of mutation, that could otherwise bias the search.

The initial conditions (selected gear, road speed) in addition to reasonable real-life variations in the mechanical parameters (lash, etc.) for the driveline nonlinear model were changed randomly for each individual in each generation, in such a way that the best controllers are the ones that could perform adequately under wide system parameter and condition variations. The variation in lash in particular replicates one of the fundamental characteristics of the ageing of the system. A further addition to this approach was the variation in road conditions and vehicle loading from one to four occupants. This approach was intended to achieve as far as possible, a robust controller. Finally, the minimisation of the control energy was included amongst the objectives in order to achieve a feasible, efficient controller. The bounds of the random variations were as follows:

- lash 0–30$^{\circ}$ at wheels,
- road conditions from $\mu$ 0.4–1,
- vehicle loading 1–4 occupants (standard occupant = 80 kg,
- road gradient $-10$–$+10\%$.

This bounding set was later utilised to assess the robustness of the robust controller.

In order to choose the best controller from all the calculated solutions, a multiobjective criterion is applied. The multiobjective optimisation can generally be expressed as the minimisation of the function $\mathbf{f}(\mathbf{x})$, where

$$\mathbf{f}(\mathbf{x}) = \{f_1(x), \ldots, f_n(x)\} \tag{14}$$

is the vector of objective functions, $n$ is the number of objectives to be minimised,

$$\mathbf{x} = \{x_1, \ldots, x_p\} \tag{15}$$

is the vector of decision variables where $p$ is the number of decision variables from which the complete solution is constructed. Utilising *Pareto dominance*, the solution to the multiobjective problem is derived. The solution vector $\mathbf{x}$ with its associated performance vector $\mathbf{u}$ dominates, or is better than another solution $\mathbf{y}$ with performance vector $\mathbf{v}, [\mathbf{x} \prec \mathbf{y}]$ if the former performs at least as well as the latter across all objectives, and exhibits superior performance in at least one objective. Thus

$$\mathbf{u} \prec \mathbf{v} \text{ iff } [\forall i \in \{1, \ldots, n\}, u_i \leqslant v_i] \\ \cap [\exists i \in \{1, \ldots, n\} : u_i < v_i], \tag{16}$$

$$\mathbf{u} \prec \mathbf{v} \Leftrightarrow \mathbf{x} \prec \mathbf{y}, \tag{17}$$

where $u_i/v_i$ is the $i$th criteria value of the performance vector $\mathbf{u}/\mathbf{v}$. The solution is described as *Pareto optimal* if it is not dominated by any other possible solution thus

$$\mathbf{x} \in X_{PO} \text{ iff } \exists \mathbf{y} \in U : \mathbf{x} \prec \mathbf{y}. \tag{18}$$

In order to make the final choice between the *Pareto-optimal* solutions, operator intervention is required to make a subjective evaluation. If the problem is well posed (as in this case), then relatively few solutions are presented for choice. A tradeoff between risetime and overshoot exists, with the choice being made to evaluate the solutions on the vehicle to choose the most realistic acceptable performance.

The GA Toolbox for Matlab with the MOGA extension tools developed at the University of Sheffield (Chipperfield, Fleming, & Polheim, 1995) was utilised to perform the search procedure. The decision variables are in this case assigned to the controller pole placement positions. The parameters associated with the MOGA set-up were as follows:

- population size: 30,
- number of decision variables: 9,
- number of objectives: 5,
- number of immigrants per generation: 6,
- coding: Gray, 20 bits per decision variable, except where varied (Zitzler & Thiele, 1999),
- selection: stochastic universal sampling (Baker, 1987),
- recombination: single-point binary crossover, probability = 0.7,
- mutation: element-wise bit-flipping, expectation of 1 bit per chromosome,
- generational gap: zero,

- random injection: 2 random chromosomes per generation,
- elitism: None,
- fitness assignment: (Fonseca & Fleming, 1993) multi-objective ranking. Transformation from rank to fitness using linear fitness assignment with rank-wise averaging.
- external population: off-line storage of nondominated solutions,
- fitness sharing: (parameter-less) Epanechnikov fitness sharing (Fonseca & Fleming, 1998) implemented in criterion space,
- mating restriction implemented: distance set to the niche size parameter found by the Epanechnikov sharing algorithm.

