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Transport and Maintenance Effective Retardation Control Using Neural Networks With Genetic Algorithms

PETER LINGMAN[1,2,3] AND MATTIAS WAHDE[3]

SUMMARY

A brake system controller is designed using the powerful techniques of neural networks and genetic algorithms. First, the problem of coordinating auxiliary brakes, foundation brakes, and gear for high transport effectiveness in down hill cruising situations is investigated. An optimization problem with constraints such as vehicle speed and disc temperature is formulated and solved, resulting in a well performing controller even compared to experienced drivers. Second, the issue of distributing a required force between auxiliary and foundation brakes in order to minimize the maintenance cost is investigated. The neural network controllers obtained from the optimization procedure significantly outperform the traditional strategy of using non-wear auxiliary brakes in order to minimize pad and disc wear cost. The performance of the brake system can be improved by controlling the whole brake system including gear.

1. INTRODUCTION

Cruising downhill with a heavy duty vehicle requires several actions from the driver. First of all a proper set speed must be decided upon. To obtain and keep this set speed the driver has to change gear and engage both foundation (FB) and auxiliary brakes (AB), i.e. Volvo Engine Brake (VEB) and Compact Hydrodynamical Retarder (CR).

A problem is that the driver is given almost no feedback regarding vehicle mass, brake disc temperature and other important vehicle and environment states. Accidents have occurred where a driver has chosen an excessive speed combined with a bad distribution of retardation force between ABs and FBs, resulting in overheating of

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both the disc brakes (known as fading) and the ABs (cooling system saturation), see [1], for an example of a fading accident.

Other more conservative drivers choose a low set speed yielding a low utilization of the capacity of the brake system and perhaps also low mean speed depending on the driving cycle. The third type of driver (most common!) is the very experienced driver with good knowledge of both vehicle and environment. By observing engine speed, coolant temperature etc., such a driver uses the AB system to keep the vehicle speed constant but never uses the FB for long periods of time in order to avoid fading. In Figure 1 the maximum stationary speed is shown as a function of slope. By choosing gear and level of the ABs, the driver finds the maximum stationary speed for downhill cruising. This is of course a difficult driver task, especially if also FBs are considered. Thus there is a need to design an integrated retardation control system for high mean speed (high transport effectiveness) while keeping the system within certain boundaries (safety and law).

Another important aspect of strategies for optimal retardation force distribution is how the tyre, pad, and disc wear are affected. FBs distribute the total retardation force demand on all vehicle axles whereas ABs use the drive axle only,

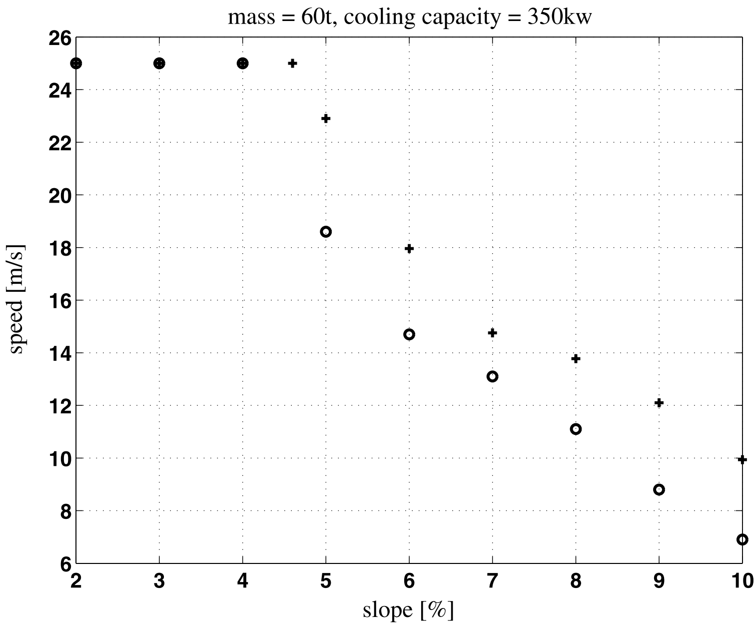

Fig. 1. Maximum stationary speed for different slopes. Circle: Normal driver using only ABs. Plus sign: optimal blending using ABs and FBs.

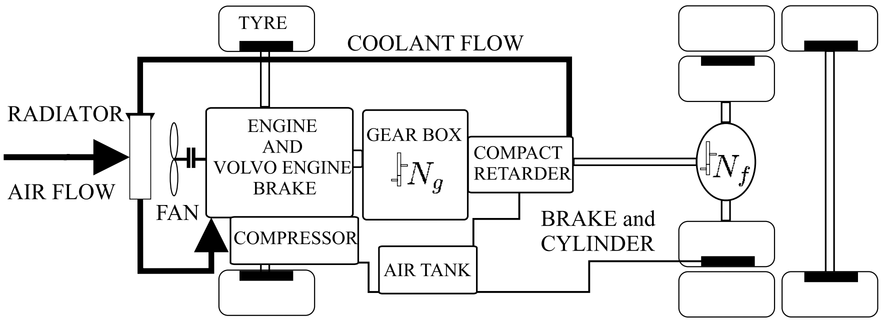

Fig. 2. Volvo retardation system.

see Figure 2. The standard strategy is to utilize ABs (known as *non-wear brakes*) in order to save brake pads and discs. However, some drivers have noticed a very high drive tyre wear causing high maintenance cost when using this strategy. Therefore the trade-off between tyre, pad, and disc wear cost has to be investigated and considered in a criterion function for optimal retardation control. See also [2] for further discussions on the importance of integrating the whole retardation system of a heavy vehicle.

