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Design of Aerodynamic Devices Using Genetic Optimization

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Abstract—The aerodynamics of ground vehicles is important for speed, stability, and fuel efficiency. Research has been conducted on various geometric shape optimization; however, there is limited research related to the design optimization of aerodynamic devices using genetic optimization algorithms. This paper performed aerodynamic optimization using genetic optimization algorithms, particularly the Non-Dominated Sorting Genetic Algorithm (NSGA -II). The method employed here involves the application of NSGA-II, OpenFOAM, and B-spline functions on a generic road vehicle geometry such as the Ahmed body. Due to computing resource constraints, the optimization was stopped after five generations. However, the resultant candidates through each generation trended towards a reduction of drag (c_d) and lift (c_l), or increase in downforce, thus, demonstrating the effectiveness of the program and proof of concept of the method. In the future, further improvement to the program can reduce the computational requirements of the optimization.

Keywords-component; Ahmed body, drag optimization, lift optimization, OpenFOAM, genetic algorithm

I. INTRODUCTION

Moving ground vehicles, such as a car, need to consider the effects of air resistance due to its impact on the physical design. Optimizing the aerodynamics of a car, where multiple objectives and constraints are considered, is difficult and time-consuming using Computational Fluid Dynamics (CFD) alone with manual adjustments. This also limits the optimization, as it will only improve the base geometries specified in the model. Reducing drag and increasing downforce is particularly challenging when optimizing the shape of the car. The addition of a rear diffuser and rear spoiler can significantly affect aerodynamic performance [1].

It can be observed that genetic algorithms are powerful tools to solve optimization problems. There are many genetic algorithm applications in aerodynamics; most of them are related to optimizing drag and lift. Plenty of research was done in this field [2] to optimize airfoils or airships. Further, there is similar work done in rotor blade optimization [3]. There are papers related to the optimization of 3D bodies [4], [5], and there are also some for 2D bodies [6]. However, there are gaps in the literature. None of them was used to generate a combination of devices, which will reduce drag and lift in order to improve performance and stability in ground vehicles. The closest articles related to this paper are [4, 5], in which [4] used a genetic algorithm to design a boat tail on a ground vehicle.

The objective of this paper is to use an evolutionary algorithm, specifically the NSGA-II, to generate geometries for a rear diffuser and rear spoiler that reduce drag and lift together, improving the overall aerodynamic performance of the ground vehicle. It is based on the idea that the aerodynamic optimization of a ground vehicle can lead to further improvements on current vehicles and also open up the development of utilizing evolutionary algorithms for more bluff body designs. The main goal of this paper is to prove the concept and the potential of the method.

II. SIMULATION

The OpenFOAM software is an open-source program that solves the Navier-Stokes equation with a proposed turbulence model [7]. The turbulence models need to be selected carefully because they have a high impact on the results. It is well known that LES models are more desirable because they produce better results than RANS [8]. However, the LES models have a considerably higher computational cost, making it a less efficient choice for a turbulence model. According to some authors, the RANS model provides accurate results [7, 9] in comparison with experimental data, which makes a suitable choice of a model since it has a lower computational cost. The turbulence model used here was $\kappa-\omega$SST. After selecting the model, the last part is to set up a simulation in OpenFOAM to handle the boundaries. In order to properly set up the boundary conditions in the inlet, the ANSYS user manual [10] was used as a reference for the inlet function in OpenFOAM. Based on the ANSYS inlet function, the following values (Table 1) were selected as boundary conditions for the simulation.

TABLE 1 BOUNDARIES CONDITIONS ON THE INLET

Inlet	***Value***
Turbulent intensity	*1%*
Turbulent viscosity	*Calculated*
Turbulent ratio	*10*

TABLE 2 EXPERIMENTAL VS NUMERICAL

	Experimental	*Numerical*
C_d	0.26 [11,12]	0.267
C_l	0.004 [13]	-0.0154

III. NSGA-II

To solve this problem, the NSGA-II algorithm was used since its effectiveness has been proven from previous works [14]. The source of the algorithm is in the work of Deb [15]. In order to find if the algorithm is working properly, a benchmark function was selected to test it prior to running it in OpenFOAM.

