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On-line PID tuning for engine idle-speed control using continuous action reinforcement learning automata

Running title : On-line PID tuning for engine control using CARLA

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Abstract

PID systems are widely used to apply control without the need to obtain a dynamic model. However, the performance of controllers designed using standard on-line tuning methods, such as Ziegler-Nichols, can often be significantly improved. In this paper the tuning process is automated through the use of *continuous action reinforcement learning automata* (CARLA). These are used to simultaneously tune the parameters of a three term controller on-line to minimise a performance objective. Here the method is demonstrated in the context of engine idle speed control; the algorithm is first applied in simulation on a nominal engine model, and this is followed by a practical study using a Ford Zetec engine in a test cell. The CARLA provides marked performance benefits over a comparable Ziegler-Nichols tuned controller in this application.

Keywords: Learning automata; Intelligent control; PID (three term) control; Engine idle-speed control

1. Introduction

Despite huge advances in the field of control systems engineering, PID still remains the most common control algorithm in industrial use today. It is widely used because of its versatility, high reliability and ease of operation (see for example Astron and Hagglund, 1995). A standard form of the controller is given in Eq. 1 and the implementation is shown in Figure 1.

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \quad (1)$$

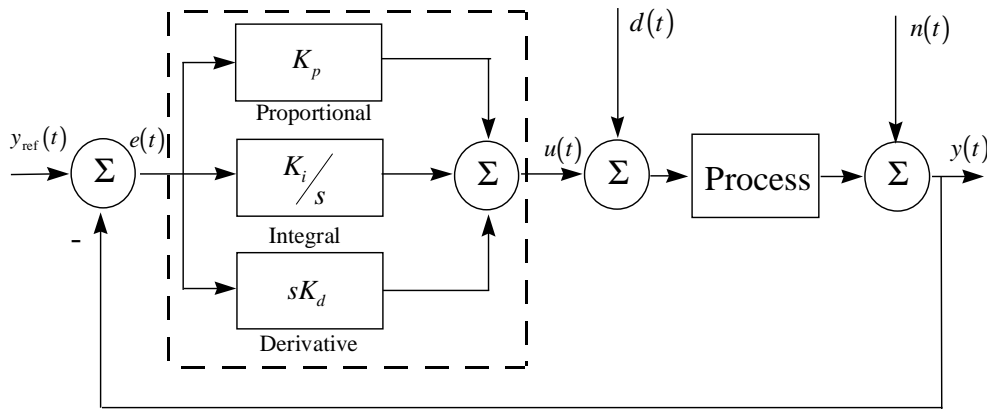


Fig. 1. PID controller implementation

The measurable output $y(t)$ is subject to sensor noise $n(t)$ and the system to disturbances $d(t)$, both of which can be assumed unknown. The control $u(t)$ is a summation of three dynamic functions of the error $e(t)$ from a specified reference (demand) output $y_{ref}(t)$. Proportional control has the effect of increasing the loop gain to make the system less sensitive to load disturbances, the integral of error is used principally to eliminate steady state errors, and the derivative action helps to improve closed loop stability. The parameters K_p, K_i, K_d are thus chosen to meet prescribed performance criteria, classically specified in terms of rise and settling times, overshoot and steady-state error, following a step change in the demand signal.

A standard method of setting the parameters is through the use of Ziegler-Nichols' tuning rules (Ziegler and Nichols, 1942). These techniques were developed empirically through the simulation of a large number of process systems to provide a simple rule. The methods operate particularly well for simple systems and those

which exhibit a clearly dominant pole-pair, but for more complex systems the PID gains may be strongly coupled in a less predictable way. For these systems, adequate performance is often only achieved through manual and heuristic parameter variation.

This paper introduces a formal approach to setting controller parameters, where the terms are adapted on-line to optimise a measure of system performance. The performance measure is usually a simple cost function of error over time, but it can be defined in any way, for example to reflect the classical control criteria listed earlier. The adaptation is conducted by a learning algorithm, using *Continuous Action Reinforcement Learning Automata* (CARLA) which were first introduced by Howell *et al*, (1997). The control parameters are initially set using a standard Ziegler-Nichols method; three separate learning automata are then employed – one for each controller gain – to adaptively search the parameter space to minimise the specified cost criterion.

As an example, a PID controller is developed for load disturbance rejection during engine idle. The idle speed control problem presents particular challenges, due to system nonlinearities, and varied predictable and unpredictable noise conditions, and the application has attracted much research interest over many years. A thorough review of the state of the art was given in (Hrovat and Sun, 1997), and recent work on control algorithms have included SISO robust control (Glass and Franchek, 1999) and a combination of L1 feedforward and LQG feedback control (Butts *et al*, 1999).

In this paper, the PID algorithm is first tuned in simulation, to an essentially linear engine idle model; it is then re-examined on a physical engine in a test cell. In both cases the throttle angle is used to regulate measured engine speed.

2. Continuous Action Reinforcement Learning Automata

The CARLA operates through interaction with a random or unknown environment by selecting actions in a stochastic trial and error process. For applications that involve continuous parameters which can safely be varied in an on-line environment, the CARLA technique can be considered to be more appropriate than alternatives. For example, one such alternative, the genetic algorithm (Holland 1975) is a population based approach and thus requires separate evaluation of each member in the population at each iteration. Also, although other methods such as simulated annealing could be used, the CARLA has the advantage that it provides additional convergence information through probability density functions.