This paper investigates the possibility of achieving an integrated retardation controller for gear shifting and blending of different retardation actuators in a heavy duty vehicle. This is done in two different cases. Case 1 focuses on maximum utilization (high mean speed, $\overline{v}$) of the brake system and Case 2 focuses on minimizing the pad, disc, and tyre wear cost in a constant speed keeping situation. In Case 1, the scenario is that the vehicle enters a descent and the driver decides upon a maximum vehicle speed. The controller guides the vehicle downhill without exceeding the maximum speed and other constraints (fading, engine speed, etc.). Case 2 focuses on a common type of constant speed controller requesting a retardation force to keep the vehicle speed constant on a downhill slope. The main question here is how the required retardation force should be split between ABs and FBs in order to minimize wear cost of tyres, pads, and discs. In both cases, the parametrization of the brake system controller is achieved by a neural network (NN) optimized with a genetic algorithm (GA).

2. THE RETARDATION SYSTEM

In Figure 2, the main components of a Volvo heavy duty vehicle retardation system are presented. The FB power is distributed on all wheels (including trailer) whereas the ABs work only on the drive axle. Pressurized air, generated in the compressor and stored in air tanks, is used as FB energy source and as control medium for both the VEB and CR. The retarder cooling system is connected to the engine cooling system making it a closed loop system where the generated heat is handled in the main engine cooler (radiator).

2.1. Vehicle Model

In order to design and evaluate an integrated retardation controller a mathematical vehicle model was built. Since the model is used in an optimization routine requiring many iterations, it is very important to have a well balanced model that describes the main dynamics of the system without being excessive in complexity. The main equations are presented below.

Longitudinal motion equation

$$m\dot{v} = F_{\text{drive}} - F_{\text{air}} - F_{\text{roll}} - F_{\text{grade}} - F_{\text{aux}} - F_{\text{found}} \tag{1}$$

F_{drive} is the propulsion force, F_{air}, F_{roll}, and F_{grade} are resistance forces and F_{aux} and F_{found} are AB and FB forces, respectively.

Foundation brake dynamics
First order dynamics is assumed and $T_f = 0.4$ s. T_1 and T_2 represent the temperature dynamics of the disc brake, discretized into two masses.

$$\dot{F}_{\text{found}} = \frac{1}{T_f}(F_{\text{req}} - F_{\text{found}}) \tag{2}$$

$$\dot{T}_1 = q_{\text{in}} - c_1(T_1 - T_2) - c_2(v)(T_1 - T_{\text{amb}}) - c_3(T_1^4 - T_{\text{amb}}^4) \tag{3}$$

$$\dot{T}_2 = c_4(T_1 - T_2) - c_5(v)(T_2 - T_{\text{amb}}) - c_6(T_2^4 - T_{\text{amb}}^4) \tag{4}$$

q_{in} is the brake force power, c_1 and c_4 are heat conduction constants, $c_2(v)$ and $c_5(v)$ are vehicle speed dependent convection variables, and c_3 and c_6 are radiation constants.

Auxiliary brake dynamics
First order dynamics is assumed with $T_{\text{veb}} = 0.3$ s and $T_{\text{cr}} = 0.5$ s.

$$\dot{F}_{\text{veb}} = \frac{1}{T_{\text{veb}}}(F_{\text{req}} - F_{\text{veb}})\frac{N_g N_f}{R_w} \tag{5}$$

$$\dot{F}_{\text{cr}} = \frac{1}{T_{\text{cr}}}(F_{\text{req}} - F_{\text{cr}})\frac{N_f}{R_w} \tag{6}$$

F_{veb} and F_{cr} are the VEB and CR retardation forces, N_g is the gear ratio of the current gear position, N_f is the gear ratio of the rear axle final gear, and R_w is the wheel radius.

Cooling system

The radiator is modelled according to [3]. From measurements it can be concluded that approximately 40% of the VEB power and 100% of the CR power transfer to the coolant, respectively. In a radiator, as for all heat exchangers, the flow rate of the medium is used to control the cooling capacity. In a heavy duty truck the system is designed so that the coolant flow is directly proportional to the engine speed (v_E) and the air flow is a function of vehicle speed, fan speed, and air temperature. The fan speed is a function of v_E and the slip in the viscous coupling, used to control the fan speed relative to v_E. Here the air density variation due to temperature variation has been omitted.

$$\text{Coolant flow} = c\, v_E \tag{7}$$

$$\text{Air flow} = f(v, \text{Fan speed}) \tag{8}$$

$$\text{Fan speed} = f(v_E, \text{slip}) \tag{9}$$

Wear dynamics

The models used for pad and tyre wear are shown below. As can be seen, the pad wear rate varies strongly with the temperature of disc whereas the tyre wear rate is only a function of the torque acting on the wheel. τ_{tyre} represents the torque on each wheel.

$$\dot{S}_{\text{pad}} = q_{\text{in}} S_0 e^{cT_1^{k_0}} \tag{10}$$

$$\dot{S}_{\text{tyre}} = v(a + b\tau_{\text{tyre}}^2 + c\tau_{\text{tyre}}^4 + d\tau_{\text{tyre}}^6) \tag{11}$$

S_0, c, and k_0 are disc pad wear constants and a, b, c, and d are tyre wear constants.

3. METHOD

Driving strategies are represented by two-layer feedforward neural networks (NNs). An NN is a non-linear function mapping a set of input signals (Y) to a set of output signals (U). The computational nodes, called neurons, are connected to each other forming a net structure as shown in Figure 3. Each neuron is represented by a summation operator and an activation function ($\sigma(s)$) that limits the output from each neuron. The sigmoid function was chosen as activation function: $\sigma(s) = 1/(1 + e^{-s})$, where s is the sum of all input signals to the neuron and the output (z) from each neuron is therefore given by: $z = \sigma(\Sigma w_{\text{ij}} x_{\text{j}} + w_{\text{bias}}\Theta)$ as shown in Figure 4.