## 4. Results

A candidate controller of the form:

$$R(s) = s(s - 20.1 + 12.1i)(s - 20.1 - 12.1i)(s - 17.3),$$

$$S(s) = (s - 167.8)(s - 41.3 + 103.2i) \times (s - 41.3 - 103.2i)(s - 18.6),$$

$$T(s) = (s - 40.6 + 3.3i)(s - 40.6 - 3.3i) \times (s - 37 + 1.71i)(s - 37 - 1.71i), \quad (19)$$

was selected from the family of potential solutions on the basis of its minimisation of all the objectives stated in the objective function, and its overall driving "feel". The controller was simulated under varying initial conditions and mechanical parameters to verify its performance, and also assess its robustness. The predicted effects of ageing (for example on lash) were found in simulation of the closed-loop system to produce acceleration responses which were within the bounds of desired "driveability". The simulated acceleration responses of the vehicle for two different initial conditions and mechanical parameters are shown in Figs. 3 and 4. Overshoot and settling time have been attenuated to acceptable levels without a sacrifice in terms of delayed response. A comparison is made with the simplest type of control which can be applied to this problem in Fig. 4, namely a rate limiter on the demand output of the accelerator pedal. It is shown that the extra design work implicit in the development of the pole placement controller is worthwhile in terms of minimising the response lag. Although experimental assessment of the controller in terms of varying lash was not possible, a number of step responses were taken under varying vehicle loading. A factorial study was undertaken at a range of road speeds and selected gear ratios, with vehicle loading being chosen randomly. A typical open-loop response is shown in Fig. 5 with the corresponding closed-loop response being shown in Fig. 6. The response is satisfactory in terms of

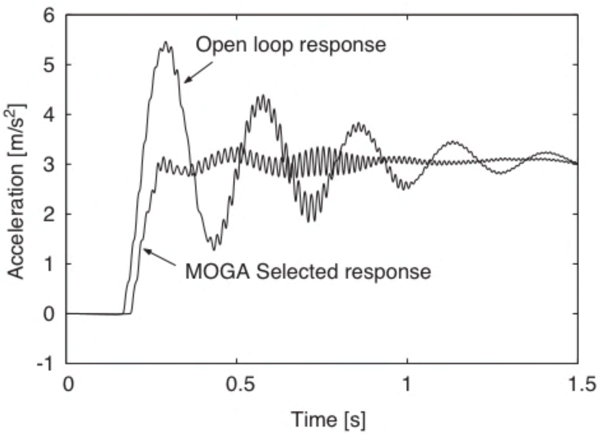


Fig. 3. Simulated vehicle acceleration response, lash = 0, delay = 145 ms, initial speed = 5 m/s.

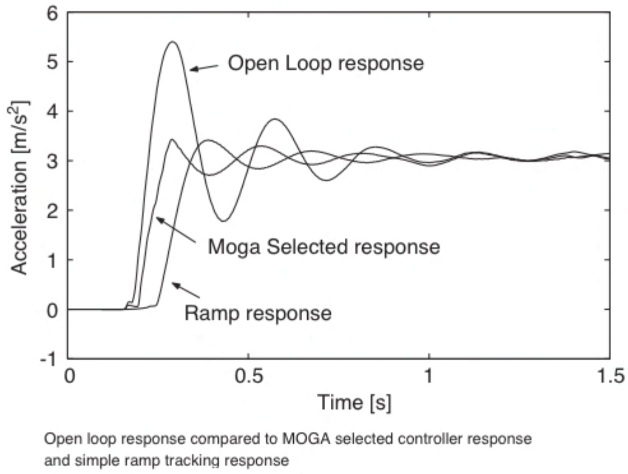


Fig. 4. Simulated vehicle acceleration response, lash = 10°, delay = 145 ms, initial speed = 10 m/s.

