ANALYSIS OF MULTI-OBJECTIVE OPTIMIZATION ALGORITHMS APPLIED TO INTERNAL COMBUSTION ENGINES

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Abstract: *Thermal efficiency is used to measure the effectiveness of an engine's combustion process and the volumetric efficiency is used to measure the effectiveness of an engine's induction process, and is highly influenced by the intake system. Maximizing these variables would optimize the whole operation of the engine as well, highlighting their importance on power, torque and emissions. The aim of this paper is to optimize these efficiencies by altering the valves' timings through two multi-objective optimization methods. A mono-cylindrical engine with a zero-dimensional, two-zone spark ignition combustion model was described for the combustion chamber due to the complexity of the simulation and the high amount of computational usage required for the iterations on the optimizations. A direct search model called "Random Search Approach" will be compared to a more complex method, an elitist multi-objective evolutionary algorithm called "Non-dominated Sorting Genetic Algorithm". When a large initial population size is applied on the former, it only reproduces a small amount of Pareto Front solutions. On the other hand, the latter, although requiring a higher computational usage, not only results in a more crowded Pareto Front but it generates better results. Both efficiencies, or 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. There is a tendency of high efficiencies in higher exhaust valve opening angle values due to the pressure pulsing in the exhaust process, and a rise on the thermal efficiency with the increase of the inlet valve closing angle is due to the fluid's inertia or RAM effect. The results confirm the early assumptions that the second algorithm has better effectiveness (higher efficiency values and more solutions), and that it should be used for the simulation of an engine, where a small gain on each efficiency has large effects on other operational variables, such as torque, power and emissions.*
Keywords: *Multi-objective optimization, Internal combustion engine, Volumetric efficiency, Thermal efficiency, Valve timing*

1. INTRODUCTION

Internal combustion engines have been the object of study of many researches ever since they were first developed, in 1876 when Nicolaus A. Otto (1832-1891) created the spark ignition engine and in 1892 when Rudolf Diesel invented the compression ignition engine (Heywood, 1988). From that day on, researchers have been trying to optimize their processes. Over the last few years, with the development of computational tools, making it more cost-benefit to perform simulations over physical tests (Torregrosa *et al.*, 2011), and by the strict legislations on the matter (Pournazeri and Khajepour, 2016), there has been an increase on studies aiming to minimize the pollution generated and the fuel consumption, and also to improve its overall operation. In this context, this paper will focus on maximizing both thermal and volumetric efficiencies.

The first one, the thermal efficiency (η_t) or fuel conversion efficiency, is used to measure the effectiveness of an engine's combustion process. It is highly linked to the specific fuel consumption, and is defined as the ratio of work supplied to the engine by the energy supplied by the fuel on the combustion process.

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).

In parallel, there are seven operational variables groups that affect the volumetric efficiency: 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). This paper will focus into the seventh operational variable group mentioned above, and precisely the opening and closing angles of both the intake and exhaust valves.

On a high engine speed and full throttle conditions, these angles - also known as valve timing - can be designed to optimize the engine operation (Dresner and Barkan, 1989). Not only that, a variable valve timing (VVT) can reduce fuel consumption and engine emissions, as well as control the torque and brake power curves (Nagumo and Hara, 1995). Due to its benefits, the VVT is being used by most of the engine manufacturers in the world, and its effects on thermal and volumetric efficiencies will be covered by this paper.

In order to evaluate how they are affected by the opening/closing angles of the valves, an optimization is required. This process will reveal which are the best sets of angles that will result on the best decision variables (the efficiencies). Since this problem presents two decision variables, a multi-objective optimization (MOO) approach should be applied.

Differently from the single-objective optimization (SOO) that finds the one best solution, the MOO finds a set of non-dominated (or Pareto-optimal) solutions. The next step would be for a designer to choose between one of them based on known constrains or requirements.

Two methods will be used, the Random Search Approach (RSA) and the Non-Dominated Sorting Genetic Algorithm (NSGA-II), as presented by Deb *et al.* (2002), and the 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. He also stated that it obtains better results and requires smaller number of simulations when compared to other methods, such as one known as ε-constrain. Its limitation lies on the non-existence of a stop-criteria, the method runs up to the number of generations desired by the user.