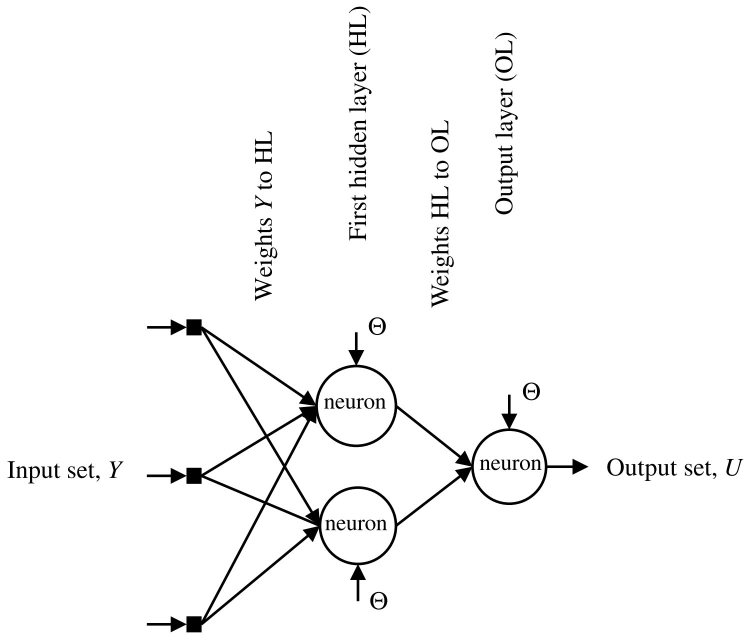

Fig. 3. A feedforward neural network consisting of three neurons, arranged in two layers. The input elements, shown as black filled squares, merely distribute the input signals.

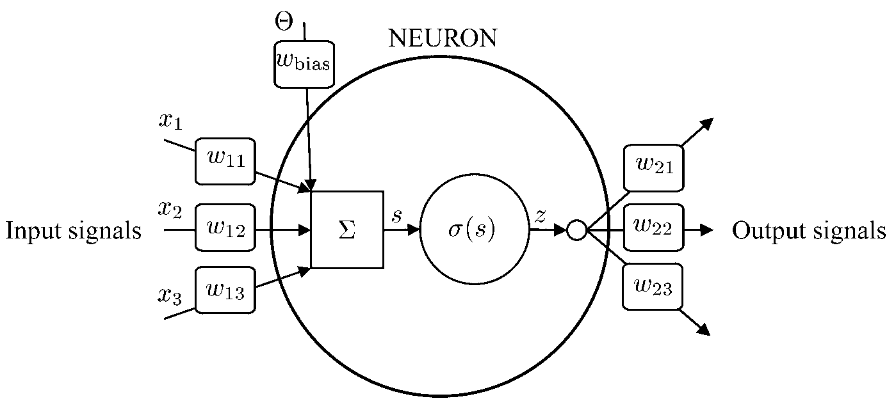

Fig. 4. A neuron.

This output signal is multiplied by a weight (w) and then transmitted as an input signal to a neuron in the next layer, as illustrated in Figures 3 and 4. $w_{\text{bias}}\Theta$ $(\Theta \equiv +1)$ is a bias term which sets the output level of the neuron in the absence of input. Typical input and output sets used are Y: {speed, disc temperature, road slope, coolant temperature, engine speed} and U: {force ratio between FBs and ABs, gear change, force ratio between VEB and CR, retardation force request}, as illustrated in Figure 5. Since the activation function limits the output to [0, 1], post- and preprocessing of signals measured in the vehicle and signals controlling the actuators have to be

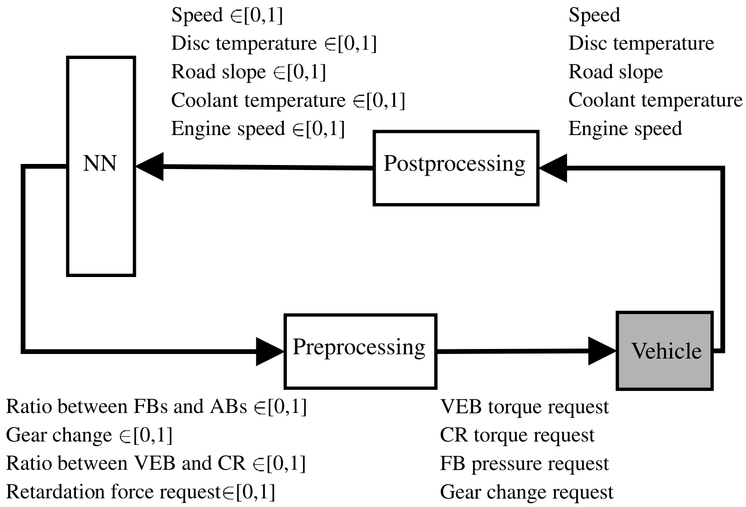

Fig. 5. Closed loop feedback.

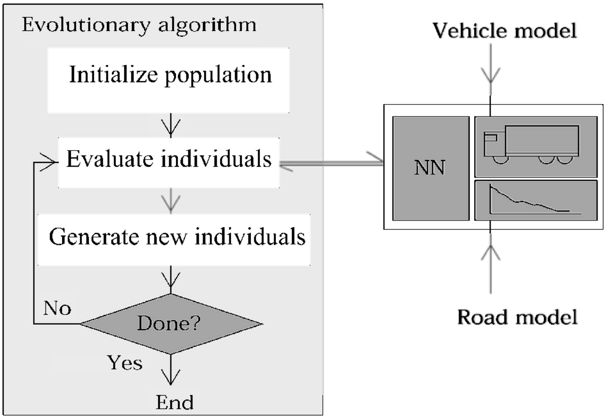

Fig. 6. The optimization loop.

performed as shown in Figure 5, see [4] for discussion. We have chosen to use a genetic algorithm (GA) for the optimization of the neural network representing driving strategies, see Figure 6.