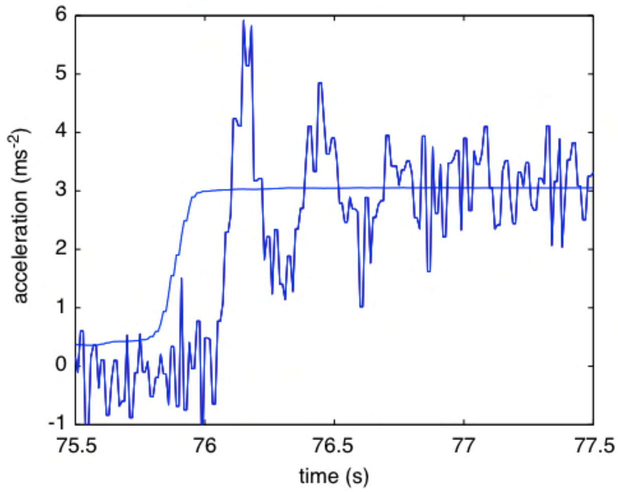


Fig. 5. Open loop experimental step response, 1 passenger, 15 mph, 2nd gear.

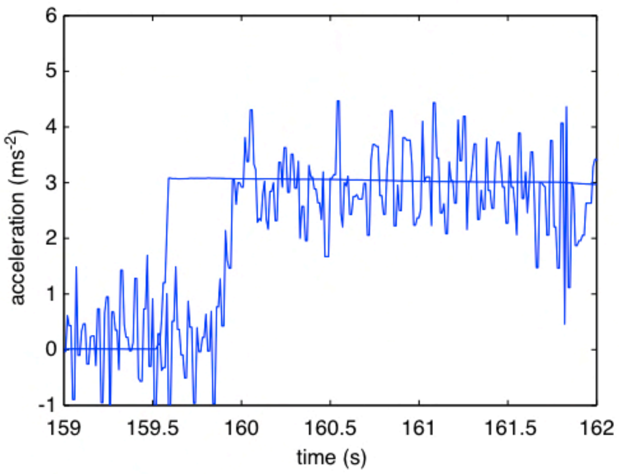


Fig. 6. Closed loop experimental step response, 1 passenger, 15 mph, 2nd gear.

driveability both in the step response and the delay time of the vehicle acceleration. The controller was found to be robust to changes in vehicle loading, and showed an excellent response across the vehicles entire operating range within the bounds described in Section 3. Although it was not possible to vary the vehicle lash, simulation results predict that the controller is again robust for levels of lash up to 30° at the wheels.

## 5. Conclusions

A driveline controller model was derived using the pole placement method. Multiobjective genetic algorithms were applied to find the optimal location of the poles for the characteristic equation. The definition of the decision variables and objectives was kept in such a way that large search spaces would be avoided. Random initial conditions were applied to each generation to achieve robust solutions. The response of the selected controller shows a dramatic improvement over the open-loop response, and also the simple control solution of using a ramp input to the throttle actuator during transients in basically two aspects: the response is faster, and it does not require tuning depending on variations in the system parameters. The controller response also proves to have a better performance than the results obtained in the literature. The combination of the pole placement method with MOGA as a technique for driveline controller optimisation results in an efficient design procedure, where the lack of knowledge of the possible solutions does not necessarily affect the result of design process. Although an accelerometer was fitted to the vehicle for verification purposes, the implemented controller worked with the vehicle speed feedback signal which was readily available.

The effect of the closed-loop controller upon the driver and passengers was perceived to be extremely beneficial. It was possible to repeat driven routes with the controller both engaged and disengaged. Although this method is extremely subjective when compared to rise-time/overshoot/settling time analysis, for the end user (a variety of drivers), the effect of the controller was found to give a distinct improvement to the driving experience.

### System simulation parameters

- Gear ratios = [3.23 2.13 1.48 1.11 0.85],
- final drive ration = [3.8],
- wheel radius = 0.3 m,
- engine and flywheel lumped inertia = 0.1 kg m$^2$,
- transmission inertia = 0.0065 kg m$^2$,
- total inertia of driving wheels = 1.8 kg m$^2$,
- engine mass = 300 kg,
- vehicle mass = 1400 kg,
- driveline stiffness = 3500 N m/rad.

