Comparative Study of Different Optimization Algorithms Used for Obtaining Diesel-Biodiesel Blends

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The purpose of this paper is to compare two different optimization methods, used in acquiring diesel-biodiesel blends. There were used five types of samples in order to enable the optimization of the final blend: there were chosen two types of hydrofined diesel fuel and there were synthesized three original types of biodiesel. The first optimization method used, dual simplex, is a classical method being used in solving linear programming problems. The second optimization method, the genetic algorithms, falls in the type of artificial intelligence algorithms, being an evolutionary method used when the problem requires searching an optimal solution in a great variety of valid solutions.

Keywords: dual simplex, genetic algorithm, optimization, diesel-biodiesel blends;

Optimization is the process of choosing the best optimum solution from a multitude of valid solutions. The origins of optimization date back to 300 B.C., when the mathematician Euclid determined the minimal distance between a point and a line. From then on, optimization algorithms have evolved greatly, at present developing into hundreds of types, being used on a large scale almost becoming compulsory [1]. Alpaslan Atmanli et al. optimized, using RSM (response surface methodology), diesel-butanol-vegetable oil blends, so as to reach maximum power and torque, and at the same time obeying legal and environmental restrictions. Based on these studies, the conclusion reached was that RSM produced optimal results concerning the problem of the blends [2]. Dinesh K. Khosla et al. has implemented genetic algorithms for a multi-objective optimization: the process of blending heavy fuel oil (HFO). The conclusion was that genetic algorithms offer as feedback a set of Pareto optimum solutions, equally good, from which the user can choose [3]. Vaibhav R. Wakode et al. used special dedicated software, Diesel-RK, so as to estimate and optimize engine parameters. The purpose of their study was to optimize fuel injection pressure and compression ratio. [4]. Genetic algorithms have been used by Zhenxia Zhu et al. to optimize diesel fuel engines that work on ecological platforms, at altitudes of over 4000 m. This optimization method was chosen as diesel fuel engines are considered to be highly complicated systems with a multitude of inputs and restrictions. After the completion of diesel engine optimization, its power increased up to 22.7%, fuel consumption decreased by 6.4% [5]. Hua Zhou et al. suggested a new optimization model for the hydrocracking installations, a model which also takes into consideration hydrocarbons cracking reactions from the hydrodesulfurization installation (HDS). The suggested model draws a comparison between genetic algorithms and sequential quadratic programming (SQP), with the purpose of increasing kerosene and diesel yield. Based on their studies and experimental lab tests, it was proved that SQP gave better results than genetic algorithm [6]. Shivom Sharma et al. used multi objective optimization in order to improve the process of synthesizing biodiesel. This model took into consideration the profit, the investment needed as well as the organic waste resulted from the synthesizing process. Genetic algorithm was used for the optimization, the results being simulated in Aspen Plus [7, 8]. Multi objective optimization using genetic algorithms was also used in their studies by Antonio Paolo Carlucci et al. for resizing and optimizing direct air capture systems of airplane engines with the purpose of reducing consumption and enhancing engine power [9].

The present study compares two optimization algorithms: dual simplex and genetic algorithm. The purpose is obtaining a diesel- biodiesel blend with minimum costs, so as to meet demands regarding its properties.

Experimental part

For the experimental part, two types of hydrofined diesel were chosen, along with synthesizing three original biodiesel samples. The three types of biodiesel were obtained as it follows: the first type was created through mechanical stirring, the other two types through ultrasound blending at two different frequencies: 37 kHz and 80 kHz. For all the five samples relative density, kinematic viscosity at 40°C and flash point have been determined and calculated, the results being presented in table 1.

Optimizing the process of obtaining the blend -Case study

It is needed to obtain a blend, with minimum costs, of 100 L of diesel- biodiesel with only: 50 L of each type of diesel and 20 L of each type of biodiesel, to meet the following requirements:

Table 1
PHYSICAL PROPERTIES OF THE SAMPLES

Test	Test method	Unit	Diesel 1	Diesel 2	Biodiesel-mechanical stirring	Biodiesel-ultrasound 37 kHz	Biodiesel-ultrasound 80 kHz
Relative density at 20°C	ISO 3507:1999/ ISO 4787:2010	-	0.838	0.837	0.883	0.885	0.883
Kinematic viscosity at 40°C	EN ISO 3104	cSt	2.8	2.5	4.5	4.6	4.6
Flash point	EN ISO 2719	°C	78	84	176	174	174

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-relative density: 20°C ≤ 0.845;
-kinematic viscosity : 40°C ≤ 3.5 cSt;
-minimum flash point: ≥ 85°C.

