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MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION AND NSGA-II OPTIMIZATION ALGORITHMS COMPARISON WHEN APPLIED TO A SINGLE-CYLINDER INTERNAL COMBUSTION ENGINE

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Abstract. *In this work, two multi-objective optimization methods were applied to a single-cylinder compression ignition internal combustion engine. The methods are the NSGA-II (Non-dominated Sorting Genetic Algorithm - II) and MODE (Multi-objective Differential Evolution). The exhaust and inlet valves opening and closing angles (valve timing) were chosen as the design variables, and the thermal and volumetric efficiencies were chosen as the decision variables. The simulation and optimizations were performed for seven different engine speeds, for a better understanding of the process as a whole. The zero-dimensional model is used for the combustion in the chamber, solved by the fourth order Runge-Kutta method, and the rate of energy release is given by Wiebe's function. The valves' lift curve is described by a parabolic model. A predictive one-dimensional model is used for the flow in ducts, whose fluid is considered a perfect compressible gas, and the flow 1D, unsteady and non-isentropic. The physical laws of mass, momentum and energy conservation are applied and this hyperbolic system is solved by two step Lax-Wendroff method with TVD flow control. The boundary conditions are applied on the method of characteristics on duct's open ends and flowing through valves. Both optimization methods performed well and according to recommendations from the literature, their results were very similar, the main difference is the computational usage being a little lower for the NSGA-II. The decision variable that most affects the efficiencies is the exhaust valve opening angle. Engines at lower speeds require no valve timing optimization for their efficiencies are not highly affected by them.*

Keywords: *Multi-objective optimization, Internal combustion engine, Volumetric efficiency, Thermal efficiency, Valve timing*

1. INTRODUCTION

Ever since internal combustion engines (ICE) were first developed, researchers have been trying to optimize their processes. Recently, by global demands and legislations, the minimization of the pollution generated and the fuel consumed by the engine have been some of the main subjects of researchers, and also the maximization of their efficiencies, such as the thermal and volumetric ones (Pournazeri and Khajepour, 2016). With the development of more advanced computational tools, simulations have been proving to be more cost-efficient than physical testing, since it requires a prototype in an advanced stage (Torregrosa *et al.*, 2011).

This paper focuses on maximizing the thermal and volumetric efficiencies by changing the exhaust and inlet valves timing. The thermal efficiency (η_t) is defined as the ratio of fuel energy supplied to the engine on the combustion process and the volumetric efficiency (η_v) is used to measure the effectiveness of an engine's induction process, which is influenced by the intake system – air filter, carburetor, throttle plate, intake manifold, intake port and intake valve – for it can restrict the amount of air the engine can induct (Heywood, 1988).

There are seven operating variables that can affect the volumetric efficiency, such as: 1. Fuel type, fuel/air ratio, fraction of fuel vaporized in the intake system and fuel heat of vaporization; 2. Mixture temperature as influenced by heat transfer; 3. Ratio of exhaust to inlet manifold pressures; 4. Compression ratio; 5. Engine speed; 6. Intake and exhaust manifold port design; and 7. Intake and exhaust valve geometry, size, lift, and timings (Heywood, 1988). As mentioned, this paper aims to interfere with the seventh operating variable - the opening and closing angles of the intake and exhaust valves.

A variable valve timing (VVT) application can reduce fuel consumption, engine emissions Sabaruddin *et al.* (2015) and improve efficiencies (Sabaruddin *et al.*, 2015). The VVT is an important process that is being used by most of the engine manufacturers in the world, its effects on engine's efficiencies are the goal of the paper.

In order to evaluate how the efficiencies are affected by the opening/closing angles of the valves, an optimization is required. It reveals which are the best sets of angles resulting on the best decision variables (the efficiencies). Since this application presents two decision variables, a multi-objective optimization approach should be applied. It differs from the single objective one, because it does not find one best solution, it results on a set of non-dominated (or Pareto-optimal) solutions that can be chosen by one designer based on their knowledge or known constraints afterwards. Two methods will be used, the Non-Dominated Sorting Genetic Algorithm (NSGA-II), as presented by Deb *et al.* (2002), and the Multi-Objective Differential Evolution (MODE), adapted by Babu and Anbarasu (2006), and their results will be compared to determine which one yields the best results.