## References


Astrom, K., & Wittenmark, B. (1997). *Computer controlled systems: Theory and design*. Englewood Cliffs, NJ: Prentice-Hall Inc..

Azzoni, P., Moro, D., Ponti, F., & Rizzoni, G. (1998). *Engine and load torque estimation with applications to electronic throttle control*. S.A.E. Technical Paper, no. 980795.

Baker, J. E. (1987). Reducing bias and inefficiency in the selection algorithm. In: Grefenstette, J. J. (Ed.), *Proceedings of the Second International Conference on Genetic Algorithms*. Lawrence Erlbaum Associates (pp. 14–21).

Best, M. C. (1998). Nonlinear optimal control of a vehicle driveline vibrations. *UKACC International Conference on Control '98*, Swansea, UK September 1–4 (pp. 658–663).

Chipperfield, A. J., Fleming, P. J., & Polheim, H. P. (1995). *The genetic algorithm toolbox for MATLAB*. Department of Automatic Control and Systems Engineering, University of Sheffield, UK: Version 1.2.

Fonseca, C. M., & Fleming, P. J. (1993). Genetic algorithms for multiobjective optimisation: Formulation, discussion and generalisation. *Genetic Algorithms*: *Proceedings of the Fifth International Conference*. San Mateo, CA: Morgan Kaufmann. (pp. 416–423).

Fonseca, C. M., & Fleming, P. J. (1998). Multiobjective optimisation and multiple constraint handling with evolutionary algorithms—Part 1: A unified formulation and Part 2: Application example. *IEEE Transactions on Systems, Man and Cybernetics—Part A: Systems and Humans*, *28*(1), 26–37, 38–47.

Goldberg, D. E. (1989). *Genetic algorithms in search, optimisation and machine learning*. Reading, MA: Addison-Wesley.

Holland, J. H. (1975). *Adaptation in natural and artificial systems*. Reading, MA: Addison-Wesley.

Kienke, U., & Nielsen, L. (2000). *Automotive control systems*. Berlin Heidelberg: Springer. ISBN 3-540-66922-1.

Michalewicz, Z. (1999). *Genetic* algorithms + data structures = evolution programs (3rd ed.). Berlin: Springer.

Richard, S., Chevrel, P., de Larminat, P., & Marguerie, B. (1999). Polynomial pole placement revisited: Application to active control of car longitudinal oscillations. *Proceedings of the European Control Conference '9*, Karlsruhe, Germany. Id.no.0770.

Rossi, C., Tilli, A., & Tonielli, A. (2000). Robust control of a throttle body for drive by wire operation of automotive engines. *IEEE Transactions on Control Systems Technology*, *8*(6), 993–1002.

Stefanopolou, A. G., Cook, J. A., & Grizzle, J. W. (1995). Modelling and control of a spark ignition engine with variable cam timing. *Proceedings of the American Control Conference*. Seattle WA (pp. 2576–2581).

Stewart, P., & Fleming, P. J. (2001). Drive by wire control of automotive driveline oscillations by response surface methodology. *IEEE Transactions on Control Systems Technology*, in press.

Stewart, P., & Fleming, P. J. (2002). The response surface methodology for rapid prototyping of real-time control systems. *2002 IEEE American Control Conference*, May 8–10, 2002, Anchorage, Alaska, USA, pp. 3343–3348.

Stewart, P., & Kadirkamanathan, V. (2001). Dynamic model reference PI control of flux weakened permanent magnet AC motor drives. *IFAC Journal of Control Engineering Practice*, *9*(11), 1255–1263.

Willey, J. (1999). *A study into various methods of dynamic feedback control of automotive driveline shuffle*. M.Sc. thesis, University of Loughborough, UK.

Zalzala, A. M. S., & Fleming, P. J. (1997). *Genetic algorithms in engineering systems*. *Institute of Electrical Engineering IEE books control series*. London, UK.

Zitzler, E., & Thiele, L. (1999). Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach. *IEEE Transactions on Evolutionary Computation*, *3*(4), 257–271.