Any given optimization problem can be divided in four stages:

-*Choosing the optimization algorithm.* This stage is highly important as for each type of problem, there is a specialized type of algorithm used for solving it. Choosing an inappropriate algorithm will lead to faulty results.

-*Elaborating the mathematical model.* At this stage, the requirements as well as the restrictions of the optimization problem will be presented in mathematical form. This will be done taking into consideration the optimization algorithm chosen, each optimization algorithm functioning by its own set of rules.

-*Optimizing the problem using chosen algorithm.* At this point, the problem will be optimized, with or without the help of software using the optimization algorithm chosen.

-*Validating the results.* This stage means checking the results offered by the algorithm, experimentally as well as theoretically. If the results check, both the mathematical model and the chosen optimization algorithm were correct. If the experimental results are different from the ones returned by the algorithm, there will be further verifications of the mathematical model and the optimization algorithm. Necessary modifications will be done in order to achieve the optimal and correct result.

The prices and the quantities available are shown in table 2. In table 2 one can also find the corresponding variables for the quantities of the samples which will be used when formulating the mathematical model. The diesel and biodiesel prices have been set taking into account their properties and the necessary cost to obtain the samples.

Choosing the algorithms

Two optimization algorithms were chosen: dual simplex and genetic algorithm. Both algorithms will be implemented using MATLAB 2017a software, through the Optimization Tool Box. MATLAB is the acronym for MATrix LABoratory, therefore the mathematical model will be elaborated in such a way so as to make working with matrices possible.

Elaborating the mathematical model

Because of the fact that both algorithms were implemented with the help of the same software, the mathematical model will not suffer substantial changes. Judging by the previous experiments as well as by the numerous scientific articles [10-14], in which the influence of biodiesel on the final blend has been studied, it was chosen to consider that the properties are additive. The equations of the mathematical model are presented as follows: formula (1) represents the function that must be minimized. In the case of the dual simplex algorithm, it is called cost function whereas in the case of the genetic algorithm it is named fitness function.

$$f = x[1]*3.5 + x[2]*4 + x[3]* \\ *4.5 + x[4]*5 + x[5]*5.5 \quad (1)$$

where: f represents the function that must be minimized;

x[i], with $i=\overline{1,n}$ represent the quantities that will be used for obtaining the blend. The following condition, formula (2), represents the targeted quantity, in our case 100 L.

$$x[1] + x[2] + x[3] + x[4] + x[5] = 100 \quad (2)$$

Formula (3), represents both the positive conditions and the availability corresponding to each sample. The left member of inequality, in the program will be encrypted as the lower bound, the available quantities, the right member of inequality, will represent in their turn, the upper bound.

$$0 \le x[1] \le 50; 0 \le x[2] \le 50; 0 \le x[3] \le 20; \\ 0 \le x[4] \le 20; 0 \le x[5] \le 20 \quad (3)$$

Formulas (4),(5) represent density and viscosity restrictions.

$$0.838*x[1] + 0.837*x[2] + 0.882*x[3] + 0.885* \\ *x[4] + 0.883*x[5] \le 0.845*100 \quad (4)$$

$$2.81*x[1] + 2.50*x[2] + 4.51*x[3] + 4.61* \\ *x[4] + 4.61*x[5] \le 3.5*100 \quad (5)$$

Because of the fact that both the dual simplex and the genetic algorithm cannot process a condition which presumes a minimum bound when implemented in the Matlab software, seen in the case of the flash point which is required to be of minimum 85°C, this formula, (6), will be multiplied by -1 and it will develop into formula (7), the one that will be used in programs.

$$78*x[1] + 84*x[2] + 176*x[3] + 174* \\ *x[4] + 174*x[5] \ge 85*100 \quad (6)$$

$$-78*x[1] - 84*x[2] - 176*x[3] - 174* \\ *x[4] - 174*x[5] \le -85*100 \quad (7)$$

Implementing the dual simplex algorithm

In the case of this algorithm, as well as in the case of the genetic algorithm, we will solve the problem using matrices. As a consequence, the cost function, formula (1) will become matrix f, presented in formula (8):

$$f = [3.5 \quad 4 \quad 4.5 \quad 5 \quad 5.5] \quad (8)$$

where f= matrix associated with the cost function.