As it has already been discussed by D’Errico *et al.* (2011), NSGA-II should be the best method for multi-objective problems, since it has few repeated solutions due to the crowding-distance parameter - the same one added to MODE. He also stated that it obtains better results and requires smaller number of simulations when compared to other methods, such as ε -constrain. Its limitation lies on the non-existence of a stop-criteria, as it is to MODE.

2. METHODOLOGY

The proposed methodology to achieve the expected results is: (1) choose an engine simulation model, (2) determine the design and decision variables and (3) choose a multi-objective optimization method. (1) and (2) will be treated in Subsection 2.1 and (3) in Subsection 2.2

2.1 Simulation Model

Regarding the first step, a FORTRAN[®] routine proposed by Och *et al.* (2016) has been chosen to simulate the single-cylinder internal combustion engine. The zero-dimensional model is used for the combustion in the chamber, solved by the fourth order Runge-Kutta method, and the rate of energy release is given by Wiebe’s function. The valves’ lift curve is described by a parabolic model. A predictive one-dimensional model is used for the flow in ducts, whose fluid is considered a perfect compressible gas, and the flow 1D, unsteady and non-isentropic. The physical laws of mass, momentum and energy conservation are applied and this hyperbolic system is solved by two step Lax-Wendroff method with TVD flow control. The boundary conditions are applied on the method of characteristics on duct’s open ends and flowing through valves. The model was compared and validated with experimental results obtained by a single-cylindrical AVL 5482 engine by Och (2014). Also, the main aspects of the engine for better understanding the simulation outputs are presented in the Table 1.

Table 1. Engine’s parameters for the simulation.

Engine type	Compression ignition
Compression ratio	16:1
Combustion chamber diameter	93 mm
Stroke	170 mm
Connecting rod length	103 mm
Injection	Direct
Inlet valves quantity	2
Exhaust valves quantity	1

When it comes to the second step, since it is needed to find the optimal parameters (opening and closing angles for the inlet and outlet valves) that result on the best volumetric and thermal efficiencies, they will be the design and decision variables, respectively. These design variables are called *ivo* (inlet valve opening), *ivc* (inlet valve closing), *evo* (exhaust valve opening) and *evc* (exhaust valve closing), all relatively to the crank angle. The design variables are easier comprehended when represented in a typical spark-ignition 4-stroke engine cycle, in Figure 2.

The exhaust valve usually closes from 15 to 30 degrees before the TC (Top-center position) and the inlet valve normally opens from 10 to 20 degrees prior to the TC. It can be seen that there is an overlap period, in which both valves are opened, and usually, engines with long overlap periods have high volumetric efficiency (Heywood, 1988). Also, the sign convention adopted for the inlet and outlet closing valve timing are: for the closing ones, a positive sign means a postponement of the process; and for the opening timings, a positive sign means an advance on the opening timing. Their acceptable ranges are listed in Table 2.

The first decision variable, the thermal efficiency (η_t), is defined as the ratio of fuel energy supplied to the engine by the combustion process and is usually calculated by Eq. 1, where η_t is the thermal efficiency, η_c is the combustion efficiency, W_c is the work generated from the combustion process, m_f is the mass of fuel and Q_{HV} is the heating value from the fuel. The second representation of the equation is how it is calculated by the numerical routine, where h_f is the