A. Benchmark

In order to make sure that the NSGA-II code is working, a benchmark function with a known solution was utilized. The function selected was the ZTD1 function and can be found in Yang's work [16]. The probability of mutation and crossover was selected as 3% and 85%, respectively. This set up (crossover and mutation) was the same used for the optimization set up for OpenFOAM. Both the test and the OpenFOAM optimization were specified with 7 bits of precision and 30-dimensional variables that can range from zero to one. The equations of the benchmark are well known and can be found in previous works [16].

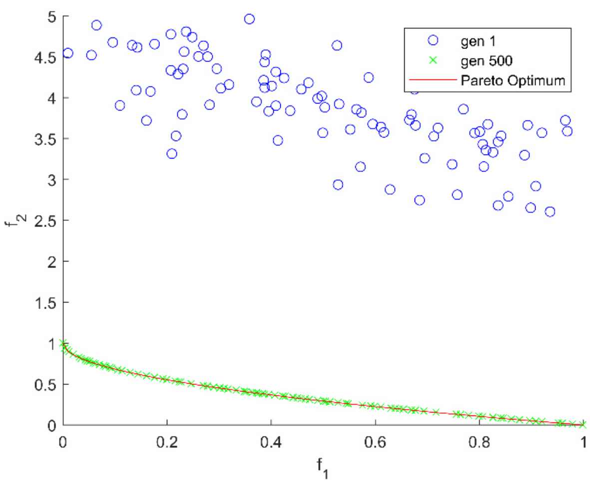

Figure 1 NSGA-II benchmarking

Fig. 1 shows that the algorithm is converging to the known (benchmarking) after 500 generations. So it is possible to state that the NSGA-II can solve a 30-dimensional problem with 7 bits of precision. This makes OpenFOAM optimization feasible for the program without issues.

IV. B-SPLINE

After testing OpenFOAM simulation and checking the algorithm, the last part is the implementation of the geometries. The methodology generates surfaces based on B-spline functions. The algorithm generates the control points responsible for developing the surfaces, and the NSGA-II will modify these control points to optimize the surfaces of the flap and diffuser based on the objective functions (drag and lift). After that, the code runs through a number of generations, in this case only five generations, as shown in Section V.

V. RESULTS

After running the code for five generations, it can be observed that a Pareto front of points was being formed (Fig. 2). This method was run using a 40-core for ten days. Obviously, five generations were not enough to see the full potential of the methodology; however, the improvements are noticeable. From the image below (Fig. 2), it can be observed how the individuals are improving over time. Each generation has better results than the previous one, as shown by Fig. 2, proving that the algorithm works and the methodology is correct.

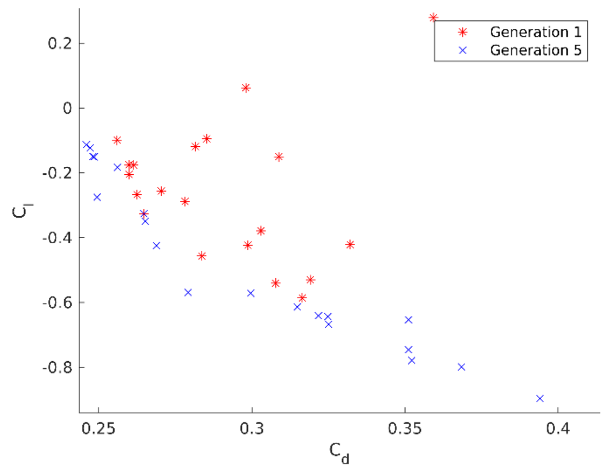

Figure 2 Progression of solutions vs generations

Two solutions were selected to be analyzed and compared with the standard Ahmed body model shown in Fig. 3. The two solutions from the twenty selected were the ones with the lowest lift (or highest downforce) and lowest drag results. Fig. 3 displays the geometries obtained by the algorithm. Fig. 3(a) displays the baseline model (Ahmed body with no device), while Fig. 3(b) shows the configuration for the minimum drag, and Fig. 3(c) shows the minimum lift obtained from the 5th generation.