The restrictions imposed by formulas (4), (5) and (7) referring to density, viscosity and flash point are called inequalities and they shall be represented by two matrices; matrix A, which will comprise the left member of inequalities and matrix b, which will comprise the right members. Both matrices are illustrated in formula (9).

$$A = \begin{bmatrix} 0.838 & 0.837 & 0.882 & 0.885 & 0.883 \\ 2.81 & 2.50 & 4.51 & 4.61 & 4.61 \\ -78 & -84 & -176 & -174 & -174 \end{bmatrix}; b = \begin{bmatrix} 84.5 \\ 350 \\ -8500 \end{bmatrix} \quad (9)$$

where A= matrix associated with the left members of inequality;

b= matrix associated with the right members of inequality.

Table 2
SAMPLE PRICES AND AVAILABLE QUANTITIES

Samples	Variable	Price (M.U.)	Available quantities (L)
Diesel 1	**x[1]**	3.5	50
Diesel 2	**x[2]**	4	50
Biodiesel- mechanical stirring	**x[3]**	4.5	20
Biodiesel-ultrasound 37 kHz	**x[4]**	5	20
Biodiesel-ultrasound 80 kHz	**x[5]**	5.5	20

The condition corresponding to the wanted quantity, formula (2), being the equality, will be represented separately, in matrices Aeq and Beq, their names being derived from equality. The two matrices are illustrated in formula (10).

$$Aeq = [1 \quad 1 \quad 1 \quad 1 \quad 1];\ beq = [100] \tag{10}$$

where Aeq= matrix associated with the left members of equality;

beq= matrix associated with the right members of equality.

Positivity conditions and also those referring to the quantity available in every sample, formula (3), will be encrypted in two matrices called: lower bound (lb) and upper bound (ub), both illustrated in formula (11).

$$lb = [0, 0, 0, 0, 0];\ ub = [50, 50, 20, 20, 20] \tag{11}$$

where lb= matrix associated with the negativity conditions of the variables;

ub= matrix associated to the maximum available quantities.

These being the entry data, the dual simplex algorithm is ready to be ran.

Implementing the genetic algorithm

Implementing the genetic algorithm does not require significant changes. The dual simplex algorithm starts from only one simple feasible solution, and it migrates towards a better feasible solution and it stops only when a primal feasible base is reached. The genetic algorithm starts from a multitude of feasible solutions, called individuals. For these individuals, which are part of the first generation, the fitness function will be calculated. Individuals will be selected for generating new solutions, using the tournament function in order to exclude weaker individuals. New solutions are obtained from: crossing over two parents, mutating a single parent or trough elite passage. These new solutions who are also called offspring individuals, will form a new generation. In the case of genetic algorithms a new generation is equivalent to one iteration. A genetic algorithm can have several stopping criteria: after a certain number of generations (iterations), after a certain time interval, if a certain specific value of the fitness function is reached or if there is a period of stalling when searching for the solution. An advantage of using genetic algorithm is the fact that it can decide the number of feasible solutions from which the algorithm will start the search. The nature of the genetic algorithm requires multiple runs, in order to examine multiple outcomes. This genetic algorithm used a default population of 50 feasible solutions and selected parents trough a tournament of 4.

Results and discussions

After implementing algorithms and analyzing the results following specifications can be outlined:

-The dual simplex algorithm came up with the optimal result after 2 iterations, whilst the genetic algorithm required 52 iterations. As the genetic algorithm does not always display the same results, it was necessary to run the program several times, to ensure that the best result was obtained.

-The solution offered by the dual simplex algorithm is presented in formula 12:

$$x[1] = 50;\ x[2] = 46;\ x[3] = 4;\ x[4] = 0;\ x[5] = 0 \tag{12}$$

-The solution offered by the genetic algorithm is presented in formula 13:

$$x[1] = 33;\ x[2] = 50;\ x[3] = 17;\ x[4] = 0;\ x[5] = 0 \tag{13}$$

where: x[i], with $i=\overline{1,n}$ represent the quantities that will be used for obtaining the blend.