CARLA was developed as an extension of the discrete stochastic learning automata methodology (see Narendra and Thathachar, 1989 or Najim and Posnyak, 1994 for more details). CARLA replaces the discrete action space with a continuous one, making use of continuous probability distributions and hence making it more appropriate for engineering applications that are inherently continuous in nature. The method has been successfully applied to active suspension control (Howell *et al*, 1997) and digital filter design (Howell and Gordon, 1998). A typical layout is shown in Figure 2.

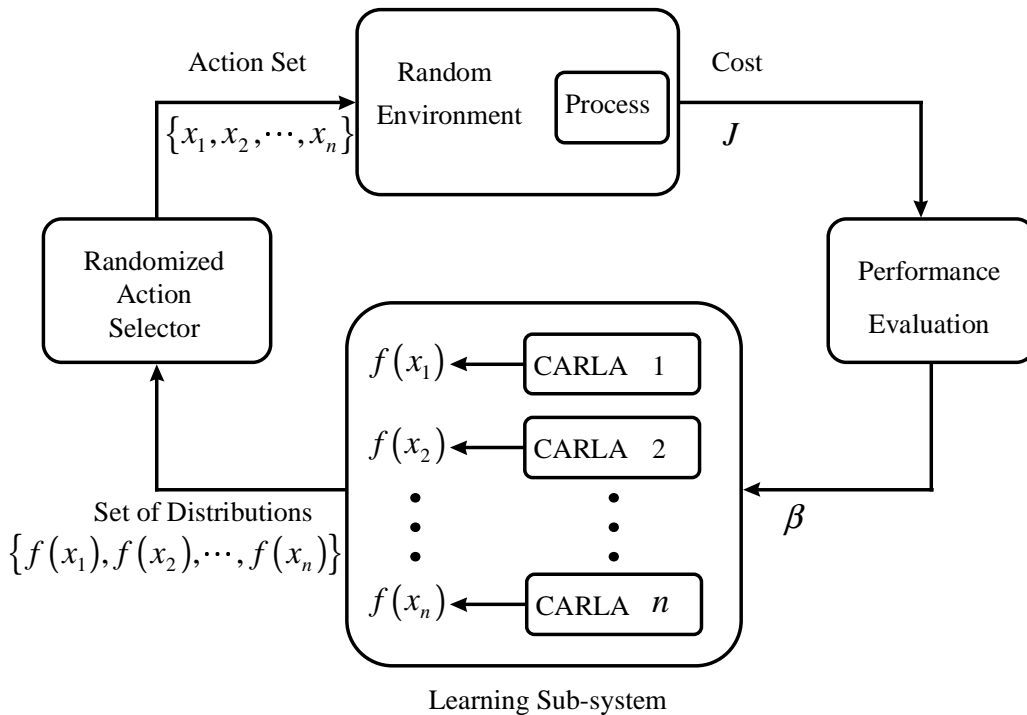


Fig. 2. Learning system

Each CARLA operates on a separate action – typically a parameter value in a model or controller – and the automata set runs in a parallel implementation as shown, to determine multiple parameter values. The only interconnection between CARLAs is through the environment and via a shared performance evaluation function. Within each automata, each action has an associated probability density function $f(x)$ that is used as the basis for its selection. Action sets that produce an improvement in system performance invoke a high performance ‘score’ β , and thus through the learning sub-system have their probability of re-selection increased. This is achieved by modifying $f(x)$ through the use of a Gaussian neighbourhood function centred on the successful action. The neighbourhood function increases the probability of the original action, and also the probability of actions ‘close’ to that selected; the assumption is that the performance surface over a range in each action is continuous and slowly varying. As the system learns, the probability distribution generally converges to a single Gaussian distribution around the desired parameter value.

Referring to the i^{th} action (parameter), x_i is defined on a pre-specified range $\{x_i(\text{min}), x_i(\text{max})\}$. For each iteration k of the algorithm, the action $x_i(k)$ is chosen using the probability distribution function $f_i(x_i, k)$, which is initially uniform :

$$f_i(x_i, 1) = \begin{cases} 1/[x_i(\text{max}) - x_i(\text{min})] & \text{where } x_i \in \{x_i(\text{min}), x_i(\text{max})\} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

The action is selected by
$$\int_0^{x_i(k)} f_i(x_i, k) dx_i = z_i(k) \quad (3)$$

where z varies uniformly in the range $\{0, 1\}$.

With all n actions selected, the set is evaluated in the environment for a suitable time, and a scalar cost value $J(k)$ calculated according to some predefined cost function. Performance evaluation is then carried out using

$$\beta(k) = \min \left\{ \max \left\{ 0, \frac{J_{\text{med}} - J(k)}{J_{\text{med}} - J_{\text{min}}} \right\}, 1 \right\} \quad (4)$$

where the cost $J(k)$ is compared with a memory set of R previous values from which minimum and median costs J_{min} , J_{med} are extracted. The algorithm uses a reward / inaction rule, with action sets generating a cost below

the current median level having no effect ($\beta = 0$), and with the maximum reinforcement (reward) also capped, at $\beta = 1$.