Optimization of neural networks is often performed using the backpropagation algorithm, see [4]. However, in order to apply backpropagation, a set of input-output

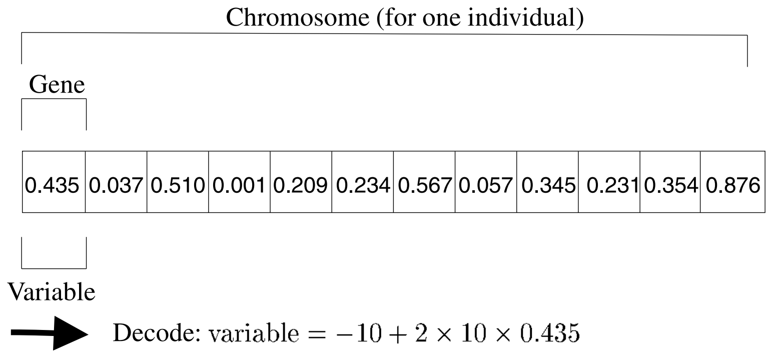

Fig. 7. Chromosome representing one individual. In this example real-number encoding is used.

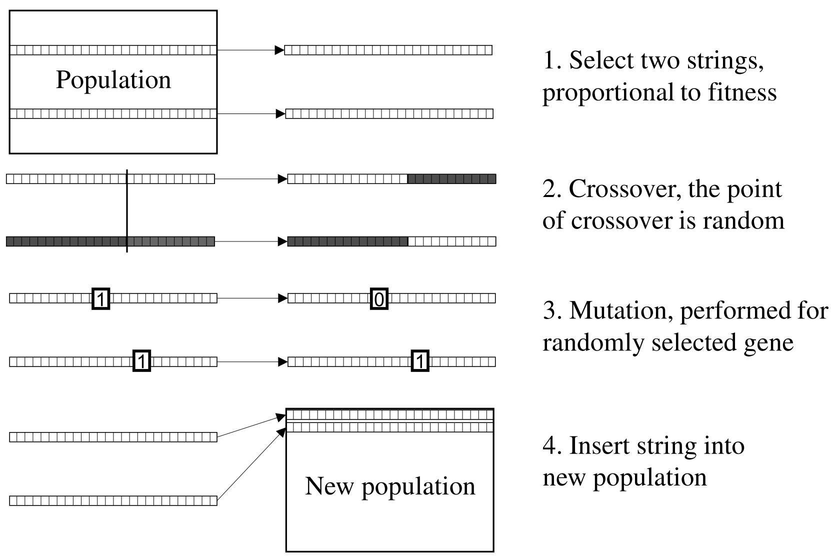

Fig. 8. One iteration in the GA.

pairs must be available, which is not the case here. In the problem considered here, the network generates a continuous stream of output signals, and the performance of the network is given as a single scalar value at the end of the evaluation, e.g. the distance traveled by the vehicle during a given period of time. In this situation, a GA is a natural choice of optimization method. GAs have been used by several authors in problems involving NN, see [5] for a review, and are particularly effective in large and complex search spaces.

A further motivation for using a GA is its ability to optimize both the structure (e.g. the number of neurons in the middle layer) and the parameters of the network. While this feature has not been used in this paper, it is important for further work since, for the problem considered here, it is very difficult to specify an optimal network structure in advance.

For this paper, a fairly standard GA with tournament selection of individuals and generational replacement has been used. The weights of the network are directly encoded (using real-number encoding) in strings called chromosomes, see Figure 7. New individuals are generated using crossover and mutations. The crossover probability was set to a rather low value (0.3), since crossover often has a negative effect on neural networks. Mutations of two kinds were introduced: *ordinary mutations*, which change the value of a gene to a new, random value (within the allowed range), and *creep mutations* for which the new value of a gene is chosen with uniform probability in a narrow interval around the previous value. In Figure 8 one iteration in the GA is shown.

4. RETARDATION ECONOMY

As discussed in [6], transport economy can be described differently depending on where the system boundary is set. If the system boundary is set around the vehicle and the owner of the vehicle, transport economy can be defined using:

- Income from transport mission.
- Fuel cost.
- Component wear (pads, tyres, etc.).
- Other maintenance costs (engine service, etc.).
- Utilization of vehicle (hours per day).
- Driver cost (salary, etc.).
- Cost of vehicle purchase or rent.
- Other costs (tax, road fee, etc.).

Looking at transport economy from a retardation control point of view, component wear for low maintenance cost and system performance for high mean speed to improve transport effectiveness are important. Formalizing this statement into a mathematical problem a criterion or fitness function (J) must be defined, e.g. as

$$\begin{aligned} J &= (\text{Cost of retardation})^{-1} \\ &= (\text{Maintenance cost})^{-1} + (\text{Cost of transport time})^{-1} \\ &= J_{\text{wear}} + J_{\text{speed}} \\ &= \frac{1}{C_{\text{tot}}} + \overline{v} \end{aligned} \tag{12}$$

Since it is difficult to quantify the cost of time (though not impossible) the criterion J was split into two different parts for maximization, as shown in Equation (12) where mean speed ($\overline{v}$) and component wear cost C_{tot} represents cost of transport time and maintenance, respectively. It should also be mentioned that efficient use of the brake system will increase the mean speed on downhill slopes, but it will not necessarily affect the mean speed on the whole driving cycle. If large parts of the driving cycle consist of relatively flat road sections, the mean speed (transport time) is not much affected by an increase in the speed on single down hill slopes. However, high mean speed on down hill slopes is often desirable also to increase the driver comfort and satisfaction (i.e. driveability). Here, a comparison with the development of engines can be made. Reducing emissions and fuel consumption are prime targets for engine developers but other customer demands like engine response, power reserve, top gear gradeability etc also have to be considered. Stronger and more powerful engines are developed, even if the mean speed on the whole driving cycle does not necessarily increase with more powerful engines.