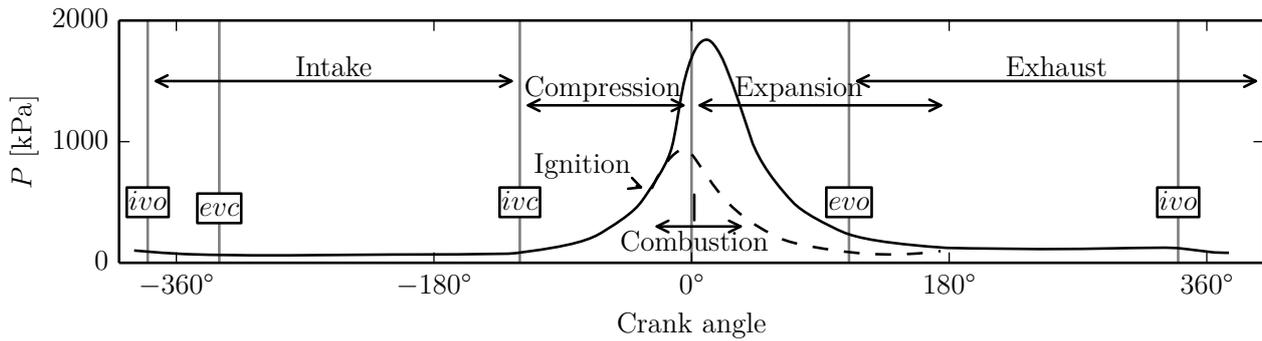


Figure 1. Four-stroke engine cycle.

Table 2. Acceptable ranges for the decision variables.

Variable	Lower bound	Upper bound
<i>ivo</i>	-30°	90°
<i>ivc</i>	-30°	80°
<i>evo</i>	10°	110°
<i>evc</i>	-30°	60°

fuel's enthalpy.

$$\eta_t = \frac{W_c}{\eta_c m_f Q_{HV}} = \frac{W_c}{|m_f h_f|} \quad (1)$$

The second decision variable, the volumetric efficiency (η_v), is used to measure the effectiveness of an engine's induction process, and is highly influenced by the intake system – air filter, carburetor, throttle plate, intake manifold, intake port and intake valve – for it can restrict the amount of air the engine can induct (Heywood, 1988). It can be calculated by Eq.2, where m_a is the mass of air inducted into the cylinder per cycle, $\rho_{a,i}$ is the inlet air density and V_d is the displaced volume. The second representation of the equation demonstrates how it is calculated by the numerical routine, where m_c stands for the mass on the interior of the cylinder, G_{the} is the theoretical mass, θ_c and θ_{cycle} are the fuel/air equivalence ratio at the end of the intake and at the end of the combustion, respectively, and F/A is the fuel-air stoichiometry ratio.

$$\eta_v = \frac{m_a}{\rho_{a,i} V_d} = \frac{m_c (1 - \theta_c / \theta_{cycle})}{G_{the} (1 + \theta_c F/A)} \quad (2)$$

2.2 Multi-Objective Optimization Methods

When it comes to the multi-objective optimization, two methods have been chosen, the NSGA-II and the MODE.

The NSGA-II, as proposed by Deb *et al.* (2002), is the second version of the same method proposed by Srinivas and Deb (1995), in which a crowded-comparison procedure has been added, represented by the \prec_n operator, that neglects additional parameters, reduce computational complexity and generates a more diverse population. It is defined as: between two solutions with differing non-domination ranks, the solution with the lower rank will be chosen and if both solutions belong to the same front, the solution that is located in a lesser crowded region will be chosen. Also, the non-dominated sorting was improved.

The NSGA-II begins with a random population. A non-domination process is applied to this population, in which a rank equal to its non-domination level is assigned to each solution. The first offspring population Q_o of size N is created by using the usual tournament selection, recombination, and mutation processes. The following populations require a different procedure, since they will be compared to prior best non-dominated solutions. Then, both populations are merged ($R_t = P_t \cup Q_t$). And, R_t is subject to the non-domination procedure, assuring the elitism.

The selection of the next generation P_{t+1} is shown in Fig. ??, where the hatched boxes are the ones neglected. The set of solutions with the best non-dominated rank F_1 is the first one stored and if its size is smaller than N , the whole set will belong to P_{t+1} . The remaining sets are chosen from decreasing non-dominated ranks (F_2, F_3, \dots, F_n) until one set cannot be fully accommodated. This set is sorted using the crowded-comparison operator in descending order and the best solutions will fulfill the remaining slots in P_{t+1} , generating the aforementioned diversity. P_{t+1} is now used for selection, crossover, and mutation to generate a new population Q_{t+1} , and the iteration begins up to the desired generation count.