After performance evaluation, each probability density function is updated according to the rule

$$f_i(x_i, k+1) = \begin{cases} \alpha(k)[f_i(x_i, k) + \beta(k)H(x_i, r)] & \text{if } x_i \in \{x_i(\min), x_i(\max)\} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where $H(x, r)$ is a symmetric Gaussian neighbourhood function centred on the action choice, $r = x(k)$,

$$H(x, r) = \left(\frac{g_h}{(x_{\max} - x_{\min})} \right) \cdot \exp\left(-\frac{(x - r)^2}{2(g_w \cdot (x_{\max} - x_{\min}))^2} \right) \quad (6)$$

and g_h and g_w are free parameters that determine the speed and resolution of the learning by adjusting the normalised ‘height’ and ‘width’ of H . These are set to $g_w = 0.02$ and $g_h = 0.3$ along with a memory set size for $\beta(k)$ of $R = 500$, as a result of previous investigations which show robust CARLA performance over a range of applications (Howell *et al*, 1997, 1998, Frost, 1998).

The parameter $\alpha(k)$ is chosen in Eq. (5) to renormalize the distribution at $k+1$,

$$\alpha = \frac{1}{\int_{x_i(\min)}^{x_i(\max)} [f_i(x_i, k) + \beta(k)H(x_i, r)] dx_i} \quad (7)$$

For implementation, the distribution is stored at discrete points with equal inter-sample probability, and linear interpolation is used to determine values at intermediate positions. A summary of the required discretisation method is given in the appendix, or for more details see Frost, 1998.

3. Engine Idle Speed Control

Vehicle spark ignition engines spend a large percentage of their time operating in the idle speed region. In this condition the engine management system aims to maintain a constant idle speed in the presence of varying load demands from electrical and mechanical devices, such as lights, air conditioning compressors, power steering pumps and electric windows. Engines are inherently nonlinear, incorporating variable time delays and discontinuities which make modelling difficult, and for this reason their control is well suited to optimisation using learning algorithms.

3.1 Model Based Learning

For comparison with real engine data, and as a demonstration of CARLA operation, the technique is first tested on a simple generic engine model. Cook and Powell (1988) presented a suitable structure, which relates change in engine speed to changes in fuel spark and throttle, with the model linearised about a fixed idle speed. Figure 3 illustrates the model, with attached PID controller.

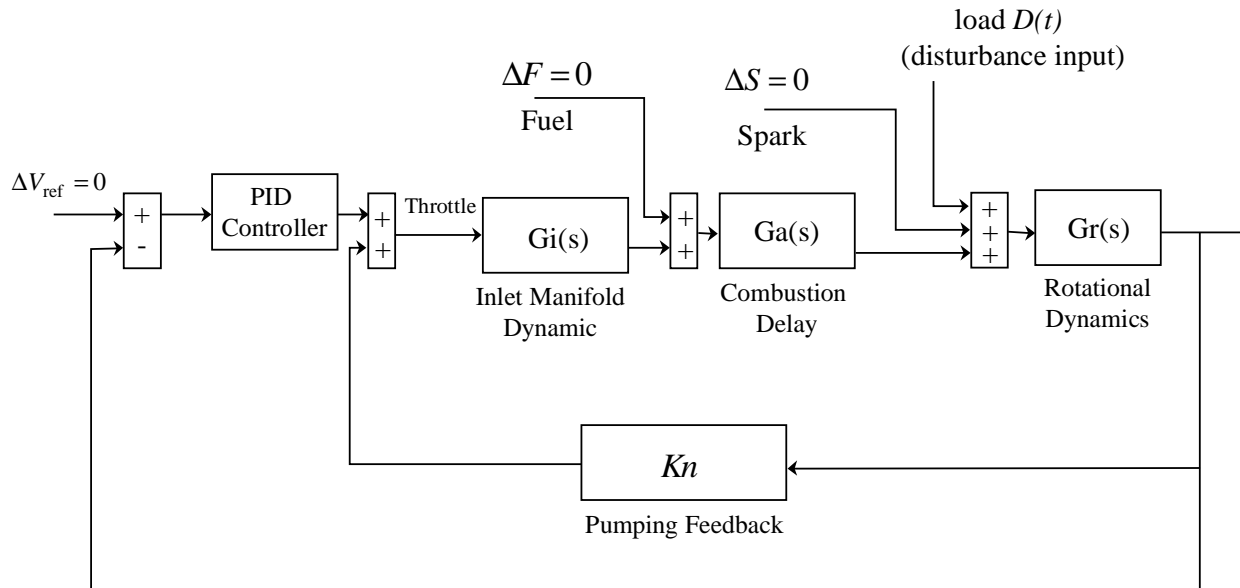


Fig. 3. Engine idle speed simulation model

Component dynamics are taken as

$$Gi(s) = \frac{K_p T_p}{(T_p s + 1)} \quad Gr(s) = \frac{20}{(3.5s + 1)} \quad Ga(s) = G_p e^{-s\tau} \quad (8)$$

where nominal system parameters are chosen: $T_p = 0.05$, $K_p T_p = 9000$, $G_p = 0.85$, $K_n = 1 \times 10^{-4}$ with a combustion time delay of $\tau = 0.1$ seconds. From earlier identification work, these settings are known to be representative of the test engine which we will consider in Section 3.2, for an idle speed of 800rpm with no electrical or mechanical load.