5. INCREASED MEAN SPEED – CASE 1

Case 1 is focused on optimal utilization of the complete retardation system including FBs, ABs, cooling system, and gearbox. Three examples are shown in Figure 9 where the objective for the controller is to guide the vehicle down a 5% descent, a 10% descent, and a road profile (nr 4 in Fig. 10) with varying slope. The objective is to achieve highest possible average speed ($\overline{v}$) over a finite time interval without violating the constraints. For this task a 5-7-4 feedforward NN with sigmoid slope equal to 1, and with inputs $\{v, T_1, \alpha, T_{\text{coolant}}, v_E\}$ and outputs $\{R_{\text{found}_{\text{req}}}, \text{Shift}_{\text{req}}, R_{\text{aux}_{\text{req}}}, F_{\text{split}_{\text{req}}}\}$ was trained with a GA. As mentioned earlier, both the input signals and the output signals were normalized to the interval [0, 1], see Figure 5.

$F_{\text{split}_{\text{req}}}$ is the total retardation force request, $R_{\text{found}_{\text{req}}}$ splits the total retardation force request between FBs and ABs, from 1 for 100% FBs linearly down to 0 for 100% ABs. $R_{\text{aux}_{\text{req}}}$ splits the AB force requested between VEB and CR, and $\text{Shift}_{\text{req}}$ indicates gear shift (up) if larger than 0.7, gear shift (down) if smaller than 0.3, and no action between 0.3 to 0.7.

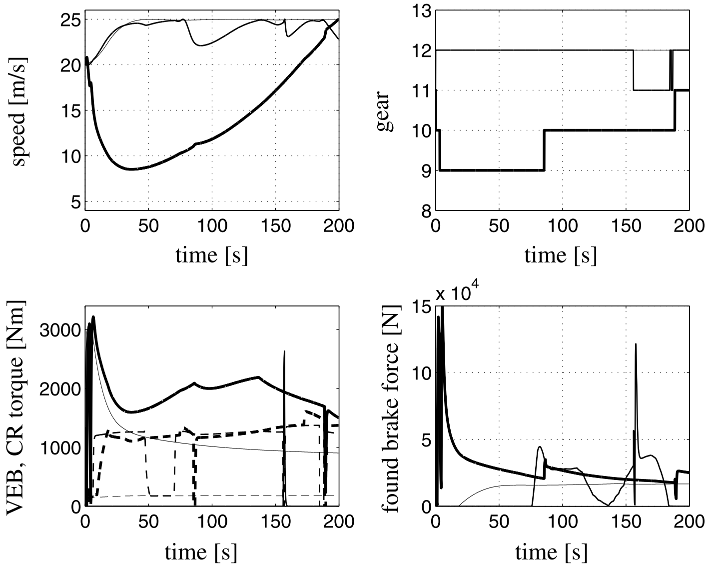

Fig. 9. Optimal blending for high mean speed on 3 roads. Thick solid line: 10% constant slope, Medium solid line: Isère 4 road, Thin solid line: 5% constant slope.

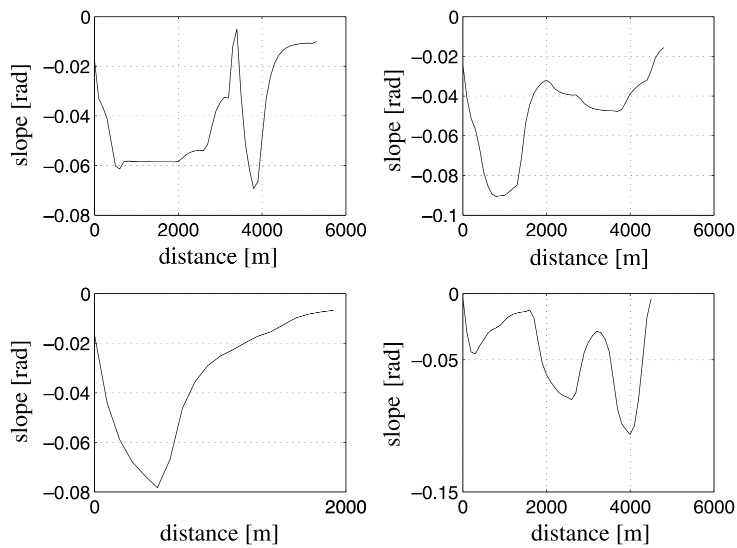

Fig. 10. Example of measured road profiles used. French Alps, Isère 1–4.

The fitness measure was defined simply as the distance travelled by the vehicle. Since the vehicle was only allowed to drive for a limited amount of time, the optimization procedure will strive to attain a high mean speed. The simulation was stopped if any of the following conditions was satisfied: $T_1 \geq 500°\text{C}$, $v \geq 25\,\text{m/s}$, $v \leq 5\,\text{m/s}$, $v_E \geq 2300\,\text{rpm}$, $v_E \leq 600\,\text{rpm}$, time $\geq 200\,\text{s}$. The solution shown in Figure 9 was obtained after 1000 generations using a population of 100 individuals. To set the structure (in this case only the number of neurons in the middle layer) some tests where performed. Seven neurons in the middle layer was found to be the minimum number required.