2. METHODOLOGY

At first, there are a few main steps that need to be followed to achieve the results expected: (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 (2014) has been chosen to simulate the internal combustion engine. The proposal is a mono-cylindrical engine wieh a zero-dimensional, two-zone spark ignition combustion model. For the air flow in the inlet and exhaust manifolds, the mixture is modeled as a compressible and perfect gas, applying the physical laws of conservation of mass, momentum and energy for 1D and non-stationary system. To solve this hyperbolic system, it was used Lax-Friedrich, Lax-Wendroff, MacCormark. The model was compared and validated with experimental results obtained in a mono-cylindrical AVL 5482 engine by Och (2014). In addition, the main aspects of the engine used are presented to better understand the simulation outputs, in the Table 1.

Table 1: **Engine's parameters for the simulation.**

Geometry	
Stroke	93 mm
Connecting Rod Length	107 mm
Compression Ratio	16
Operation	
Inlet Pressure	0.92 bar
Inlet Temperature	360 K
Outlet Pressure	0.92 bar
Outlet Temperature	1000 K
Fuel	
Number of Carbons	14.4
Number of Hydrogens	24.9
LHV (Lower Heating Value)	42.12E6 J/kg

As reported by Sher and Bar-Kohany (2002), the engine speed has a linear dependency on the optimal timing of each valve. Of course, for the VVT system to work properly, it would require the optimal timings at all speeds. But in this case, only a few speeds have been selected and applied to the simulation model, since the main objective here is to compare the optimization methods.

When it comes to the second step, as this paper aims to find the optimal parameters (opening and closing angles for the inlet and outlet valves) that result on the highest volumetric and thermal efficiencies, these will be the design and decision variables, respectively. These design variables are ivo (inlet valve opening angle), ivo (inlet valve closing angle), evo (exhaust valve opening angle) and evc (exhaust valve closing angle). To better comprehend what these angles mean, a typical spark-ignition 4-stroke engine cycle is helpful, in Figure 1. At its bottom, it can be seen the sign convention adopted for the angles; in which for the closing angles, a positive sign means a postponement of the process and for the opening ones, a positive sign means an advance on the process.

Usually, the exhaust valve closes from 15 to 30 degrees before TC (Top-center potion) and the inlet valve opens from 10 to 20 degrees prior to TC. In Figure 1, it is seen an overlap period, in which both valves are opened, and engines with long overlap periods have high volumetric efficiency (Heywood, 1988). The acceptable ranges of the in design variables are listed in the Table 2.

As mentioned earlier, the values presented in the Table 1 are only the main ones, and when concatenated with the design variables, they became inputs into the simulation routine and result in the decision variables, the efficiencies. The routine calculates both decision variables via Eq. 1 for the volumetric efficiency and by Eq. 2 for the thermal one.

$$\eta_v = \frac{m_c(1 - \theta_c/\theta_{cycle})}{G_{the}(1 + \theta_c F/A)} \quad (1)$$

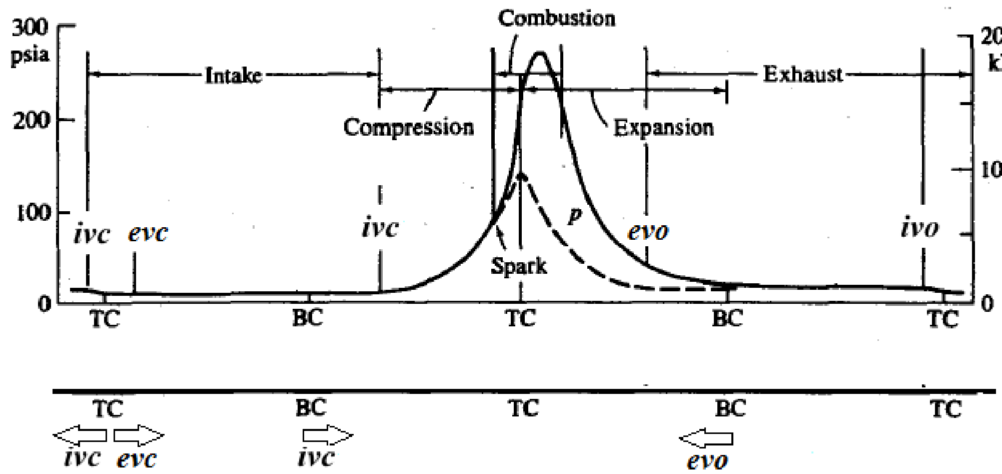

Figure 1: **Typical engine cycle on the top of the figure, and on the bottom the positive vectors for the the valve timing values. (Heywood, 1988)**

Table 2: **Acceptable range for the design variables, in degrees.**

Variable	Lower Bound (°)	Upper Bound (°)
ivo	-30	90
ivc	-30	80
evo	10	110
evc	-30	60

$$\eta_t = \frac{W_c}{|m_f h_f|} \tag{2}$$

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 admission and at the end of the combustion, respectively, and the F/A is the fuel-air stoichiometry ratio. Obviously, as the design variables are not explicitly at Eq. 1 or at Eq. 2, their effects are embedded in the explicit variables.