In this paper, control is applied via modulation of the throttle only, to minimise the change in engine speed (ΔV) in the presence of load torque variations $D(t)$. Adopting the stability boundary method for Ziegler-Nichols tuning, reference PID gains were obtained, and these are recorded in Table 1.

The CARLA algorithm is applied by defining three actions – one for each controller gain – with wide search ranges, of $\pm 200\%$ of the Ziegler-Nichols settings. The optimisation was conducted by minimisation of integrated time and squared error,

$$J = \int_0^T \tau \cdot (\Delta V(\tau))^2 d\tau \quad (9)$$

over a suitably long period ($T = 5$ seconds) following an applied 10Nm step in load at $t = 0$. By time weighting the error signal less emphasis is placed on the initial error, which is largely unavoidable, and greater emphasis on reducing long duration oscillations.

Figure 4 shows how the probability density functions varied for each of the three parameters over a series of 3000 iterations. The proportional term has converged to a value close to the Ziegler-Nichols value, but the integral and derivative terms have converged to one end of their range. Critically though, all three terms have converged distinctly, and it can be shown that further learning only has the effect of reducing variance about the selected values, to a minimum specified by H , $\sigma_{\min}^2 = (g_w \cdot (x_{\max} - x_{\min}))^2$. Taking the three modal values of the final distributions, the optimal controller is given along with a cost comparison in Table 1. Note the significant performance benefit of the new controller – cost has been reduced by around 60%.

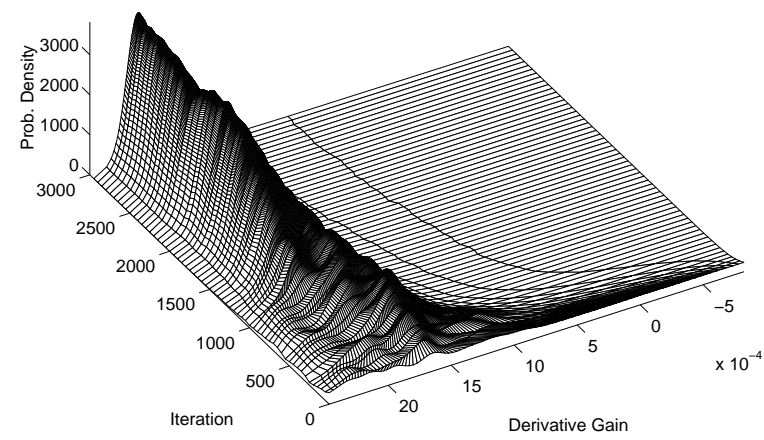
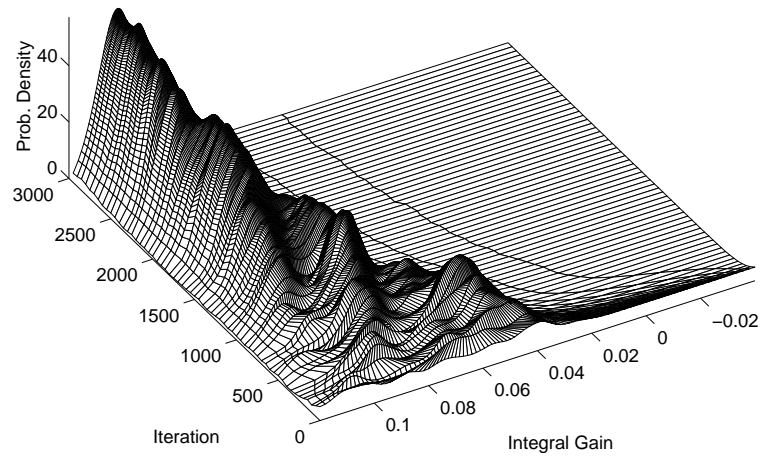
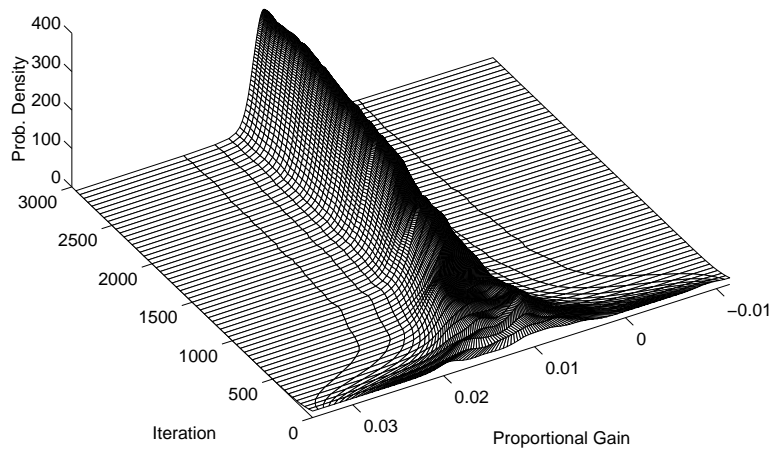


Fig. 4. Controller parameter convergence

Table 1. Comparison of PID parameter settings and associated cost

	Ziegler-Nichols	CARLA Optimised
K_p	0.0115	0.0137
K_i	0.04	0.1034
K_d	0.00082	0.0021
Cost, J	216	87

Figure 5 shows a comparison of responses to the load step; the benefits of increased integral and derivative action are clear, with the error approaching zero more quickly and having lower initial overshoot in the learnt controller. In this noise-free test however, high gains are suitable, so we might not expect the same trends in a physical engine test.