From the figure, it can be seen that the NN works very well with our choice of objective function. The mean speeds of the three runs are 24.9, 14.1, and 23.8 m/s, respectively.

The maximum mean speed that a skilled driver, driving as explained in Section 1, can achieve on different slopes is shown in Figure 1. Also the mean speed obtained from the NN controllers is shown. The NN controllers have the same structure and constraints as above, except that the simulation stop constraint is now time $\geq 2000\,\text{s}$, in order to make possible a comparison with the results for a skilled driver. For example, it is seen that the mean speed can be improved by 44% on the 10% slope and 22% on the 6% slope using the whole brake system optimally.

5.1. Generalization

When an NN obtained by training against a single road profile is tested on other roads, it is often found that performance is poor even for small changes in the road profile. It is thus clear that the training road must reflect a variety of obstacles in order for the NN to work in all situations found in reality. For this reason, we constructed a training road that reflects different obstacles encountered in a realistic driving situation. Measured road profiles from the French alps (Isère) and the Kassel hills in Germany were used for this purpose, see Figure 10. These road sections were then discretized and randomly put together to make up a realistic training road. Also, sections of constant slope were put into this training road.

The main task now is to see to what extent the GA can find an NN that can perform well, i.e. attain a high mean speed, on different roads. Obviously, the ability of the GA to find such an NN depends on several things, such as e.g. the choice of the input and output signals, the shape of the training road, the definition of the fitness measure etc. In this paper we focus on the definition of a training road for generalization. To quantify how well the NN is able to generalize we use the measure G and V, defined as

$$G = \frac{1}{N_\text{r}} \sum_{i=1}^{N_\text{r}} \frac{d_i}{L_i}; \qquad V = \frac{1}{N_\text{r} v_{\max}} \sum_{i=1}^{N_\text{r}} \overline{v}_i \tag{13}$$

where d_i is the distance travelled by the vehicle on road i, L_i is the length of road i, and N_r is the number of roads. We used $N_r = 14$ different realistic road sections and the

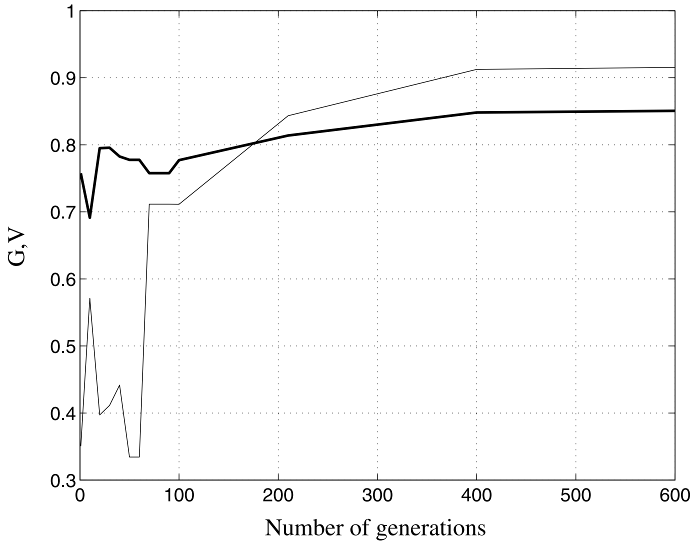

Fig. 11. Generalization measures, G and V. Thick solid line: V, Thin solid line: G.

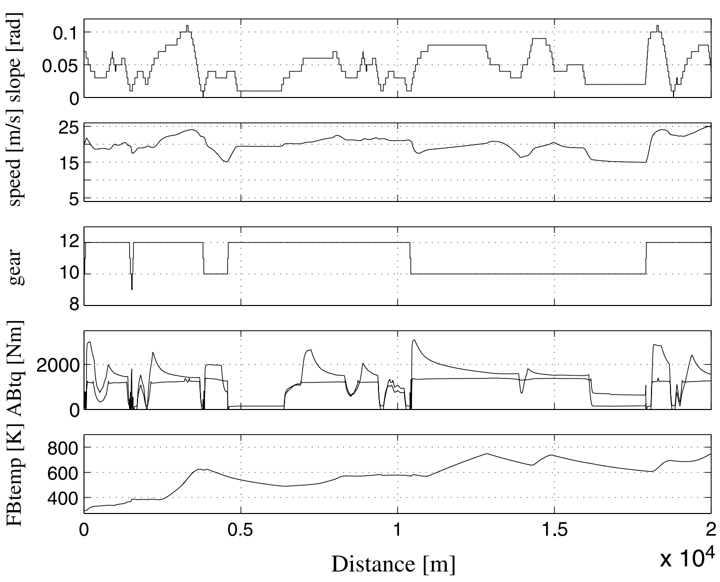

Fig. 12. First half of the training road used and the resulting NN trajectories.

