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Use of genetic algorithms as an innovative tool for Race Car Design

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ABSTRACT

Design processes of modern race car are often developed in short time; during this period a large number of parameters has to be tuned to reach best results. Many kind of vehicle dynamics simulation models have been developed by car manufacturers and private suppliers to investigate car behavior on racing tracks. Such models have a high degree of complexity but they can be employed, in a simplified mode, during design processes of racing cars for which tracks technical data (for such circuits where they will race) are well known. During the first stages of the design activity very complex numerical models (such as multibody simulations) are not necessary and it is possible to use simplified methods to locate optimal solutions in a fast way. In present work a numerical model, able to reproduce car behavior on a defined circuit or simply analyze meaningful test cases (breaking, steering,…), is used to appraise performances of race car with different technical configuration. Besides is proposed a method to reduce designing field of investigation through genetic algorithms (GA's) using vehicle numerical model to individuate such solution that gives best performances on each circuit. Numerical algorithm is tested to choose best from a large number of technical configurations on different tracks. Several types of genetic algorithms are used: results show that GA's can be a useful tool to fasten design processes narrowing the field of investigation. In some cases the optimization method developed gives analogous results as what would be carried out by an experienced engineer.

INTRODUCTION

Race car vehicle design should be developed in a fast and efficient way to achieve success in the competitive world of car races. Modern vehicles have a large number of degree of freedom that must be tuned in an optimal way: aerodynamics, gear ratios, suspension geometry, suspension stiffness, weight distribution and so forth; usually engineers choose best solutions following their intuition. Optimal design parameters selection can receive useful support from numerical modelling.

Many research activities have been carried out to develop lap time simulation in order to improve race car performance [1]. In some cases [2] simulation is applied on field to define optimal car setup and it is interfaced with on-board data acquisition systems; other activities [3] are finalized to car handling simulation and they need experimental data for validation. Such kind of numerical simulations can produce very complex computing processes, and simplified strategies to improve computing time should be developed [4]. Main aim of the present work is to provide a useful tool to the designer of race vehicles for defining optimal set-up of a race car given a set of tracks. During the first stages of the design activity very complex numerical models (such as multibody simulations) are not necessary and it is possible to use simplified models to locate optimal solutions in a fast way. The following numerical tools are employed for this process:

1. A vehicle model used to test car performance [5];
2. An optimization model based on genetic algorithms (GA's) to locate best solutions.

The vehicle model has been developed choosing a number of parameters which allow fast computing speed and reliable results; such model has been applied successfully in the past to evaluate the performance of F3, F.FORD and several types of competition sport cars. The optimization model exploits results from the vehicle model to search for the best set of parameters within the space of possible results. The present work investigates a simplified case where optimization is applied only to aerodynamics loads and gear ratios for a vehicle with technical characteristics similar to Formula 1 cars. The choice of such parameters is only for demonstration purposes; the method can be extended to a higher number of parameters, the only drawback being computing time.

THE VEHICLE MODEL

Vehicle model summarizes car performances by the lap time obtained by the car with given technical characteristics.

Simulation has been developed following two steps:

- Vehicle simulation;
- Circuit and driving simulation;

Vehicle dynamics has been reproduced by an outline including most representatives parameters such as engine performances, aerodynamics, gear ratios and so on. Such parameters allow to define dynamic behaviour of vehicle from engine power curve and circuit characteristics. Driving simulation has been simplified with the hypothesis of steady-state cornering; each curve has been represented as a constant radius arc with vehicle running at constant speed. Neglecting gearbox (but not wheels) inertia, the torque needed to move vehicle in an acceleration phase can be written:

$$T_d = r_r * \{[m_{tot} + 2(m_f + m_r)] * a + R\} + 2a * \left(m_f \frac{\rho_f^2}{r_f} + m_r \frac{\rho_r^2}{r_r} \right) \quad (1)$$

where:

- r_r and r_f are respectively rear and front wheels radius;
- m_{tot} is the overall mass of vehicle including driver but excluding wheels;
- m_r and m_f are respectively rear and front single wheel mass;
- R is aerodynamic drag;
- ρ_r and ρ_f are respectively rear and front wheel radius of gyration.