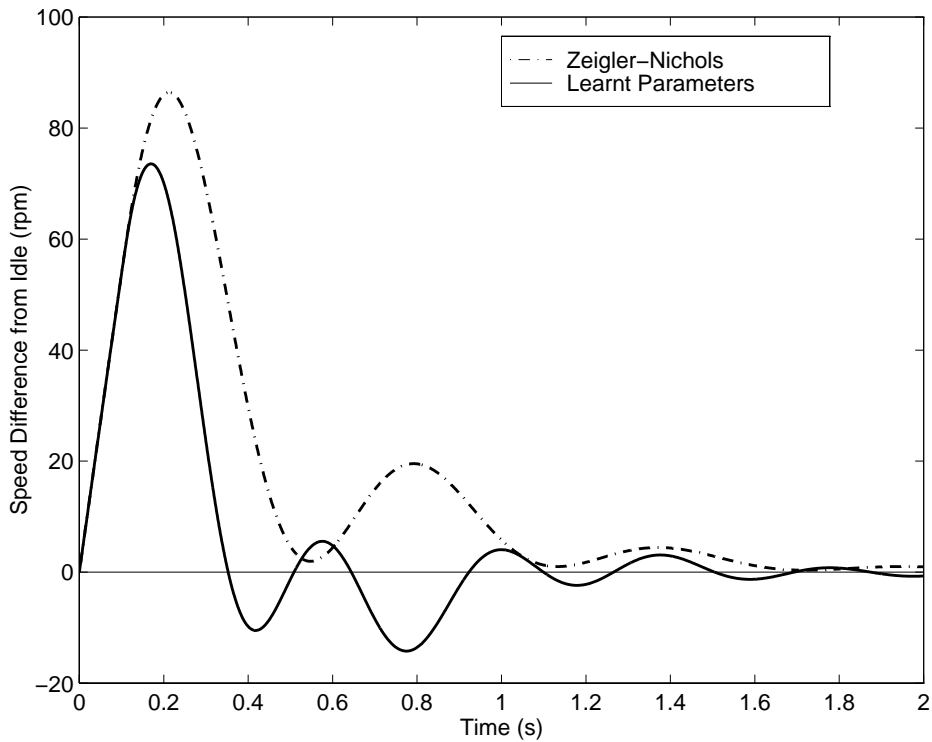


Fig. 5. Comparing controller performance for a 10Nm step change in load

3.2 On-Line Learning

To examine CARLA in the physical test environment, a Ford Zetec 1.8l engine was connected to a PC-based digital control system in a test cell. Test equipment was arranged to emulate the measurement and control that was simulated in section III(A); the equipment, operation and settings are illustrated in Figure 6 and summarised below.

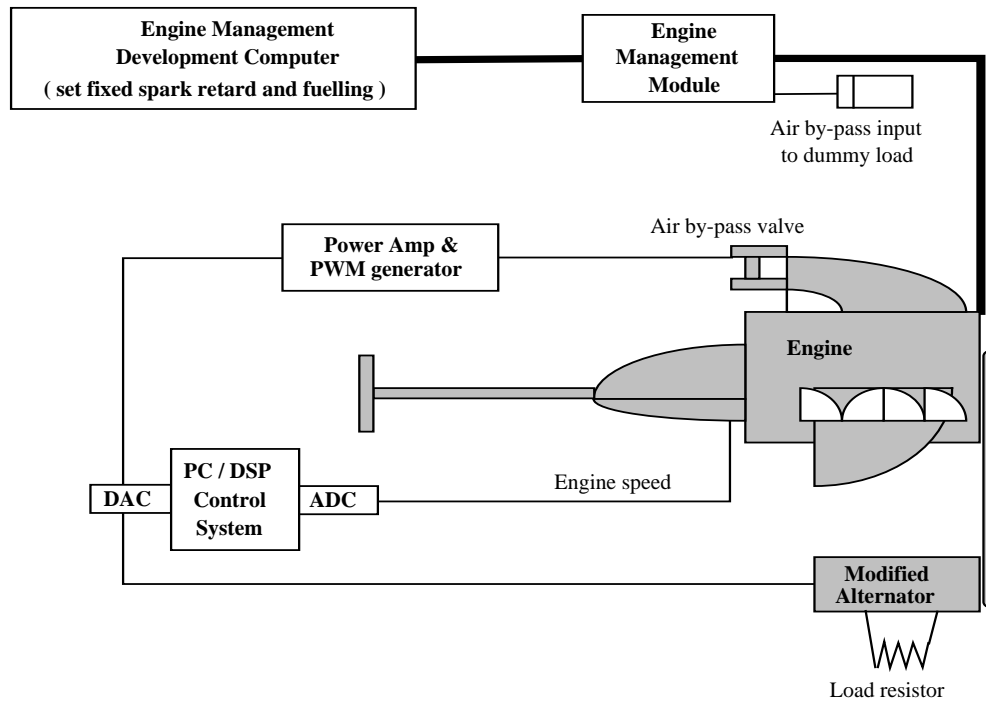


Fig. 6. System implementation

- (i) The control system consisted of a TMS320C40 digital signal processor, with Matlab, Simulink and dSPACE software. A Simulink hardware-in-the-loop system was designed, measuring engine speed and supplying a continuous control output to maintain idle at 800rpm. PID parameters were set on-line via a Matlab program running the CARLA algorithm; to implement the controller, the derivative term was approximated

$$\text{as } \frac{s}{(1/200)s + 1}.$$

- (ii) A pulse-width modulated voltage was generated from the PC control signal, and applied to the engine air bypass valve.

