

Optimization of wheel suspension geometry using a genetic algorithm

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1. Introduction

This work deals with the optimization of the geometry of the independent wheel suspension, which is part of an experimental chassis with air springs. These springs, specifically the pressure inside their bellows, are controlled by deep reinforcement learning (DRL) algorithm. This chassis platform does not allow turning and driving, it is used exclusively for the research and application of DRL algorithms to control non-linear suspension elements on a system with multiple degrees of freedom. The geometry of the chassis, specifically the length and position of the individual arms, is optimized by a genetic algorithm (GA) in order to achieve the smallest possible displacement of the bottom edge of the tire and appropriate tilting of the wheel. Manufacturing possibilities are taken into account during the optimization, since the assembled suspension consists of steel rods and components produced by 3D printing technology, which can only have limited dimensions.

2. Genetic algorithms

Unlike traditional optimization techniques that rely on mathematical derivations and gradient-based methods, GA are inspired by the principles of natural selection and evolution. They work by evolving a population of potential solutions over multiple generations, gradually improving the quality of solutions until an optimal or near-optimal solution is found. GA are well-suited for finding global optima in complex and multi-modal search spaces but can be computationally expensive, especially for large-scale problems [1]. The following paragraph will describe the operation of the GA, which is also shown in the (Fig. 1).

The first step is initialization, in which an initial generation of randomly generated solutions is created. The second step is the evaluation of the solutions, i.e., the calculation of the fitness value of all solutions in the population, after which the given number of solutions with the highest fitness values is selected in the third step during selection. The fitness function is a crucial element of a genetic algorithm. It quantifies how well a particular solution performs with respect to the optimization problem's objectives. The higher the fitness value, the better the solution. The fourth step is the crossover of the solutions selected in the previous step, and mutation is applied to them in the fifth step, i.e., random percentage changes of the individual solutions. It adds diversity to the population and prevents premature convergence. In the sixth step, a new generation of solutions is created, which may include parents, offspring, or a combination of both. Then steps 2 to 6 are repeated until the desired fitness value is reached.

Setting appropriate parameters, such as population size and mutation rates, can be challenging and may require experimentation. If these parameters are set incorrectly, GAs may converge to suboptimal solutions [2].

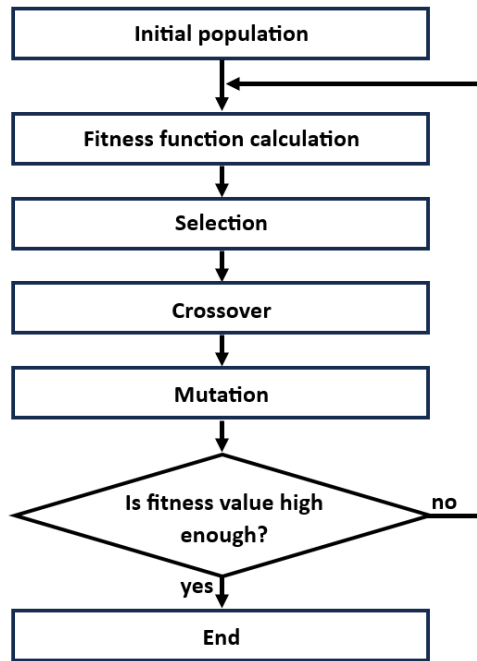


Fig. 1. Flowchart of the genetic algorithms

3. Wheel suspension geometry

The geometry of a wheel suspension system refers to the lengths and positions of various components, such as control arms, springs, shock absorbers, spindles and wheel hubs. Proper suspension geometry is crucial for achieving the desired balance between ride comfort and handling stability. It plays a pivotal role in determining a vehicle's ride quality, handling characteristics, and overall performance. All optimized dimensions are shown in the diagram (Fig. 2). These are the length of the upper and lower arms, the length of the spindle and the relative position of the bearings that ensure the connection of the suspension to the vehicle frame.

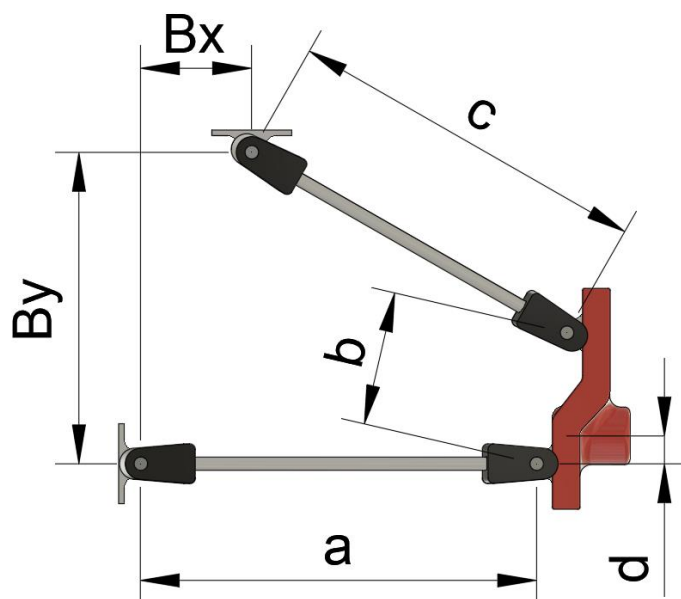


Fig. 2. Wheel suspension dimensions

The aim of the optimization is to achieve the smallest possible displacement of the bottom edge of the tire and appropriate tilting of the wheel. The resulting suspension must allow the installation of an air spring, which will be located between the upper arm and the frame. Tilting of the upper arm with respect to the height of the spring in its working area is 25 to 35 degrees to the horizontal part of the frame. In this angle range, the horizontal displacement of the lower edge of the tire will therefore be required to be minimised.