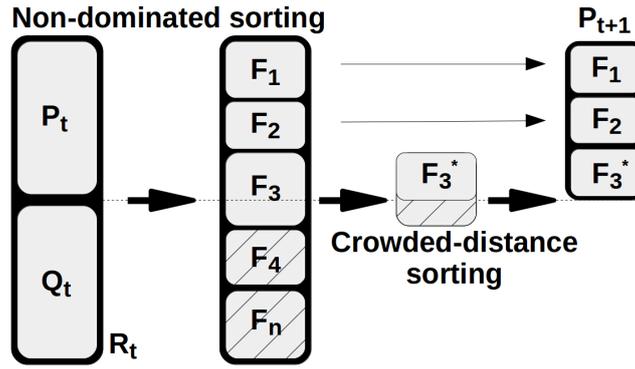


Figure 2. NSGA-II sorting procedure.

The Differential Evolution (DE) method was first developed by Ken Price and his professor Rainer Storn circa 1995, when trying to solve a mathematical problem by applying differential perturbations to the solution vectors. It has been developed ever since and according to Das and Suganthan (2011), it has been showing a good performance when optimizing multi-dimensional, multi-objective and multi-modal problems.

The main difference between MODE and NSGA-II lies on the mutation phase, when new vector are generated by adding the weighted difference between two vectors of the population to a third one. Basically, according to Price *et al.* (2005), the DE starts with a random initial population ($x_{i,G}$) with dimension $i = 1, 2, \dots, NP$ and G being the generation number. Based on this first population, the first offspring generation is determined beginning by mutation.

On the mutation, for each target vector ($x_{i,G}$), a mutant vector is created according to Eq. 3, where $r_1, r_2, r_3 \in \{1, 2, \dots, NP\}$ and are random indexes different from i , $F \in [0, 2]$ and is the constant that controls the differential variation amplification ($x_{r_2,G} - x_{r_3,G}$). Fig. 3 demonstrates $v_{i,G+1}$ creation process with these indexes.

$$v_{i,G+1} = x_{r_1,G} + F \cdot (x_{r_2,G} - x_{r_3,G}) \quad (3)$$

On the crossover phase, the parameters from both target and mutant vectors are combined randomly to crate a trial vector ($u_{i,G+1}$) based on the CR_{XC} parameter, as seen on Fig. 4

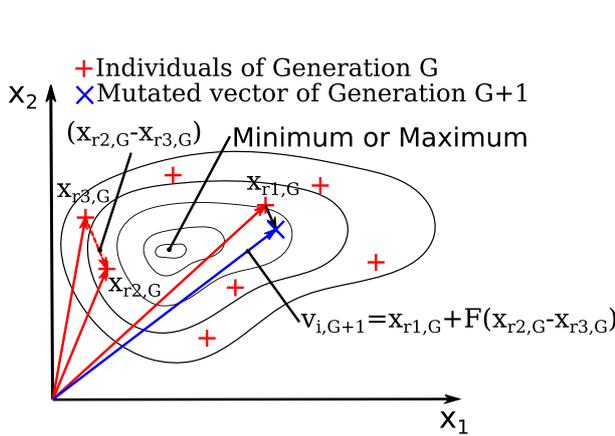


Figure 3. Mutant vector ($v_{i,G+1}$) generation process .

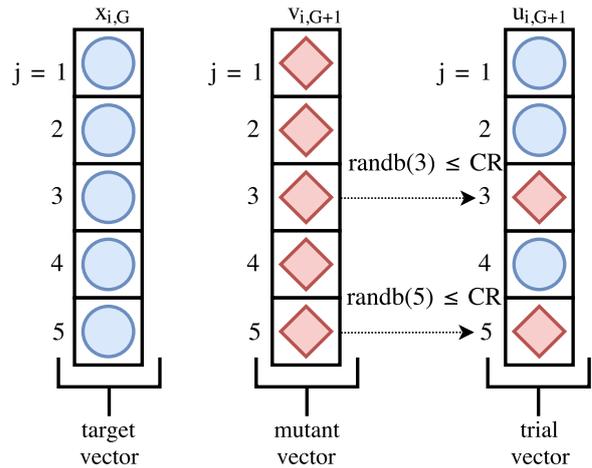


Figure 4. DE crossover phase.

where $randb(j)$ is the j -th evaluation of a random number generator between 0 and 1. $CR \in [0, 1]$ and is the crossover constant. $rnbr(i)$ is a randomly chosen index between 1 and D which ensures that at least one $v_{i,G+1}$ parameter in $u_{i,G+1}$, being D the quantity of decision variables.