2.2 Multi-Objective Optimization Method

When it comes to the multi-objective optimization, two methods have been chosen, the RSA and the NSGA-II. For the first one, considered as a Direct search model, one thousand randomly generated values have been created for each one of the design variables within the acceptable range. These one thousand different sets of variables were used in the simulation routine to result in one thousand different sets of decision variables.

Since some of these sets can be worse in both decision variables in comparison to other sets, a filtering method has been applied. This method is called Dominance Filtering, and it compares every set of decision variables with all the other ones. If one of these compared sets is worse (presents a lower value) on both decision variables, it is called a "dominated set" and is purged as an optimal solution. These optimal solutions are usually called the Pareto Front and the design variables that generate them are usually called the Pareto Set, as shown by Caramia and Dell'Olmo (2008).

The second method - the NSGA-II - is proposed by Deb *et al.* (2002) and is the second version of the method proposed by Srinivas and Deb (1995), in which the main differences are the replacement of the sharing function approach with a crowded-comparison one (that neglects additional parameters, reduce computational complexity and generates better diversity of the population), a faster non-dominated sorting and the introduction of a crowded-comparison operator ($\prec_n$), 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.

The NSGA-II starts with the creation of a random population. The population is sorted based on the non-domination, in which each solution is assigned a fitness (or rank) equal to its non-domination level. The first offspring population Q_0 of size N is created by using the usual binary tournament selection, recombination, and mutation operators. The next populations require a different procedure, because they are compared to previously found best non-dominated solutions. Afterwards, both populations are combined ($R_t = P_t \cup Q_t$), with size as $2N$. Then, the population R_t is sorted according to non-domination, assuring the elitism.

The selection of the next generation P_{t+1} begins, as shown in Fig. 2, where the hatched boxes are the ones neglected. The set with the best non-dominated rank F_1 is chosen first and if its size is smaller then N, all of its members will be part of P_{t+1}. The remaining members of the population are chosen from subsequent non-dominated fronts ($F_2, F_3, ..., F_n$) in the order of their rankings until no more sets can be fully accommodated. The last set - the one that has not been fully placed into P_{t+1} - is then sorted using the crowded-comparison operator ($\prec_n$) and the best solutions are chosen to fill all P_{t+1} slots.

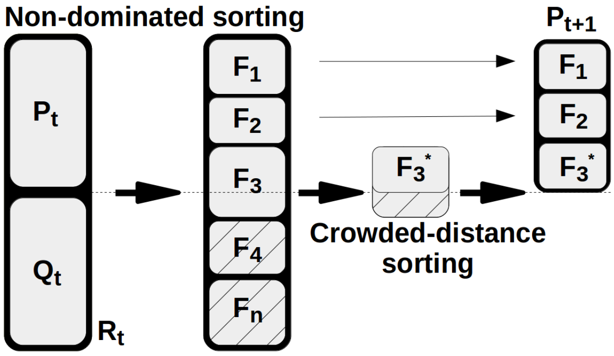

Figure 2: **NSGA-II sorting procedure.**

P_{t+1} is now used for selection, crossover, and mutation to create a new population Q_{t+1}, and the process repeats itself up to the desired generation. It is important to note that a binary tournament selection operator is used but the selection criteria is now based on the crowded-comparison operator ($\prec_n$) . The diversity among non-dominated solutions is introduced by using the crowding comparison procedure in the tournament selection and on the population reduction phase.

3. RESULTS

It is imperative that main parameters for the optimizations are declared before analyzing the results, considering they have a high impact on the convergence time and diversification of results for NSGA-II; and on the amount of Pareto Front sets obtained for both methods. It is important to note that each method will be repeated four times, with four different speeds (1000, 2000, 3000 and 4000 rpm) to better understand the whole process.

For the RSA method, the sole parameter that must be set is the population size, which has been set as 1000 individuals. Naturally, for the RSA method, results are as good as the size of the population, there is no iteration process, only the non-domination filtering is performed on the final population. The results obtained with the RSA method are plotted in the Fig. 3. As expected, it illustrates the normal behavior of a Pareto Front as shown by Caramia and Dell'Olmo (2008); some of the experiments generated fewer points than others, though. Each one of the experiments took around 12 hours to be performed.