- (iii) The engine management module was connected to a proprietary development computer, in order to over-ride standard idle management. Spark retard was fixed at 13° before TDC, and fuelling set to vary with mass air flow only, with no exhaust oxygen control. The air bypass valve lead was attached to a dummy load.
- (iv) The alternator was attached to a low resistance (0.2Ω) load with its field voltage switched via a power amplifier, by the PC / DSP control system.

For each learning iteration, new PID gains were set and allowed to settle before a 400 Watt load was switched on for four seconds and then switched off. If during the test the control gains invoked an unstable engine response – detected by $\Delta V > 200\text{rpm}$ – the system was stabilised by resetting the control parameters to Ziegler-Nichols values, and the iteration was aborted. The cost was then evaluated according to time and speed error after both transients, using a record of engine speed sampled at 1kHz :

$$J = \sum_{k=0}^{2000} t_k \cdot (\Delta V_k)^2 + \sum_{k=4000}^{6000} (t_k - 4) \cdot (\Delta V_k)^2$$

After 1500 iterations – an on-line test of just over four hours – the cost had settled, and two of the three probability distributions had converged. The cost – filtered using a 100 point moving mean – is shown in Figure 7, and the probability distributions are given in Figure 8.

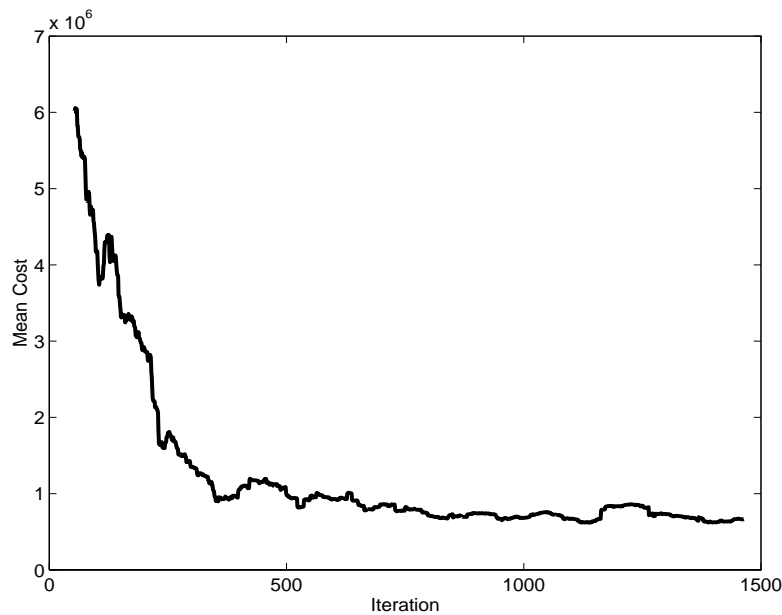


Fig. 7. Mean cost reduction as a result of learning

Ziegler-Nichols values :