The selection process is where Babu and Anbarasu (2006) performed the alteration to apply the ED in a multi-objective problem, adding the elitism considerations of NSGA-II itself. Therefore, the initial population and the one created by the trial vectors are merged, creating a population of $2NP$ elements, where the non-dominated sorting is applied fulfilling the new generation until a whole set of solutions with the same rank can be inserted. The first set not fully accommodated is subject to the crowded-comparison operator in descending order and the best solutions will fulfill the remaining slots.

3. RESULTS

It is imperative to declare, before analyzing the results, the main parameters for the optimization methods, considering they have a high impact on the diversification of results and on the amount of Pareto Front sets. It is important to note that each method was repeated seven times for different speeds (1000, 1500, 2000, 2500, 3000, 3500 and 4000 rpm) to better understand the whole process as, according to Sher and Bar-Kohany (2002), the speed has a linear dependency on the optimal valve timing.

For NSGA-II, there are a few parameters that have high impact on the results achieved: a population size of 100 individuals for 100 offspring generations, mutation and crossover probabilities of 0.8 and 0.5, respectively. For the sake of comparison, the whole process took around 90 hours to be completed, 13 hours per experiment. The results obtained with the NSGA-II method are plotted in the Fig. 5. As expected, most of the experiments illustrate the behavior of a regular Pareto Front, as described by Caramia and Dell’Olmo (2008). It can also be seen that both decision variables rise from 1000 to 3000 rpm, then decrease at 4000 rpm, meaning that the optimal engine speed should be between 2000 and 4000 rpm.

The same results are presented for MODE method, plotted in Fig. 6. The method was performed with a crossover probability CR of 0.5, a mutation factor F of 0.8 and a population size of 100 vectors for 100 generations. It took 97.5 hours to be performed, with a mean duration of 14 hours per experiment, a difference of 1 hour from the other method.

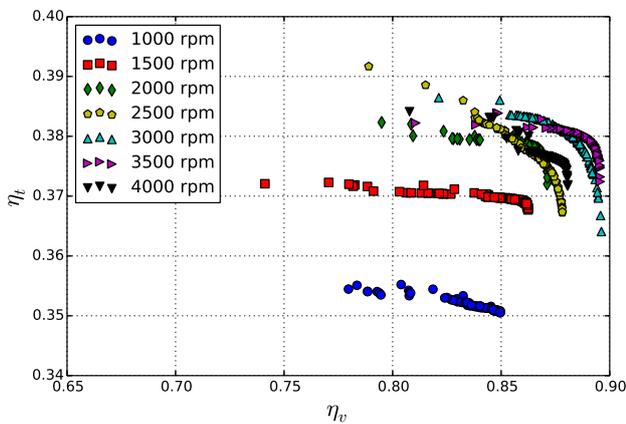


Figure 5. NSGA-II results for all speeds.

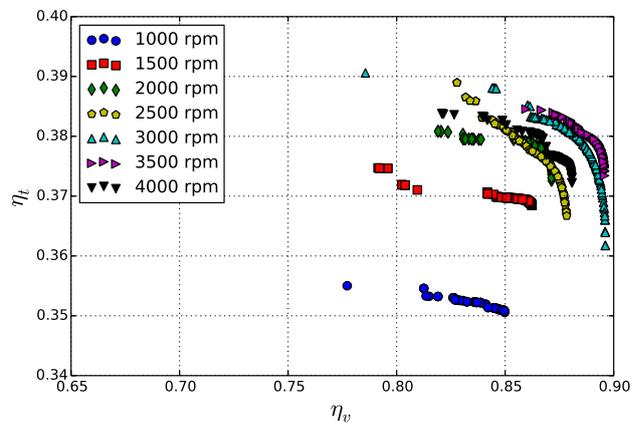


Figure 6. MODE results for all speeds.