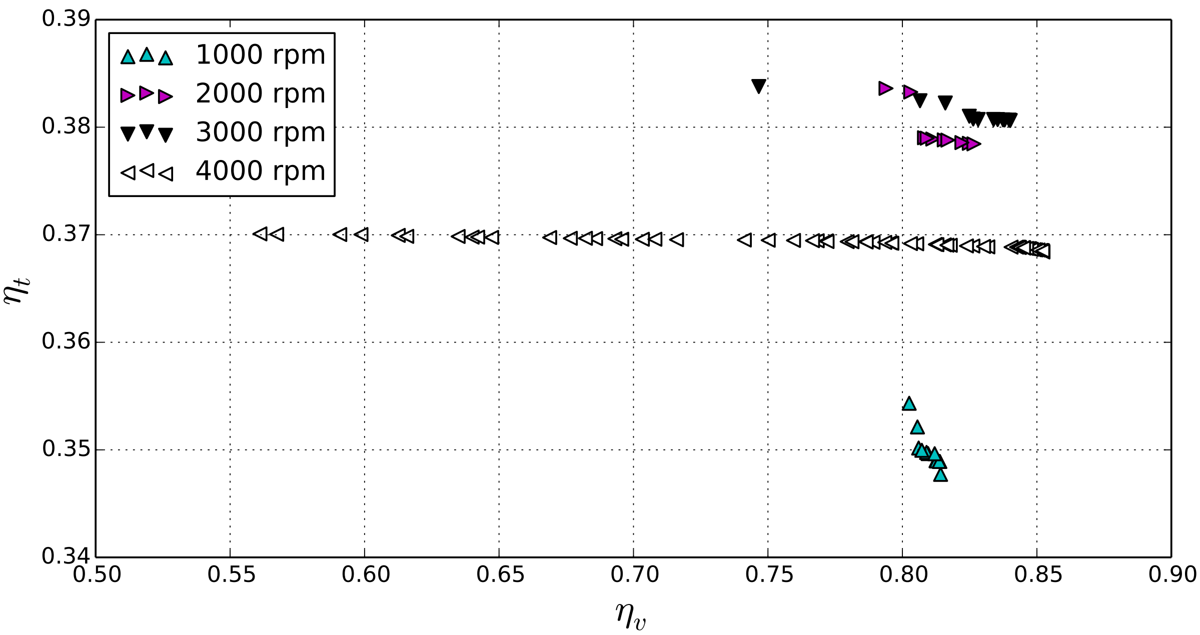

Figure 3: **RSA results for each speed.**

For the NSGA-II method, there are a few parameters that have high impact on the results achieved, and they are shown at the Table 3. Where $ipopsize$ is the size of the population, $maxgen$ is the number of offspring generations, $nmute$ and $ncross$ are the number of permutation and crossovers, respectively and $pmute$ and $pcross$ are the probability of them happening, finally, $lchrom$ is the total length of the chromosome used. For the sake of comparison, each experiment took around 48 hours to be completed.

The results obtained with the NSGA-II method are plotted in the Fig. 4. As expected, it illustrates a normal (and

Table 3: **Main parameters set for the NSGA-II.**

Parameter	$ipopsize$	$maxgen$	$nmute$	$ncross$	$pmute$	$pcross$	$lchrom$
Value	100	100	10	10	0.2	0.9	2000

better than on the previous method, because it yields more points) behavior of a Pareto Front as shown by Caramia and Dell'Olmo (2008). Plus, for most of the cases almost all NSGA-II sets would dominate the RSA ones, as it happens with 1000 and 4000 rpm. It can also be seen that both decision variables rise from 1000 to 3000 rpm and decrease at 4000 rpm, meaning that the optimal engine speed should be between 2000 and 4000 rpm.