$K_p = 4 \times 10^{-3}$

$K_i = 1.5 \times 10^{-3}$

$K_d = 2.5 \times 10^{-4}$

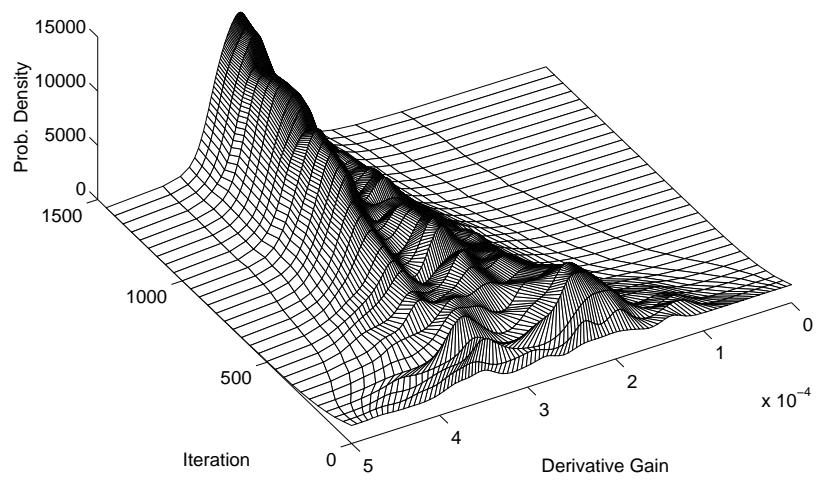
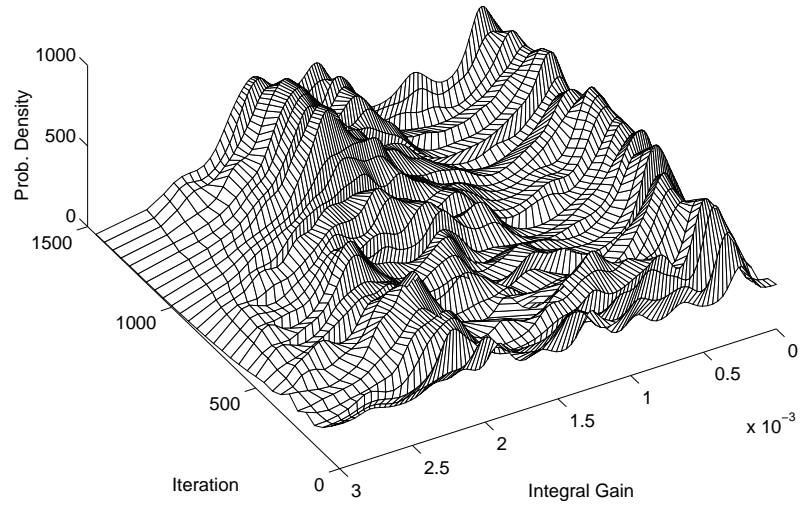
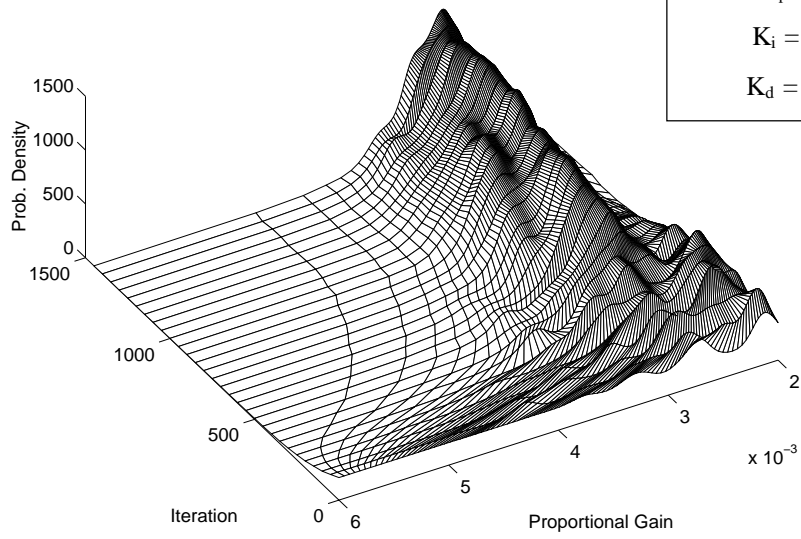


Fig. 8. Probability density function variation about Ziegler Nichols values

Again the P and D terms are distinct, with modal values $K_p = 0.0028$, $K_d = 3.48 \times 10^{-4}$. Interestingly, the integral term is not well defined – the distribution indicates two candidate parameter ranges, with little cost difference between them. Here we choose $K_i = 0.0019$, which is a modal peak from the wider of the two ranges. The choice is nominal, but selecting from the wider range we might reasonably expect a more robust control solution. The performance benefit of the learnt controller is shown separately for the load on and load off switches, in Figure 9. Note the high amplitude disturbance process at the engine firing frequency of 27Hz. Compared with the engine fundamental response frequency of around 1Hz, this is one complexity of the plant which may explain the lack of convergence in K_i .