Comparing both figures, it can be stated that both of them present, for most speeds, the expected behavior of a Pareto front for the solutions. One of the main differences between the methods is that NSGA-II provides a broader diversity on the solutions, mainly for the low speed configurations. On the other hand, MODE’s results are closer to the upper right portion of the graphic, where the best results are located.

Although, on a different approach, the maximum values obtained by each method for each speed are presented in Table 3, and it can be seen that both methods issue maximum values with a negligible variation. For better understanding the table, note that the maximum value for η_v and the maximum value for η_t do not occur at the same set of design variables, so each maximum value is presented with its correspondent pair.

Table 3. Maximum values, in percentage, obtained in both methods for each speed, correspondent values between brackets.

rpm Method	1000		1500		2000		2500		3000		3500		4000	
	MODE	NSGA-II												
η_v	84.98	84.97	86.24	86.25	87.14	87.12	87.83	87.82	89.62	89.62	89.58	89.56	88.08	88.07
(η_t)	(35.07)	(35.06)	(36.85)	(36.80)	(37.26)	(37.31)	(36.67)	(39.17)	(36.18)	(36.41)	(37.34)	(37.24)	(37.22)	(37.19)
η_t	35.50	35.52	37.47	37.23	38.08	38.23	38.90	39.17	39.06	38.65	38.46	38.39	38.38	38.41
(η_v)	(77.72)	(80.39)	(79.14)	(77.05)	(81.91)	(79.49)	(81.91)	(78.90)	(78.56)	(82.13)	(85.96)	(84.81)	(82.09)	(80.78)

The next analysis consists in checking how each design variable (ivo , ivc , evo and evc) affects the efficiencies. For such, some speeds must be chosen for better visualization. At low speeds, at 1000 rpm in Fig. 7, it can be seen that there is a large amplitude on the results for all valve angles with low variation on the efficiencies, meaning that there is no optimal configuration for these conditions.

At 2000 rpm, there is an increase on the volumetric efficiency and a decrease on the thermal one for higher evo and ivo . This is explained due to the fact that an early opening of the exhaust valve makes the energy provided from the combustion to be lower, affecting η_t in the same way. There is, also, a tendency for evc values to happen between 40 and 60°.