The expression of vehicle acceleration can be derived from equation (1). Integrating with finite time step it is possible to define vehicle's movement. With a simplified model for vehicle's chassis we can calculate loads that wheels have to transfer on ground within grip's limit. We consider that suspension geometry and rolling center don't change during vehicle's running. On the barycenter point is applied total weight:

$$W_{tot} = \lfloor m_{tot} + 2 * (m_r + m_f) \rfloor * g \quad (2)$$

where g is gravity acceleration.

Force on rear driving wheels is:

$$F_d = \frac{T_d}{2 * r_r * R_{ra} * G} \quad (3)$$

where R_{ra} is the rear-axle ratio and G is the ratio of the selected gear. During braking F_d is equal to zero and forces on wheels are opposite to motion; we consider in this case constant forces equal to grip's limit (ideal braking).

The cornering phase is characterized by lateral load due to centrifugal force F_c applied on the center of gravity:

$$F_c = \frac{W_{tot} * u^2}{g * r_c} \quad (4)$$

where u is the vehicle's speed and r_c the cornering radius; such load creates a rolling moment M_r proportional to the center of gravity height:

$$M_r = F_c * h_{cg} \quad (5)$$

where h_{cm} is the height from ground of center of gravity.

Modern race car are usually equipped with aerodynamic flaps to increase vertical loads and improve grip condition. Aerodynamic loads are applied on center of pressure and can be brake down by two force contribution on vertical direction L (lift) and movement direction R (drag):

$$L = \overline{L} * \left(\frac{u}{\overline{u}} \right)^2 \quad R = \overline{R} * \left(\frac{u}{\overline{u}} \right)^2 \quad (6)$$

where $\overline{L}$ and $\overline{R}$ are reference loads measured from wind tunnel test with corresponding speed $\overline{u}$.

Tire model has been defined on the concept of transverse traction-reaction ellipse. In a reference system fixed to tire (where x is the rolling, y the transverse and z the vertical direction) forces close to grip's limit are:

$$\begin{aligned} F_{xl} &= \mu_x * F_z - \Theta_x(F_z) \\ F_{yl} &= \mu_y * F_z - \Theta_y(F_z) \end{aligned} \quad (7)$$

with:

- F_z vertical load;
- F_{xl} limit load in rolling direction;
- F_{yl} limit load in transverse direction;
- μ_x and μ_y known parameters;
- Θ_x and Θ_y known functions of vertical load.

For loads with unknown direction the hypothesis is that forces in x and y direction (F_x and F_y) belong to the following ellipse:

$$\left(\frac{F_x}{F_{xl}}\right)^2 + \left(\frac{F_y}{F_{yl}}\right)^2 = 1 \qquad (8)$$

Considering that tire under loads has a slip angle α (see figure 1) transverse force F_t should be derived by projection of loads on the reference system fixed to wheel.

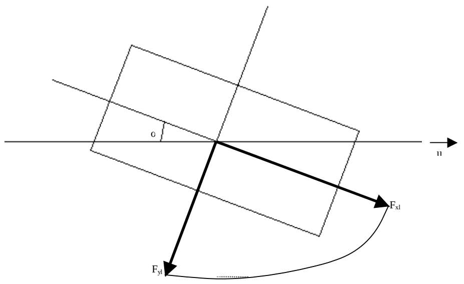

Figure 1 - Tire slip angle.

The precede equations allow to define loads on each wheel on every point of a defined track to check grip's limit; then, by integration, it is possible to calculate total lap time. A C-code program has been developed for this purpose to evaluate total lap time. Car and circuit characteristics are given as input by ascii files reading. The program has been tested on four circuits shown in figure 2; tracks (a), (b) and (c) are ideal tracks while track (d) has been inspired from Silverstone circuit (1990 version).

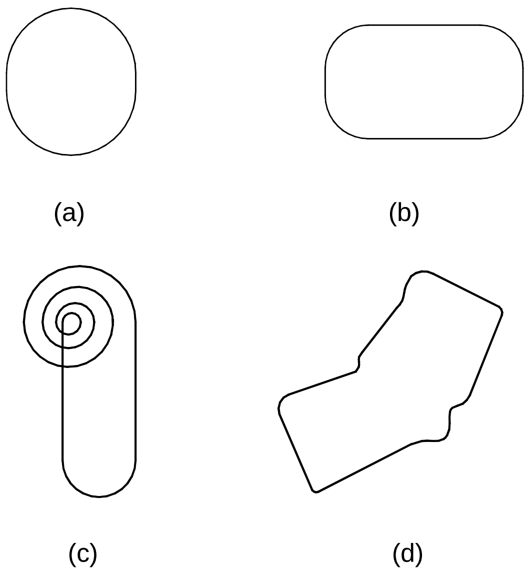

Figure 2 – Circuits used to test vehicle and optimization models

For a race car very similar to Formula 1 best lap time for each circuit are listed in the following table.