Tables 3 and 4 display the improvement of these two (Fig. 3(b) and (c)) solutions compared with the standard Ahmed body. Improvement in a drag reduction of almost 8% and a huge improvement in downforce (up to 633%) for both solutions can be observed. Apart from the code being computationally costly, it can find solutions that can improve the design with interesting geometries.

TABLE 3 LOWEST C_D VALUE

	Value	*Improvement*
C_d	*0.245*	*7.9%*
C_l	*-0.112967*	*633.8%*

TABLE 4 LOWEST C_L VALUE

	Value	*Improvement*
C_d	*0.394031*	*-48%*
C_l	*-0.895762*	*5025.6%*

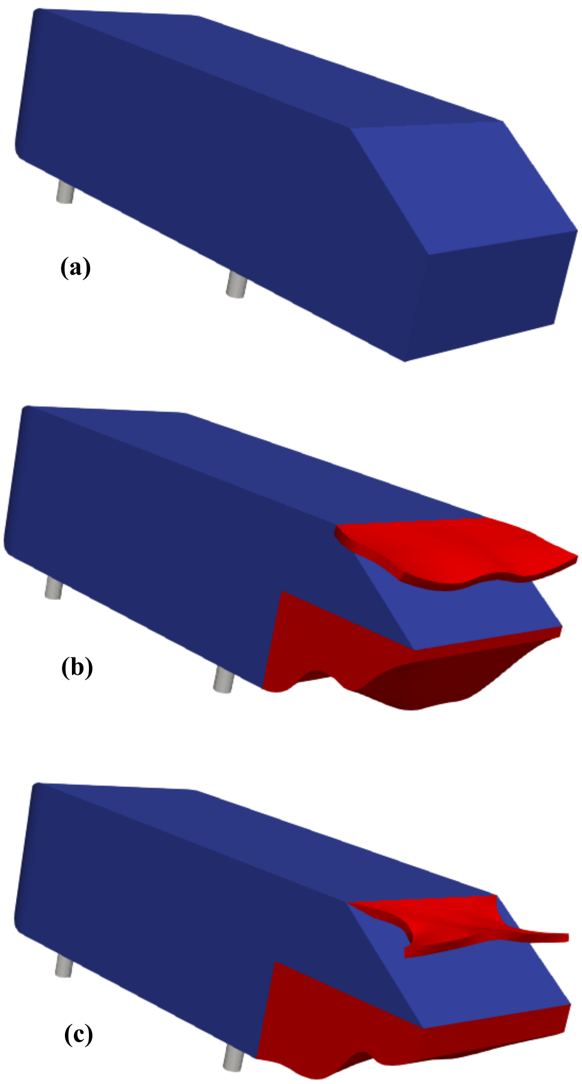

Figure 3 Geometries displays for (a) baseline, (b) minimum drag and (c) minimum lift

The solutions above were analyzed to better understand the flow physics. The pressure plots (Fig. 4) show the variation of pressure around the model. Fig. 4(b) shows the lowest pressure region shifted to an upper location and a general increase in the pressure at the rear of the model compared with the baseline model (Fig. 4(a)). The general increase in the base pressure leads to a decrease in drag, as expected.

However, the pressure distribution around the minimum lift model (Fig. 4(c)) has different characteristics. Fig. 4(c) shows a higher pressure region above the flap compared with similar regions in both Figs. 4(a) and 4(c). The higher pressure at the top translates to higher downforce (or negative lift) and drag on the model.