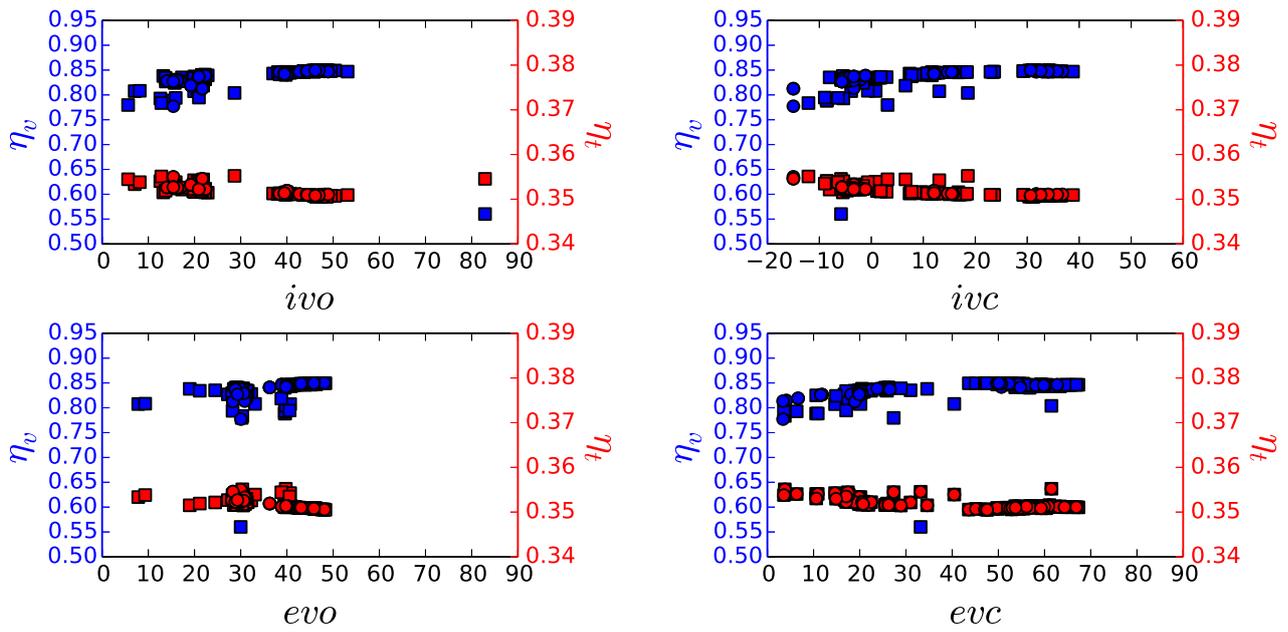


Figure 7. Effect of design variables at 1000 rpm. Squares for NSGA-II and circles for MODE.

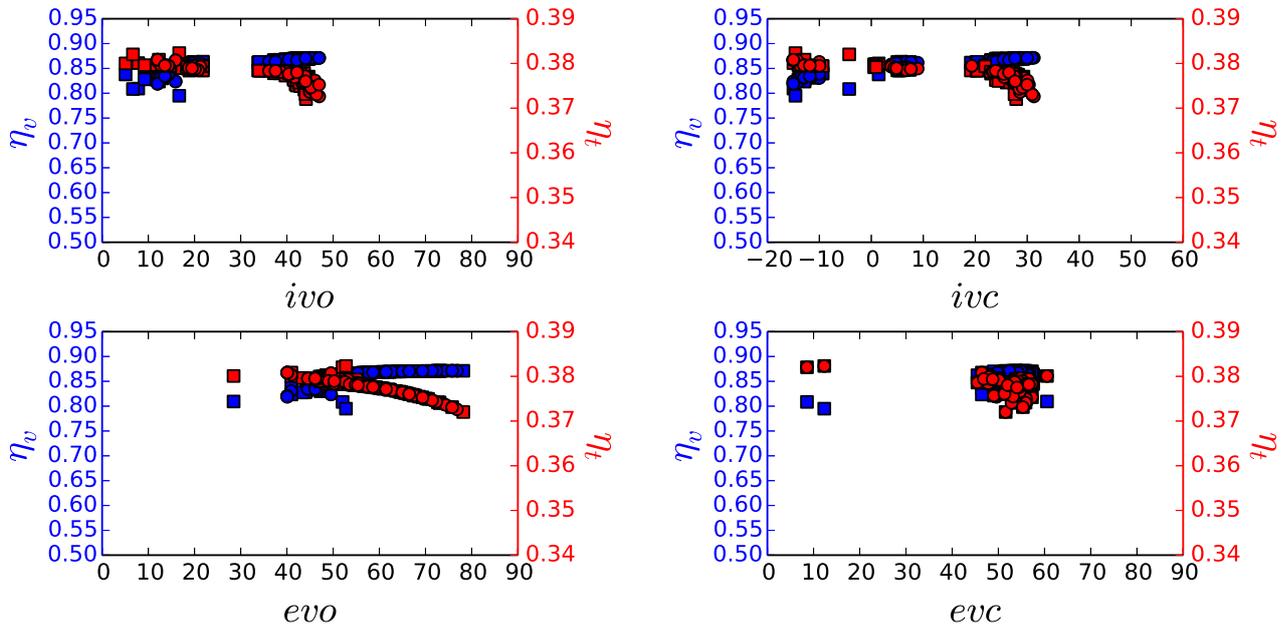


Figure 8. Effect of design variables at 2000 rpm. Squares for NSGA-II and circles for MODE.

For higher speeds, at 3000 rpm in Fig. 9, there is an opposite behavior regarding the opening angle of the exhaust valve, where for early opening angles, η_t is higher and η_v is lower. This can also be seen on higher speeds, for instance, at 4000 rpm. The high values for the closing angles of the inlet valves (ivc) are explained by the fluid's inertia and the RAM effect, and high evc are due to the pressure waves on the exhaust process.

After analyzing all the results, it can be inferred that the design variable that has the higher impact on the decision variables is the evo , in all cases when one decision value increases, the other decreases, representing the contradiction a multi-objective problem usually brings. It is inferred, once again, the similarity on the results obtained by both methods, the difference is almost irrelevant for the whole process, meaning that the method requiring less computational usage should be selected - therefore, the NSGA-II.