Circuit	Total lap time (s)
(a)	39.496
(b)	70.505
(c)	158.397
(d)	91.469

Table 1 – Results from vehicle numerical model.

Of course the numerical model converge faster for simple circuits such as (a) and (b) while results for real tracks such (d) need much more computing time. A set of aerodynamic load configurations and a set of gear configurations have been prepared to test optimization method.

THE OPTIMIZATION METHOD

Genetic Algorithms (GA's) are optimization techniques which use search methods that imitate mechanisms of natural selection [6] [7]. As for biological individuals, whose characteristics are contained in their genetic material, GA's encode the contents of each candidate solution for a numerical optimization problem into the genome of a hypothetical individual. Individuals compete between themselves for survival and to gain higher probability of reproduction; their success depends on their fitness score, i.e. the objective score of the candidate solution they represent. Mating mechanism are based on crossover and mutation and manipulate the genomes of the parents to produce offsprings, which will form a new generation. GA's start an evolution process where individuals improve their genetic characteristics generation after generation, until they reach optimal fitness, i.e. that encode the best solution to the search problem. GA's are not influenced by the search start point, or by the continuity of the search space, or by the combinatorial explosion of the problem. The use of probabilistic parameters (i.e. in determining the crossover or mutation probability) characterizes their stochastic nature, which in turn raises the problem of reliability since there is no guarantee that they always get to the same result, or they may get trapped into local optima, which is called "premature convergence". Different choices of evolution strategy and genetic operators characterize each type of genetic algorithm. The Simple GA completely replaces the old population with the new offsprings at each generation; the Steady State GA carries on to the next generation the n best individuals of the current generation while replacing the remaining individuals with new offsprings (this is called overlapping populations). Simple and Steady-state GA's allow competition and mating between any two individuals in the current population, other GA's introduce restrictions based on similarity between individuals [8, 9]. In deterministic crowding (DC), the offspring replaces the most similar individual amongst its two parents [9]. In Restricted Tournement Selection (RTS) GA [10] the offspring competes with the most similar individual selected from a random subset (window) of the current population. Restrictions based on similarity encourage a wider differentiation of the population during the evolutionary process, which resembles the formation of species in natural biology. Thus such algorithms are often called Speciating GA's. Speciating GA's need a quantitative measure of similarity; the advantages are in the identification of several local optima in the same run (which is useful for gaining a better understanding of multimodal search spaces), while sometimes also increasing the reliability of the algorithm to locate the global optimum. In present work genetic algorithms are used to optimize lap time for a given car in a given circuit; optimization operate for demonstration only over two parameters: aerodynamic loads and gear ratios (for a vehicle with technical characteristics similar to Formula 1'cars). For aerodynamics and gear ratios two catalogues (respectively with 77 and 62 configurations) have been created so that the total number of possible configurations is 4774. Chromosome used to define descendants has fixed length with two genes each containing a real number between 0 and 1; each number is decoded to individuate one solution on the two catalogues.

RESULTS

On each track of figure 2 four types of genetic algorithm have been tested:

1. Simple (s);
2. Steady State (ss);
3. Restricted Tournement Selection (RTS);
4. Deterministic Crowding (DC).

Computing times are different and are mainly affected by track complexity (number of curves and straight intervals); this is due to the time needed to compute lap time by the vehicle numerical model. Genetic Algorithms create ten individuals each generation step; after a certain number of generations the population reaches optimal solutions. The distribution of the optimal population is related to the type of genetic algorithm used. For tracks (a) and (b) optimal solutions are reached very quickly while solution for track (c) and (d) need much more time. For this reason a wider analysis has been performed on track (d) which has technical characteristics of a real circuit: Silverstone (1990 version). The optimization problem has been defined through an objective score of the candidate solution equal to 1000 minus the total lap time estimated; in this way we can set the algorithm to search the maximum of the objective function. The results for the Silverstone circuit obtained by the four types of GA's are shown in figure 3. Objective score related to the best solution for each generation are plotted versus generation number.