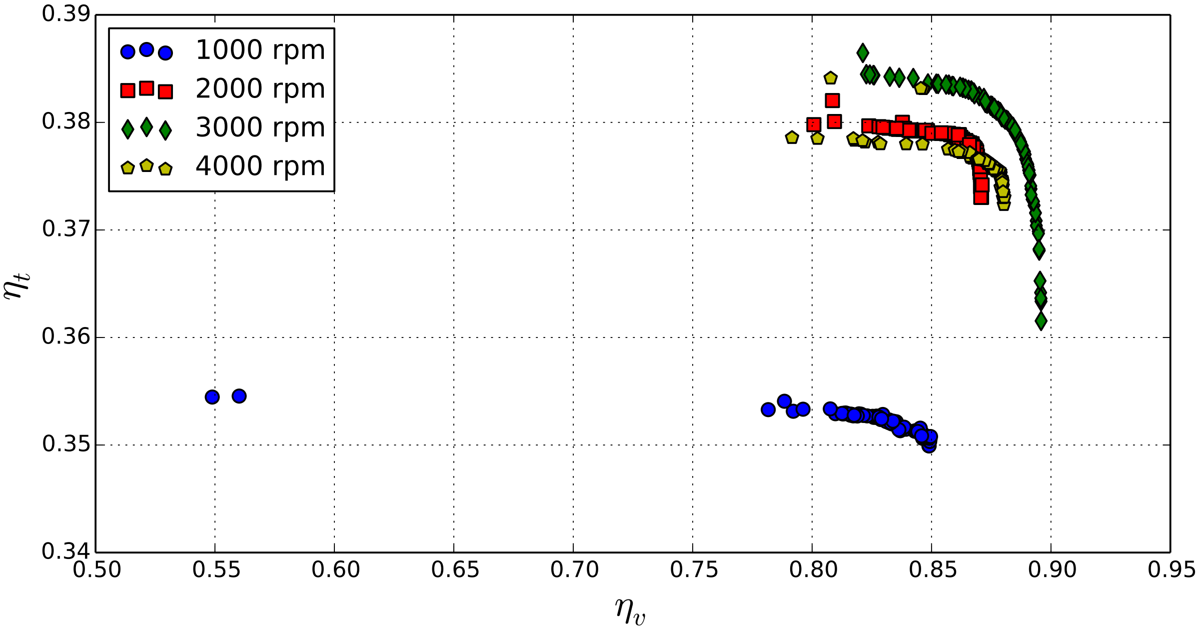

Figure 4: **NSGA-II results for each speed.**

For an even deeper analysis, the maximum values obtained by both methods are presented at the Table 4. Note that the maximum values for η_v and η_t do not occur at the same set of design variables, therefore each maximum value will be presented with its correspondent pair. It can be seen, once again, that NSGA-II brings better results in every speed and in both decision variables, with the exception of one element (η_t @ 2000 rpm). Likewise, if both decision variables are considered, the results are even more evident. For instance, for 4000 rpm and the maximum value of η_t, there is an one percent difference on η_t and an expressive variation of 24% on η_v.

Table 4: **Maximum values obtained by both methods for each speed, correspondent values between brackets.**

rpm	**1000**		**2000**		**3000**		**4000**	
Method	RSA	NSGA-II	RSA	NSGA-II	RSA	NSGA-II	RSA	NSGA-II
η_v (η_t)	0.8141 (0.3477)	0.8496 (0.3508)	0.8266 (0.3784)	0.8712 (0.3731)	0.8401 (0.3806)	0.8958 (0.3668)	0.8523 (0.3684)	0.8805 (0.3717)
η_t (η_v)	0.3543 (0.8025)	0.3545 (0.7796)	0.3836 (0.7939)	0.3823 (0.7949)	0.3838 (0.7466)	0.3865 (0.8212)	0.3701 (0.5611)	0.3841 (0.8078)

By the discussions made above, it can be inferred that NSGA-II provides better results in general - with large amount of solutions, few repeated ones and better efficiencies - even though it takes around 4 times the computational time that the RSA requires. Hence, the next analysis will only be performed with the NSGA-II results. This analysis consists in checking how each design variable (ivo, ivc, evo and evc) affects the efficiencies. For such, one speed must be chosen at each time for better visualization and the first one is the 1000 rpm, shown in Fig. 5. A tendency can be perceived for η_v to increase with the increase in all design variables and the opposite behavior happens to η_t. However, the two highest values for ivo show a different result, there is a drastic decrease on the volumetric efficiency and that is where the best thermal efficiencies lie on this case.