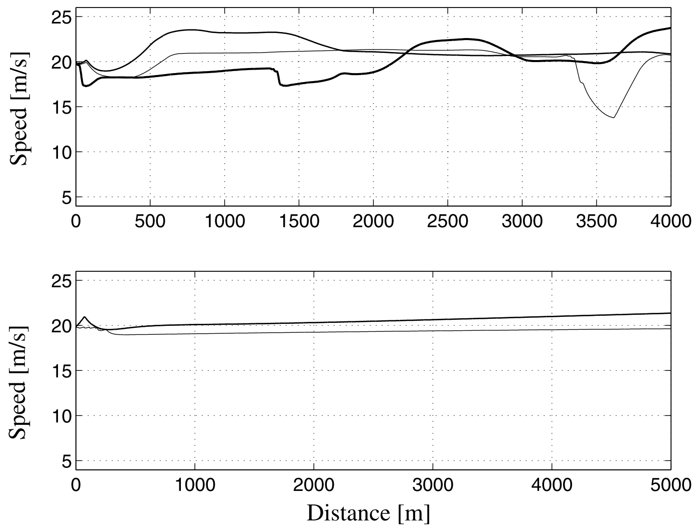

Fig. 13. Final NN tested on 5 road profiles. Isère 1, 2, 4 and flat 2% and 4%.

result is shown in Figure 11. Since G increases with the number of iterations, it is clear that the training road reflects most of the obstacles found in the 14 test roads. When the NN can cope with most of the roads in the test set (high G) it is interesting to see that also the mean speed is improved (V is increases). These are two important indications that the generalization is successful.

In Figure 12 the first half of the training road is shown together with the trajectories for the final NN. Clearly, the NN performs very well on this difficult training road and in Figure 13 the speed trajectories for 5 other road profiles are shown. The performance is excellent on Isère 1, 2, and 3 (4 is not shown since it is rather short) whereas on the two flat roads the NN is somewhat conservative, as can be seen by comparing with Figure 1.

6. DECREASED WEAR COST – CASE 2

When distributing a required retardation force between drive line and chassis it is interesting to look at wear characteristics of tyre, pad, and disc. The usual driver strategy is to keep the vehicle stationary using only ABs and, if necessary, lower the vehicle speed with the FBs to a level where the ABs can keep the vehicle stationary. However, one might ask oneself whether this is optimal from a wear cost point of view.

The economical model to calculate cost can be formulated in several different ways, and one of the main questions is whether or not to include the time of maintenance stops. As mentioned in Section 4 we do not and the total cost (C_{tot}) is formulated as in Equation (14). The work cost (C_w) and the material cost (C_m) are what the truck owner had to pay for changing pads, discs, or tyres at a Volvo workshop in Sweden in 2002. Since the disc wear is not modelled we have used the rule of

Table 1. Components in Equation (14).

W_{disc}	Disc wear [mm]
C_{discm}	Material cost of disc [Euro]
C_{discw}	Work cost to change disc [Euro]
δ_{disc}	Available thickness of disc [mm]
W_{pad}	Pad wear [mm]
C_{padm}	Material cost of pad [Euro]
C_{padw}	Work cost to change pad [Euro]
δ_{pad}	Available thickness of pad [mm]
W_{tyre}	Tyre wear [mm]
C_{tyrem}	Material cost of tyre [Euro]
δ_{tyre}	Available tyre thread [mm]

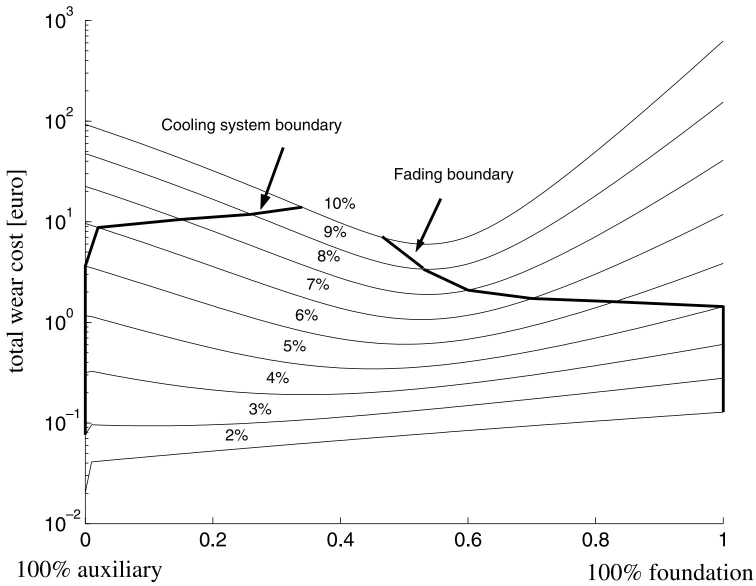

Fig. 14. Vehicle of 60 t and 6 axles travelling at constant speed 15 m/s down a 3000 m descent for 9 different slopes.

thumb often practiced at the workshops that every second time pads are changed, discs are also changed. δ denotes the original disc thickness, pad thickness, and tyre tread thickness. In Table 1 all components of Equation (14) are described.

$$C_{\text{tot}} = W_{\text{disc}} \frac{C_{\text{discm}} + C_{\text{discw}}}{\delta_{\text{disc}}} + W_{\text{pad}} \frac{C_{\text{padm}} + C_{\text{padw}}}{\delta_{\text{pad}}} + W_{\text{tyre}} \frac{C_{\text{tyrem}} + C_{\text{tyrew}}}{\delta_{\text{tyre}}} \tag{14}$$

In Figure 14 it is seen how the optimal distribution for minimum cost varies with retardation force demand. The vehicle is travelling with constant speed (15 m/s) on 9 different slopes of length 3000 m. Clearly, the optimal distribution is different for different slopes. This is due to the non-linear and time varying dynamics of Equations (11), (10), and (4). Thus, there is a need to design and investigate controllers that minimize wear cost. The idea is to have an NN that shifts gear and splits the force required for constant speed keeping in such a way that the wear cost is minimized. In reality, a PI controller can produce the force request, but here it is solved directly from Equation (1) and, for this case, the inputs to the neural network are $\{F_{\text{req}}, T_1, \alpha, T_{\text{coolant}}, v_E\}$ and the outputs are $\{R_{\text{found}_{\text{req}}}, \text{Shift}_{\text{req}}\}$. For simplicity