The relationship for calculating the vertical displacement of the lower edge of the tire was obtained by solving a vector loop with the angle between the frame and the upper arm as the independent variable.

4. Results

The parameters of the GA have been optimized to achieve a minimum vertical displacement of the bottom edge of the tire. Experimenting with these parameters, it was found that a sufficient size of the population is 100, and its changes do not have a noticeable effect on the course of optimization, unless there was a substantial reduction. Increasing the size of the population increases the computational complexity of the optimization, which would not be a problem given the speed of the optimization in the order of seconds. The parameters that had an influence on the course are crossover and mutation rates. The crossover rate indicates the probability of two solutions crossing over, and the mutation rate indicates the probability of mutation of a solution. Crossover rate was set to 0.9 and mutation rate was set to 0.05. Increasing these parameters encourages exploration, while lowering them favours exploitation. In this case, the set parameters ensure sufficient exploration and at the same time prevent convergence to a sub-optimal solution.

The most important aspect of genetic algorithm optimization is the use of an appropriate fitness function, which was created in such a way that the optimization process is terminated when the lower edge of the wheel moves less than 1 mm. A higher value of the fitness function means a better solution, so the inverse of the deviation was used. A value corresponding to the desired displacement was calculated, and when it was reached, the best solution from the current population was declared as the result.

The resulting dimensions achieved with this fitness function could not be realized, therefore the fitness function was supplemented with a member that penalizes the algorithm if the length of the upper arm does not allow the installation of an air spring. Furthermore, the initial population was initialized so that the length of the upper arm is a random number from the interval of values at which spring installation is possible. The algorithm adapted in this way provides a resulting geometry that is feasible and at the same time achieves the desired displacement of the bottom edge of the wheel. The obtained dimensions were rounded to whole millimetres and according to this geometry, the wheel spindle, red component in the (Fig. 3), was created using 3D printing technology and the steel bars that make up the wheel suspension arms were cut.

Wheel displacement calculated for rounded optimized dimensions is 0.5 mm. A displacement of 1.4 mm was measured for the assembled suspension. For the purposes for which this experimental chassis is made, such displacement is very acceptable.

The measurement of the distance of the lower edge of the wheel was done with a laser length sensor optoNCDT 1420, and the angle between the frame and the upper arm was set with a digital protractor INSIZE 2179-360. The resulting deviation is mainly caused by the inaccuracy of the dimensions produced on the 3D printer.

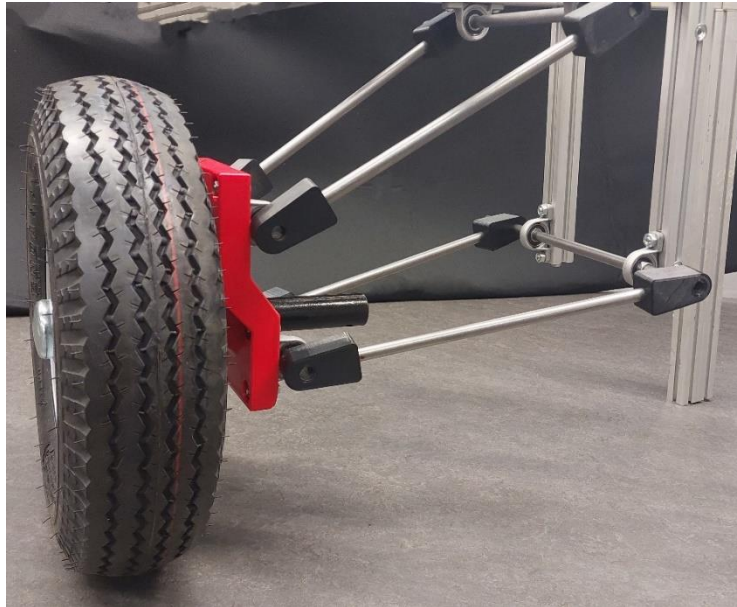


Fig. 3. Assembled wheel suspension

Acknowledgement

This publication was written at the Technical University of Liberec as part of the project "Research of advanced materials, and application of machine learning in the area of control and modelling of mechanical systems" nr. SGS-2022-5072 with the support of the Specific University Research Grant, as provided by the Ministry of Education, Youth and Sports of the Czech Republic in the year 2022.

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