The solution returned by the dual simplex algorithm uses 50 liters of the first type of diesel, 46 liters of the second type of diesel and 4 L of the first biodiesel.

The genetic algorithm solution uses 33 L of the first type of diesel, 50 L of the second type of diesel and 17 L of the first type of biodiesel.

Table 3
COMPARISON BETWEEN DUAL SIMPLEX AND GENETIC ALGORITHM

Criterion \ Algorithm	Dual Simplex	Genetic Algorithm
Minimum function value	377	392
Time required	≤1 second	≈10 seconds
Iterations required	2	≈52
Required runs needed to achieve result	1	≈2
Modifications needed to achieve result	0	≈2
Experimental tests	2-passed; 1- failed	all 3 passed
Degree of difficulty	basic	complex

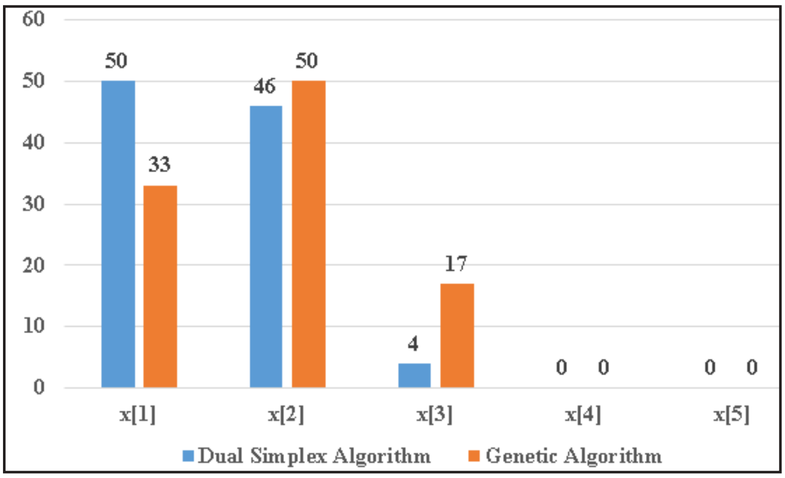

Fig. 1. Comparison between solutions

Both algorithms chose the first type of biodiesel, instead of the other two types of biodiesel available, because it was the closest to the desired blend properties but also the cheapest.

The genetic algorithm selected a higher quantity of the second type of diesel, in comparison to the solution given by the dual simplex, because it was closer to the required blend specifications, despite being a bit more expensive than the first type of diesel fuel. It also selected 17 liters of the first type of biodiesel, compared to the dual simplex algorithm, which selected 4 liters. These things led to a blend a bit more expensive than the one returned by the dual simplex algorithm.

The two blends were checked experimentally in the laboratory and not all the restrictions imposed were met in the case of the solution returned by dual simplex:

-The blend optimized using dual simplex had: density: 0.840, viscosity: 2.7 cSt and flash point: 83°C. The minimum flash point required is 85°C.

-The blend optimized using genetic-algorithm had: density: 0.844, viscosity: 2.8 cSt and flash point: 86.5°C

A synthesis of these observations is presented in table 3 and the optimal solution returned by the algorithms is illustrated in figure 1.

Conclusions

The purpose of this study was to draw a comparison between two optimization algorithms: the dual simplex and the genetic algorithm. Therefore there have been selected two types of hydrofined diesel fuels and there have been synthesized three original types of biodiesel. In order to enable optimization, samples as well as their interaction, have been analyzed in order to determine the nature of the properties, a fundamental thing to be taken into consideration when elaborating the mathematical model. The aim of the proposed case study was to optimize a blend, obeying imposed restrictions, its main objective being to minimize costs.

As a result of running the two programs, it was reached the conclusion that the dual simplex algorithm focused on returning the best minimum possible, leaving the imposed restrictions to second place. This resulted in returning the cheapest blend possible, which does not meet the flash point restriction. The genetic algorithm found a middle way, a way that while it does not return the absolute best minimum result, it does ensure that the restrictions are met, which is why it selected more of the second hydrofined diesel, since it was closer to the imposed restrictions than the first hydrofined diesel.

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