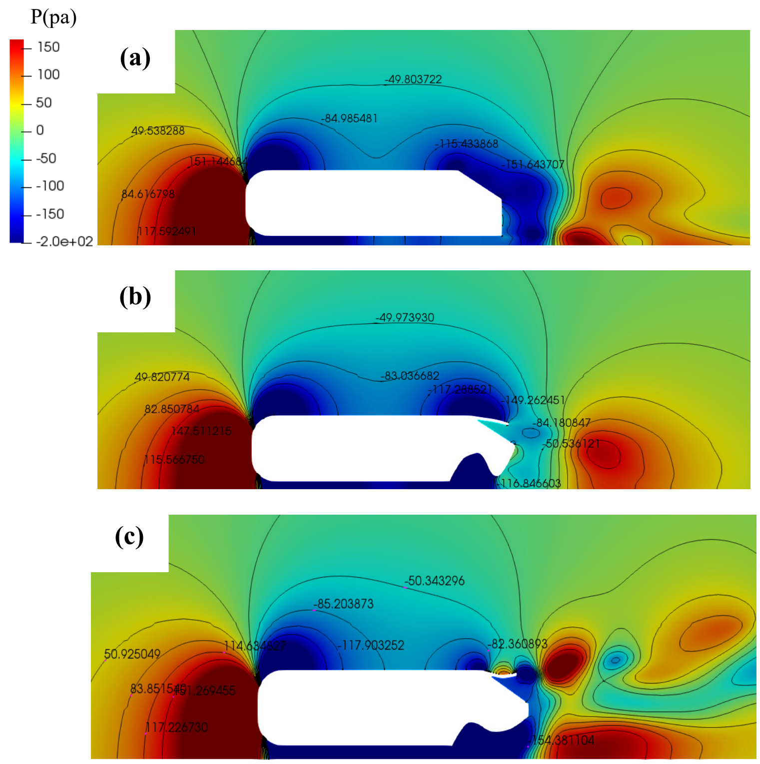

Figure 4 Pressure contours for (a) baseline, (b) minimum drag and (c) minimum lift. Legend applies to all.

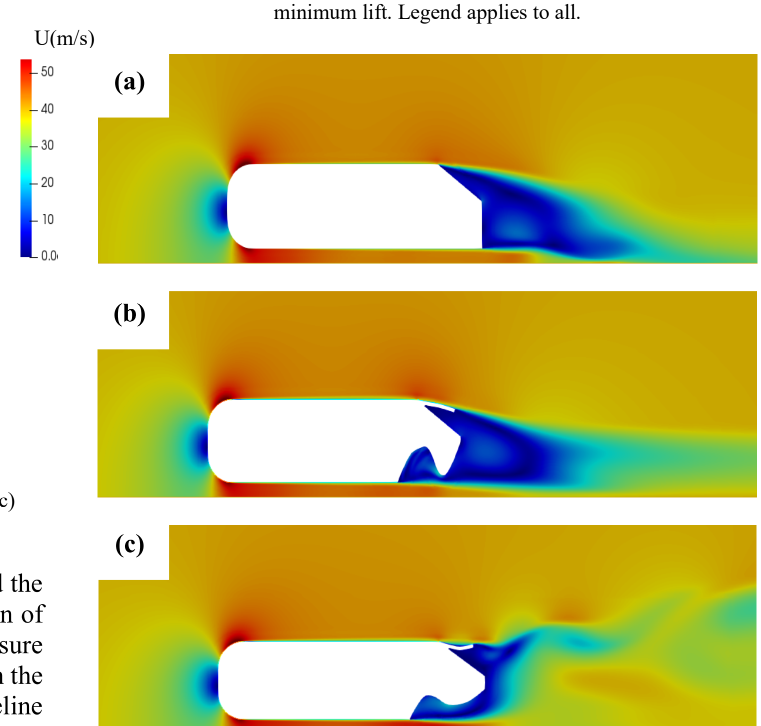

Figure 5 Velocity magnitude for (a) baseline, (b) minimum drag and (c) minimum lift. Legend applies to all.