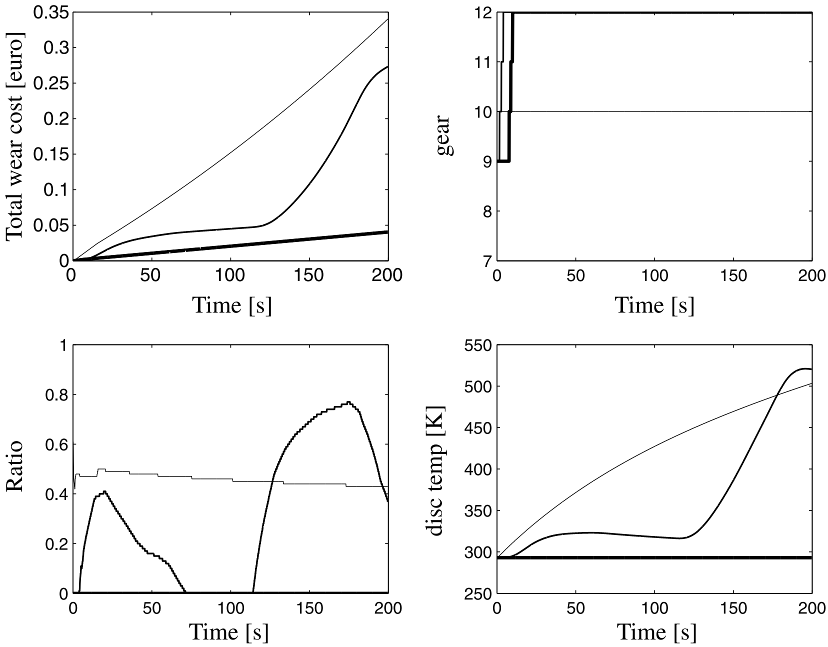

Fig. 15. Optimal blending for low wear cost at 15 m/s on 3 roads. Thick solid line: 2% constant slope, Medium solid line: Isère 4 road, Thin solid line: 5% constant slope. The *ratio* is the distribution between FBs and ABs.

only two outputs are used, and the VEB has priority over the CR, i.e. the AB force demand is first requested from the VEB, and if the VEB is unable to deliver the demanded torque the remainder is requested from the CR.

Three examples where the NN guides the vehicle down a 2% descent, a 5% descent, and the varying road profile 4 from Figure 10 are shown in Figure 15. The fitness function is here defined as $e^{\alpha(t-T_{\mathrm{stop}})}/C_{\mathrm{tot}}$, where t is the time when the vehicle was stopped (either because a constraint was violated, in which case $t < T_{\mathrm{stop}}$, or because the stop time was reached). The constraints used are the same as earlier, except that the allowed range of variation for v is much narrower. It can be seen that the total wear cost for cruising down the 3000 m long 5% slope is approximately 0.38 euro in the optimal case. From Figures 1 and 14 it can be concluded that a very experienced driver can keep 15 m/s by only using the ABs and the wear cost is then 1.1 euro. Thus, the wear cost of the NN controller is almost 65% lower.

7. DISCUSSION

In this paper, optimization of driving strategies has been carried out using GAs only, and it has been shown that this method yields NNs that are able to cope with general road profiles in many cases.

A further improvement of the procedure would be to generate a set of basic situations, and to provide both input and output signals for these situations. In this case, the NN could first be trained, using e.g. backpropagation, to cope with the basic situations, and then be further trained against a road profile, using a GA.

A setback with the GA approach is that it does not guarantee optimality of the networks obtained. However, finding a provably optimal solution is not crucial in this problem. Instead, what is important is to find an NN that outperforms even an experienced truck driver.

A common objection to the use of NNs is the difficulty of interpretation. NN are sometimes considered to represent a black-box solution to the problem at hand. While interpretability is not necessarily relevant, it would be useful also to consider other architectures, such as for instance fuzzy logic controllers (which can also be optimized using a GA). The issue is currently being investigated, and will be addressed in a forthcoming paper.

The input signals used here are a feasible choice, since all of the signals can be obtained in a real vehicle. The vehicle speed, engine speed, and coolant temperature are all signals measured in a modern heavy duty vehicle. The road slope and the vehicle mass (which is not used as an input signal here but can, in reality, vary significantly) are not as easy to access, but they be estimated, see [7]. The disc temperature is usually not measured or estimated today, but temperature sensors and estimation algorithms are under development.

For some road profiles, the NN trained for generalization is somewhat conservative (low mean speed) compared to real drivers. This can be explained by the fact that a real driver has road profile preview whereas the NN only has information about the current slope. In future work, preview will be included as well, since such a feature will probably become available in real vehicles in the near future (using e.g. GPS and maps).

8. CONCLUSION

Controllers have been obtained for several different road models (with different slopes). Their performance is shown to be much better even than that of an experienced driver. It is shown that there is a potential to improve mean speed in down hill cruising by optimal usage of the whole brake system, including FBs, ABs, gear box, and cooling system. It is also shown that it is possible to obtain a general NN that can handle a wide variety of different road profiles.

An additional advantage is that the resulting NN controllers are, in principle, directly implementable in an actual vehicle, as opposed to the infinite-dimensional trajectories obtained by optimal control methods. It should also be noted that the resulting optimization problem, when transforming the problem at hand into an optimal control problem, is very large (not suitable to solve using search methods) and non-convex due to the nonlinearities of the differential equations, [8, 9]. The problem must therefore be solved using gradient based optimization and, again, no guarantees can be given regarding optimality.

When considering wear cost of pad, disc, and tyres it is concluded that the strategy currently used by drivers is non-optimal. It is clear that the wear cost can be lowered by distributing the retardation force in an optimal way between FBs and ABs.

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