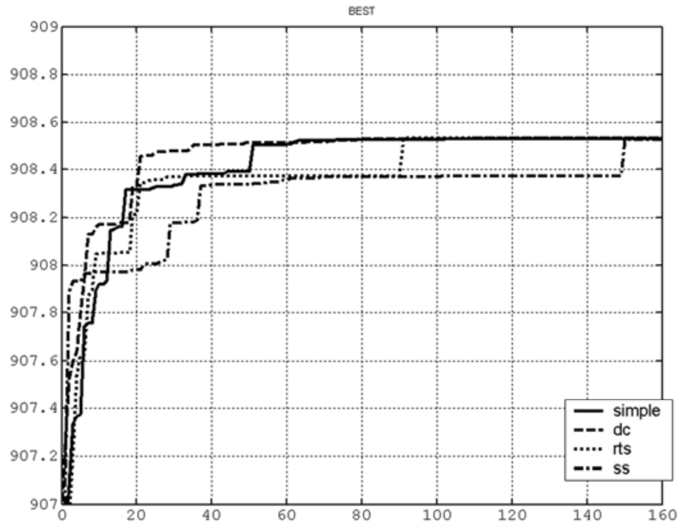

Figure 3 – Results from Silverstone circuit: objective score for best solution .

All GA's types reach optimal solution within 200 generations; best results are from deterministic crowding (DC) which seems to work better for this application and reach optimum within 100 generations. The differentiation level of the possible solutions is related to the type of algorithm used; results obtained for track (d) are plotted in figure 4. In the x axis is represented the position (a number from 0 to 76) to define the parameters in the aerodynamic catalogue while in the y axis the gear ratios catalogue is represented so that the graph covers all possible solutions. For each position in the solution field a circle is plotted whose dimension is proportional to the number of individuals encountered within the last populations of ten runs with 200 generations. Steady state algorithm presents higher differentiation level because it completely replaces the old population with the new offsprings at each generation. RTS gives only two solutions because it allows survival of best individuals through generations. It is interesting to perform an analysis on solutions proposed by DC which is the algorithm that seems to give better results (figure3). Technical solutions and the correspondent lap time are listed in table 2. It is interesting to notice that the solution for gear ratios set-up is well defined while uncertainty remains on aerodynamics set up: two different aerodynamics configuration give the same lap time.

Figure 5 shows investigated solution for Silverstone circuit (DC Genetic Algorithm) with objective score represented in the three-dimensional graph; best solutions are highlighted with black filled dots. It is interested to notice that optimum location is well defined for gear set-up while the choice for aerodynamic setup is doubtful. For this reason algorithm investigates almost all possible aerodynamic solutions for the best gear setup (nr. 29).