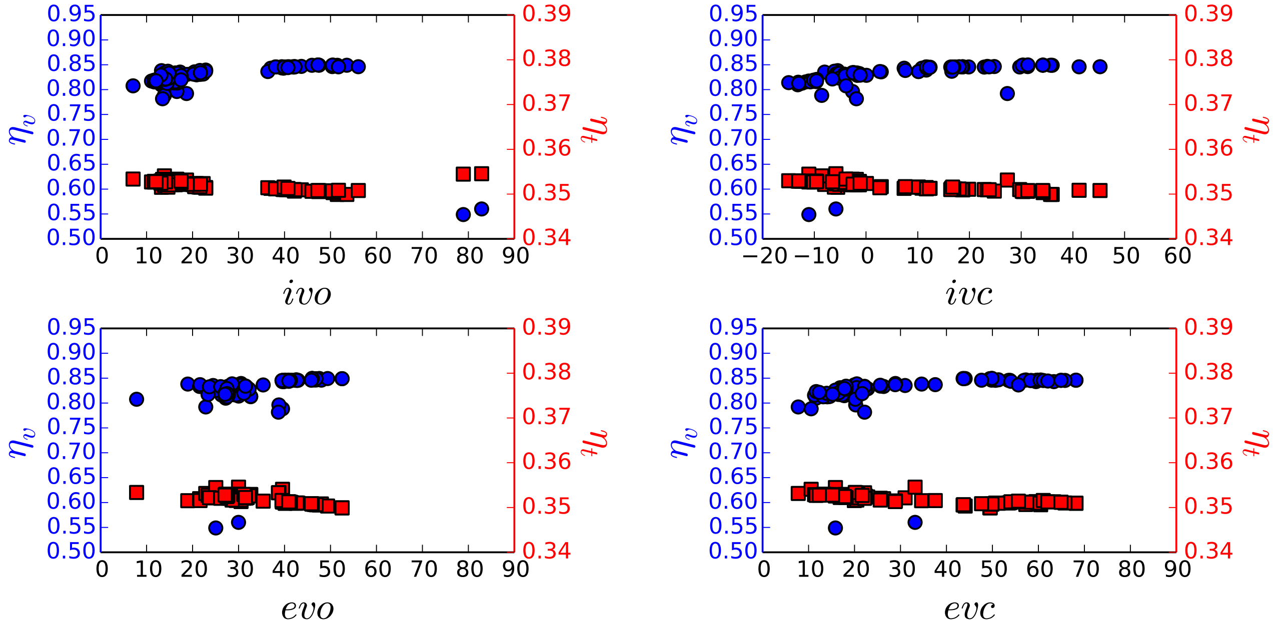

Figure 5: **Effect of design variable on the 1000 rpm simulation.**

The second speed, 2000 rpm, is plotted in Fig. 6. It has a similar behavior as the previous one, yet the results are located at a better region, where the lower values increase from 0.35 to 0.37 for η_t and from 0.55 to 0.79 for η_v. A distinguish effect can be seen with the evc, where its values are concentrated mainly between 40 and 60 degrees.