According to Siddiqui [17], Ahmed [12] and Choi [18], one of the methods of reducing drag is to maintain the flow fully attached to the slant of the Ahmed body. Another is reducing the strength of the longitudinal vortex on the body. These two sources of drag can be illustrated by analyzing Fig. 5 and 6. Fig. 5(b) shows that the flow is attached to the flap with no large flow separation region compared to the baseline case in Fig. 5(a). This results in drag reduction. On the other hand, Fig. 5(c) flows the separation happening upstream of the flap with the wake flow deflected upwards. It is evident that the flap slowed down the flow at the top of the model while the underbody flow is faster. The combination of these two effects increased the downforce (negative lift). These behaviours are consistent with the values of drag and lift obtained (Table 3 and Table 4).

(a)

(b)

(c)

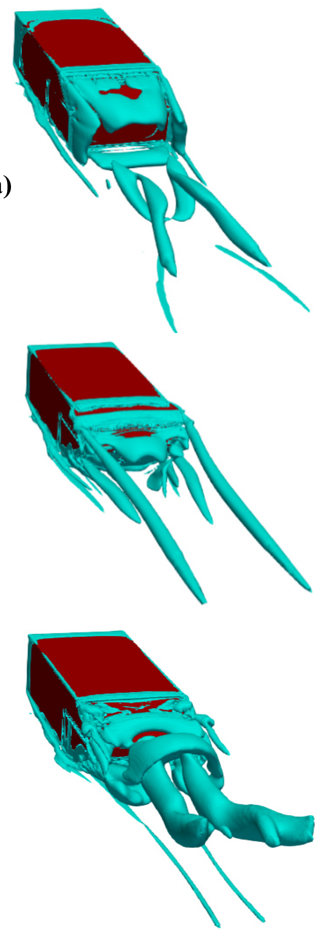

Figure 6 Okubo-Weiss parameter Q, where Q =15000/s^2 and (a) baseline, (b) minimum drag and (c) minimum lift

Lastly, Fig. 6 shows the Okubo-Weiss parameter Q, which is a vortex identification technique. This method is based on the second invariant of the velocity gradient [19]. This method was used because it is the most popular, as reported by Liu [20]. The equation for this method can be found in the work of Holmén [19]. In Fig. 6(b), it can be observed that longitudinal vortices attached to the rear edges of Ahmed body are not weaker compared with those produced by the base model (Fig. 6(a)). As mentioned earlier, the drag depends on the strength of the longitudinal vortex and the attachment of the flow to the body [12,17,18]. Although the vortices are not weaker, the drag is still reduced because the flow is more attached to the body. The results are, therefore, consistent with the flow physics revealed by the vortex structure. However, the strength of the vortex in Fig. 6(c) is not reduced. In fact, the vortices formed on the rear are pointing upwards at the end of the flap, displaying the behaviour of the upward vortex stream, as illustrated in Fig. 5(c). It can be observed that the solution with the highest downforce also has the highest drag since these two objective functions are contradictory. These behaviours shown in Fig. 6 also illustrate a consistency with the values in Table 3 and Table 4 and also the flow physics.

VI. Conclusion

This paper performed aerodynamic shape optimization using genetic algorithms, particularly the Non-Dominated Sorting Genetic Algorithm (NSGA-II). The method involves the application of NSGA-II, OpenFOAM CFD, and B-spline functions on the Ahmed body. The immediate goal was to prove the concept and the potential of genetic algorithms in the aerodynamic shape optimization of bluff bodies. The results are satisfactory since there are clear improvements made by the program through only five generations. The code can find more suitable solutions if left running for a considerable amount of time. For this work, only five generations were selected as the stopping criteria. However, the final results can be improved significantly if the user selects 20 or 100 generations as the stopping criteria.

VII. Future Work

The long-term goal of this research is to create libraries of devices in which the algorithm can select which device (or devices) is more suitable for a specific ground vehicle. For example, imagine that there are ten libraries available for different devices for a specific car model, and the user wants to include two active devices. The algorithm will design the devices and select which two out of the ten devices available should be applied to the vehicle. Furthermore, since the main goal is to prove this concept, other algorithms can be implemented to give the user options for their selected methodology.

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