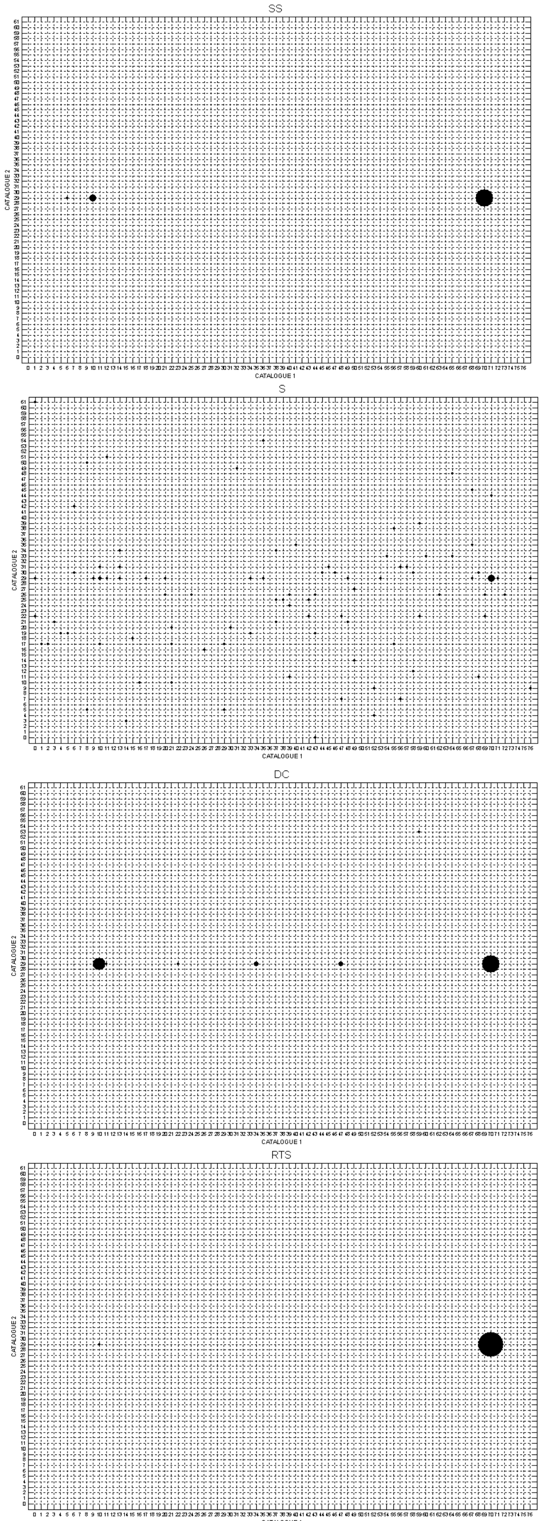

Figure 4 – Distribution of optimal population with different type of Genetic Algorithm (last population after 200 generations in 10 runs).

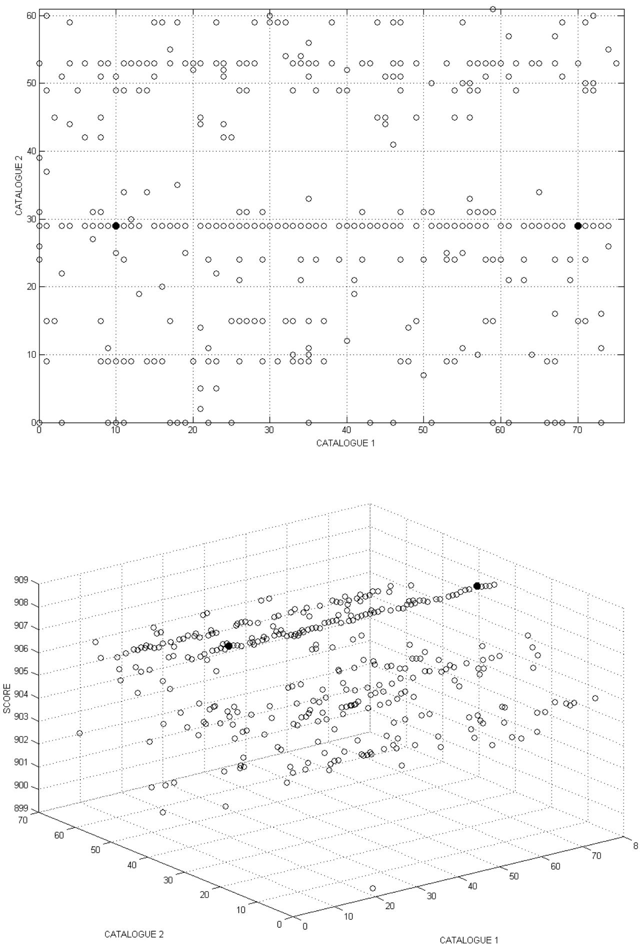

Figure 5 – Investigated solution with DC Genetic Algorithm.

Individual nr.	Aerodynamic set-up nr.	Gear set-up nr.	Total lap time (s)
1	70	29	91.469
2	70	29	91.469
3	70	29	91.469
4	70	29	91.469
5	70	29	91.469
6	70	29	91.469
7	10	29	91.469
8	47	29	91.474
9	47	29	91.474
10	22	29	91.476

Table 2 – Results obtained from track (d): optimizated population after 200 generation of a single run with DC algorithm.

CONCLUSION

The optimization method developed in the present research has given analogous results as what would be carried out by an experienced engineer. Set up parameters for Silverstone circuit obtained with the implemented numerical method are similar to those adopted in real competition. On track (d) it is very interesting to note the existence of two different configurations that gives the same lap time. Such situation is common on tracks with long straight sections and fast curves. In these cases high performances on curves due to high aerodynamic loads are balanced by lower speeds on straight sections. Optimal solutions should be tested on field depending on variables (such ground condition, temperature and so on) that are not included in the vehicle numerical model. If the optimal solution is not well defined by the numerical model (Silverstone), since the car set up has to be performed in a short time span, engineers prefer to adopt the solution in which aerodynamic drag is minimal, because it allows for higher speeds on straight sections making overrunning easier during the race.

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