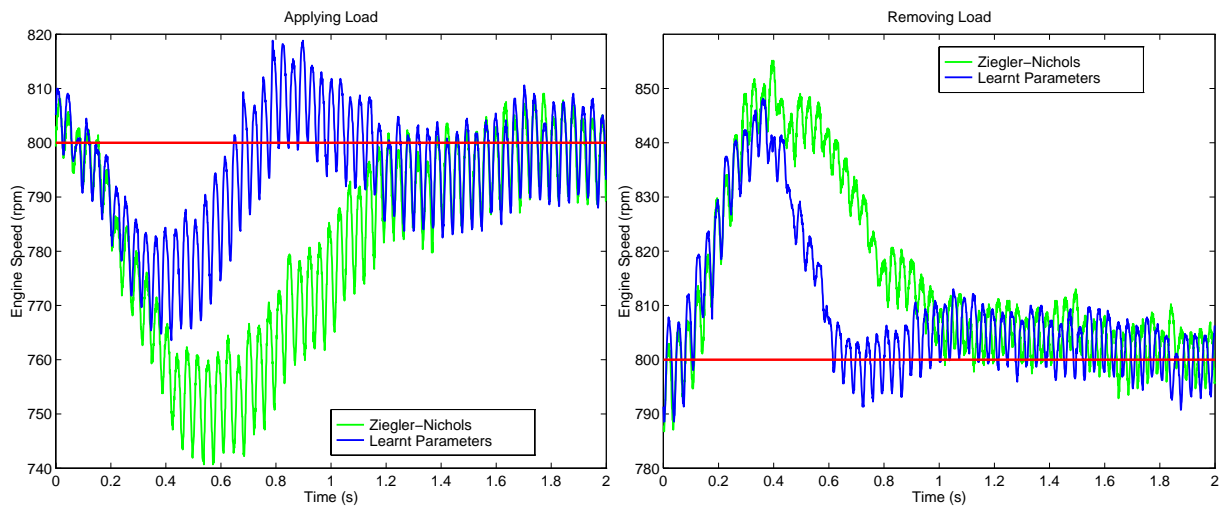


Fig. 9. Resulting improvement over Ziegler-Nichols

4. Concluding Remarks

Whilst it is recognised that the Ziegler-Nichols compensator is not optimised for the same criteria, the learnt controller's performance is excellent, with very different control gains achieving significant cost benefits. Also, from this simple study and given the flexibility of CARLA, it seems likely that the system's scope can be extended. Restricting discussion to the engine idle application, feedforward control is a good candidate; some engine loads can be anticipated (eg air conditioning pump demands), and CARLA might usefully be applied to parametrise a model for feedforward control under expected load conditions.

The control algorithm itself can also be extended – for example by considering full state feedback; CARLA has already been successfully employed in this way for optimising suspension control. More informally, gains could be optimised for multiple feedback paths in a general classical controller; in addition to engine speed, manifold pressure and mass air-flow may be measurable, and spark and fuelling actuation could be introduced. The method would also have similar applications in the wider remit of engine management.

One notable disadvantage of learning is its specificity to the individual test environment; plant variations can have significant implications for robustness. Again, potential solutions exist however – for example the learning algorithm could be implemented on-line in service. By restricting gain ranges, it should be possible to slowly adapt to individual plant variations throughout service life.

In summary, the continuous action reinforcement learning automata has been successfully applied to determine PID parameters for engine idle speed control, both in simulation and in practice. The technique does not require *a-priori* knowledge of the system dynamics, and it provides optimised control of complex nonlinear systems.

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Appendix

In order to implement CARLA, the probability distributions f_i must be stored and updated at discrete sample points. The most efficient data storage can be achieved using equal inter-sample probability rather than equal sampling on x_i , but this is at some computational expense, as the sampled vector \mathbf{x}_i must be redefined after each iteration k , according to the updated distribution $f_i(\mathbf{x}_i, k+1)$.

The data management is carried out by first executing the algorithm as described in Section 2, but using $\alpha = 1$ and evaluating equations (5) - (7) at the N current sampled points $\mathbf{x}_i(k)$. A new set of sample points $\mathbf{x}_i(k+1)$ is then selected sequentially from $x_i(\min)$ to $x_i(\max)$; with regard to Figure A1 (and dispensing with the subscript i), $x_1 = x(\min)$, $x_N = x(\max)$ and intermediate samples are defined for $j = 1, N-1$ by the following :

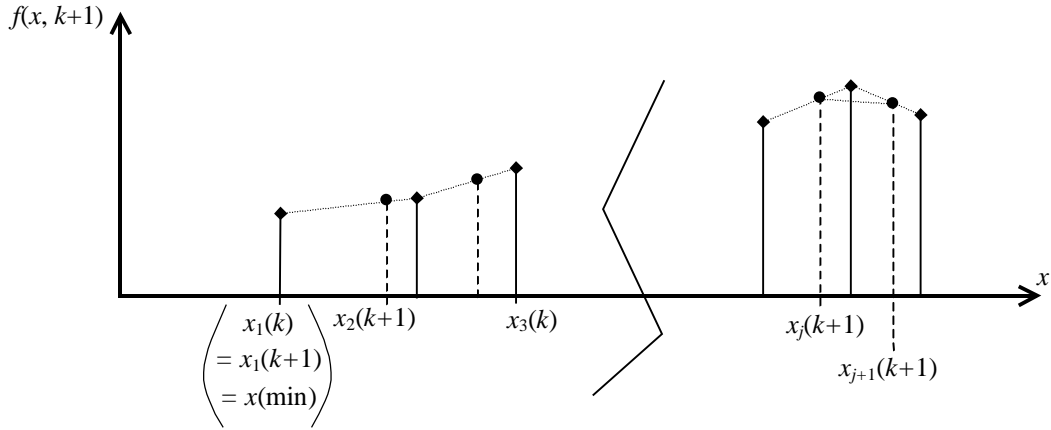


Fig. A1. Re-sampling on the linearly interpolated probability density function

$$a_{j+1} = \frac{1 - A_j}{N - j} \quad (\text{A1})$$

$$0.5[x_{j+1}(k+1) - x_j(k+1)][f(x_{j+1}, (k+1)) - f(x_j, (k+1))] = a_{j+1} \quad (\text{A2})$$

$$A_{j+1} = A_j + a_{j+1} \quad (\text{A3})$$

Here a_j refers to the j^{th} intersample probability, and A_j records the cumulative re-sampled probability at j ($A_1=0$).

In each case, equation (A2) is solved for $x_{j+1}(k+1)$ by interpolating $f(x_{j+1}, (k+1))$ between known values on

$f(x_j, k+1)$, and solving the resulting quadratic equation. The sequential re-calculation of target intersample probability – equation (A1) – prevents cumulative interpolation errors from corrupting the probability distribution function as it develops with iterations. This algorithm was used successfully in the paper using the relatively small sample set $N = 100$.