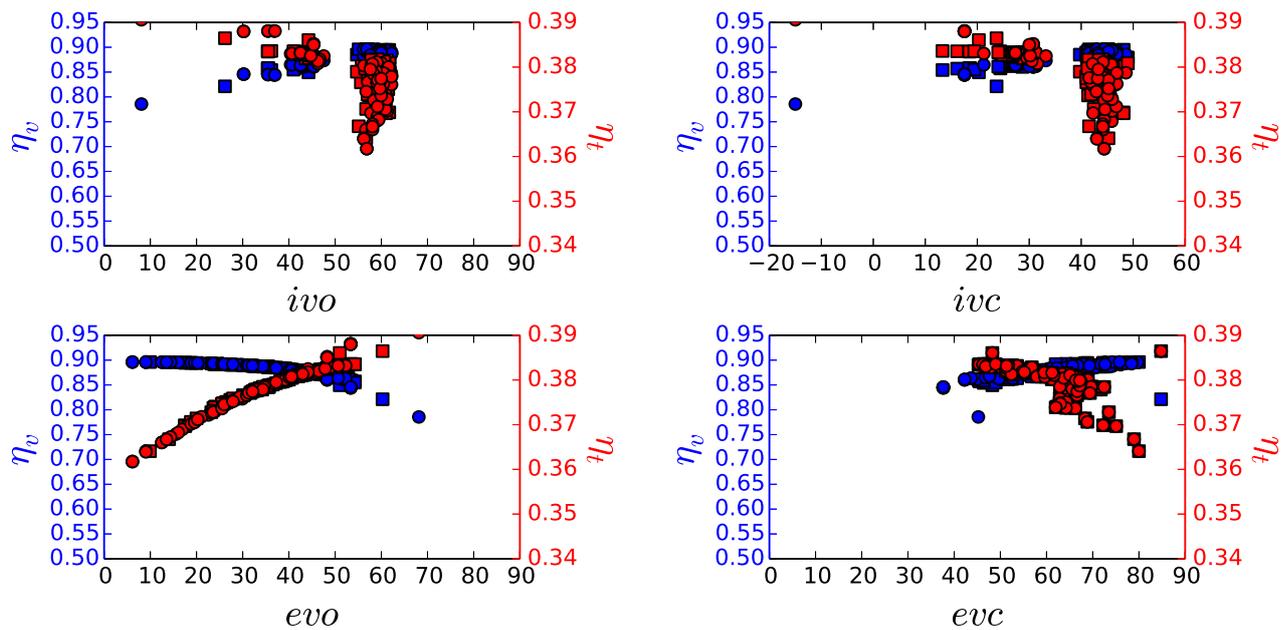


Figure 9. Effect of design variables at 3000 *rpm*. Squares for NSGA-II and circles for MODE.

4. CONCLUSIONS

The main objective has been achieved, which was to find which multi-objective optimization method is best for this engine simulation. As previously mentioned by D'Errico *et al.* (2011) (when compared to alternative methods), it is the NSGA-II. Actually, it cannot be stated that it issues better results, but it is the recommended one for performing at least as good as MODE, but with a lower computational usage.

It can be stated that the engine performs better at higher speeds and worse at lower ones. Also, regarding the design variables, there is no need for optimizations at lower speeds since the efficiencies vary few for these conditions. At 2000 *rpm*, an early opening of the exhaust valve makes the energy provided from the combustion to be lower, affecting η_t in the same way and there is tendency for *evc* values to happen between 40 and 60°. Also, opposite behaviors are seen regarding *evo* when comparing the 2000 and 3000 *rpm* speeds, and for the latter, high *ivc* values are explained by fluid's inertia and RAM effect, and high *evc* are due to the pressure waves on the exhaust process. Finally, it can be inferred that the design variable that has the higher impact on the decision variables is the *evo*.

Future work possibilities: analyzing the physics of how and why each design variable affects the efficiencies, adding one more decision variable (such as emission) and/or another design variable (inlet and outlet pipe lengths, for instance); and evolving the engine's model to a more complex one (e.g. a multi-cylinder approach), closing the gap between the simulation and real world applications.

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