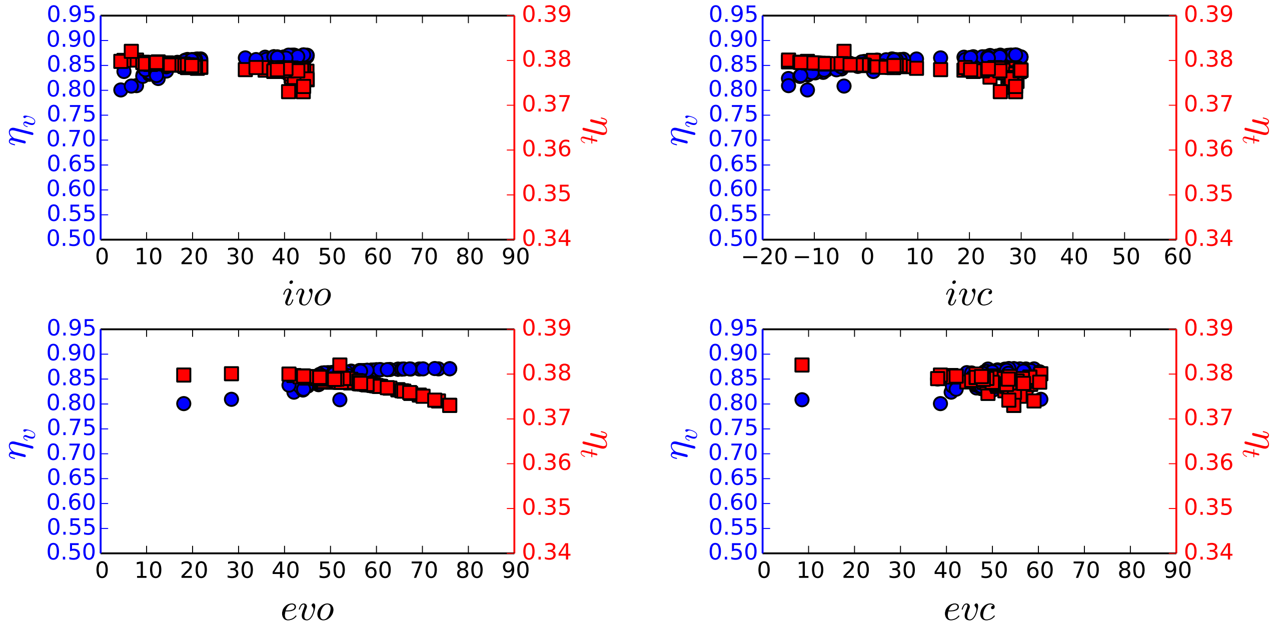

Figure 6: **Effect of design parameters on the 2000 rpm simulation.**

In Fig. 7, the design variables are shown for the engine speed at 3000 rpm and this is where the results can be more clearly seen. The most noticeable effect is within the evo variable, in which the opposite tendency as the parameter increases is very evident and abrupt (a small variation on this variable modifies both efficiencies greatly). On the other hand, all other variables (mainly for ivo and ivc, but evc as well) display a behavior similar to a Pareto Front for η_v and a linear tendency for η_t. On these ranges (50 to 60 for ivo, 40 to 50 for ivc and 60 to 85 for evc) the highest volumetric efficiencies are found, but there is a huge fluctuation (10%) in η_t, making this a not so good decision making range.

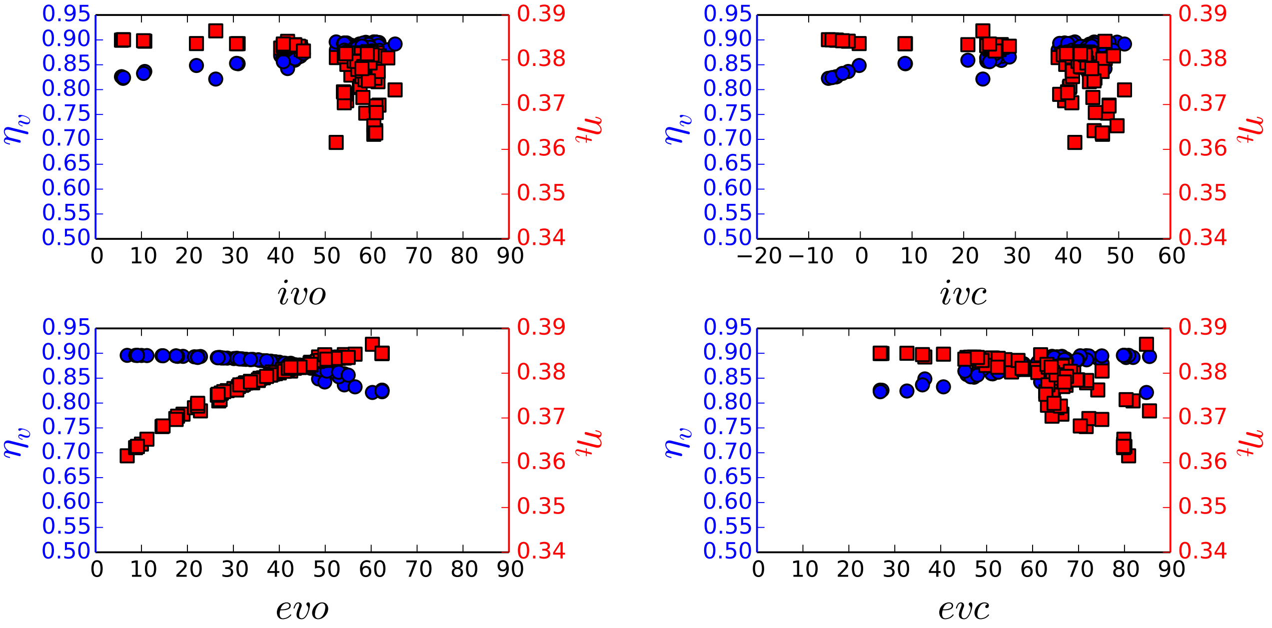

Figure 7: **Effect of design variables on the 3000 rpm simulation.**

In Fig. 8, the 4000 rpm simulation is shown. The results obtained in this optimization and the ones for 2000 rpm are analogous, although the condensation happens at evo instead of at evc, with values from 50 to 85 degrees; this high values might be due to the pressure pulsing in the exhaust process. Also, on the ivc parameter, higher angles result in higher η_t and lower η_v values, this rise on the thermal efficiency could be explained by the fluid's inertia, or RAM effect Och (2014).

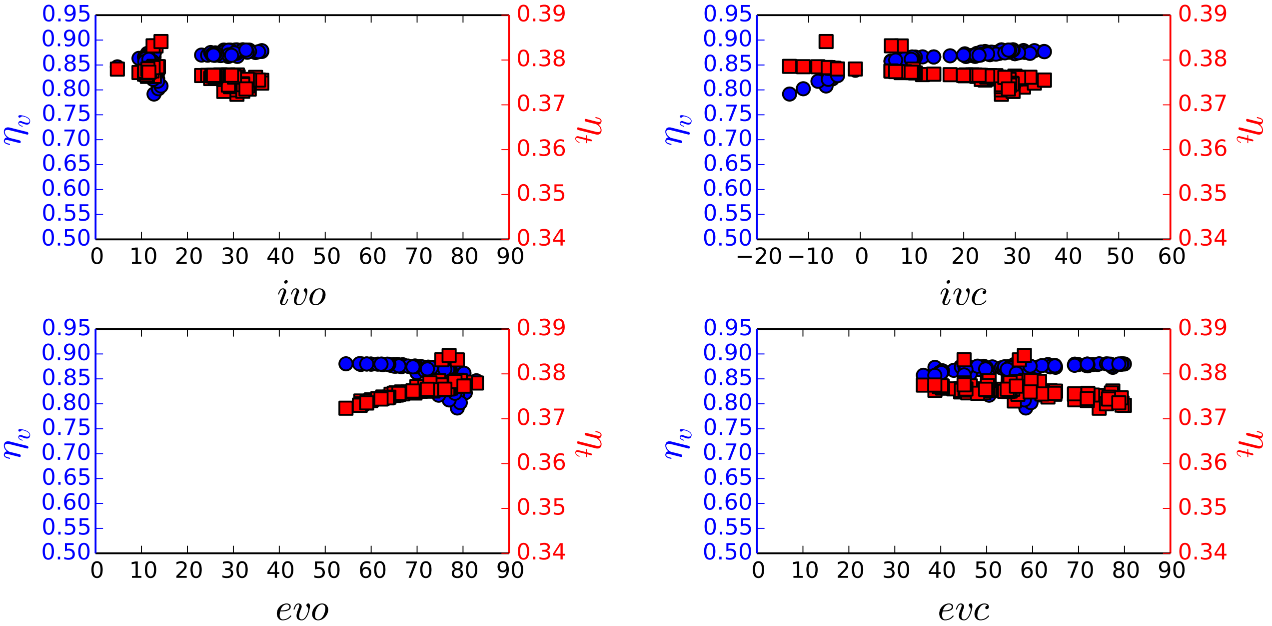

Figure 8: **Effect of design variable on the 4000 rpm simulation.**

After analyzing all the figures above, it can be inferred that the design variable with more influence on the decision variables is the evo, where there is always a trade-off happening on the decision variables. Still, not only resulting on the best approximation for the expected result, the 3000 rpm simulation issues the best results (best volumetric and thermal efficiencies) for the engine as a whole, as seen in Fig. 4.

4. CONCLUSIONS

The main purpose has been met, which was to determine which multi-objective optimization method delivers the best results. As previously mentioned by D'Errico *et al.* (2011) (when he compared it to other methods) and here proven, the NSGA-II works better in this simulation. The RSA had an acceptable result, aside from the few results obtained, with less computational usage. Hence, if no deep analysis should be done or only few points are needed, the RSA method could be the one implemented. Nevertheless, the NSGA-II provides better results in general (large amount of solutions with few repeated ones, and better efficiencies), even though it takes around 4 times more computational time than the RSA. The computation usage difference is mitigated considering that for an engine, a small gain on each efficiency has large effects on other operational variables, such as torque, power and emissions.

It could be stated that the engine performs better at 3000 rpm (higher speeds) and worse at 1000 rpm (lower speeds). Also, optimal results for 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. Regarding the design variables, there is a tendency of high efficiencies in higher evo values due to the pressure pulsing in the exhaust process, and the rise on the thermal efficiency with the increase of ivc is due to the fluid's inertia or RAM effect.

Some future researches can be proposed: analyzing deeply why each design variable affect efficiencies the way they do, repeating the process for more speeds; adding one more decision variable (emissions, for instance) and/or another design variable (inlet and outlet pipe lengths, for example); and improving the engine model to a more complex one.

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7. RESPONSIBILITY NOTICE