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IDENTIFICATION OF WIEBE AND WOSCHNI PARAMETERS USING STOCHASTIC METHOD OF DIFFERENTIAL EVOLUTION

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Abstract. *Engine testing is an expensive process, and in order to better understand the engine behavior at different conditions simulations are performed, making its research less expensive. Most simulations use empirical correlations to describe complex phenomena associated with the fast and transient nature of the combustion process, two of the most well know correlations are the Wiebe and Woschni correlation, that describe the fuel burn rate and heat transfer between gas and cylinder walls respectively. Both correlations are dependent on constants that can be adjusted to a specific engine, therefore accounting for its geometry and operation conditions used during testing. Consequently, the accurate identification of these parameters is an important step for reliable result when simulating combustion processes. This paper proposes a parameter identification of the Wiebe and Woschni correlations with the use of a stochastic method algorithm called differential evolution. The objective function used is the sum of the squared errors that compares the results of simulations using the correlations to standard test data from an engine in order to minimize variation with the test data and identify the parameters values. Results show that the algorithm can reliably reach a good solution within few iterations in a given set of predetermined domain of solutions. The found objective function value for the Wiebe correlation is 0.0255 [$(m_{burned,gas}/m_{total})^2$] with R^2 of 0.9995, and for the Woschni formulae the values are $6.38x10^{-9}$[Bar²] for the objective function and 0.999 for R^2, therefore accurately describing the test data, used for both correlations, using the differential evolution method. Furthermore, a sensibility analysis was performed for the Woschni correlation, revealing that these parameters are more easily identifiable at high engine speed, when analyzing the condition number of the coefficient matrix used.*

Keywords: *Differential Evolution, Woschni, Wiebe, Parameter Identification*

1. INTRODUCTION

Engine testing is an expensive process, and in order to better understand the engine behavior at different conditions simulations are performed, making its research less expensive. Engine simulations according to Och, (2014) fall under three categories: zero-dimensional, quasi-dimensional and multi-dimensional, each one with its specific calculation characteristic.

The simplest of those and used in this paper are the zero-dimensional models which can be further stratified in predictive and diagnosis models. Predictive models are those in which empirical equations are used to describe how the fuel burn takes place. One of the most used empirical correlations is known as the Wiebe function according to Heywood, (1988), where from burned mass fraction is possible to calculate cylinder pressure and temperature.

Diagnosis models are those where the cylinder pressure is measured during the thermodynamic cycle and used to calculate cylinder temperature and the fuel burned mass fraction.

Another key feature to consider for zero-dimensional simulations is how the heat transfer is calculated for both predictive and diagnosis models, since according to Borman and Nishiwaki, (1987), the heat flow throughout the cylinder surfaces can very between 0 and 10 MW/m² in a single point in less than 10 milliseconds and that the difference of heat flows between two point with 1 cm of distance can reach 5 MW/m² concluding that this phenomena is very complex and of transient nature, according to Velasquez, (1993). Due to the nature described, empirical correlations are used to approximate how the heat transfer occurs in the cylinder surfaces, three of the most used models are the Annand, Woschni and Honenberg correlations according to Caton, (2016), in this paper the Woschni correlation will be used.

Both correlation models of Wiebe and Woschni, use standard constants in their formulae derived from the physical characteristics of the engine and operational condition adopted during testing. The standard values used for Wiebe correlation can be found at Wiebe, (1962) and for the Woschni model at Woschni, (1967), where both authors indicate that the values can be fitted to different kinds of engine configuration to more accurately describe the fuel burn and heat transfer respectively occurring inside the cylinder. These correlations remain actual as they are currently used in most engine simulations, as reviewed by Kumar, (2013) and indicated by Broekaert, *et al*., (2017) that calibrating the adjustable parameters to a specific engine is essential for good simulations results, especially when dealing with cylinder heat transfer.

To fit the parameters described by the Wiebe and Woschni correlations, mathematical models need be used. In this paper a stochastic method will be adopted, since according to Och, (2014) they utilize only the information of the objective function used, that can be of non-linear, of difficult representation and unable to be differentiate. Several kinds of stochastic method exist, one being evolutionary algorithms following a similar principle of the evolution of populations of diverse individuals in which different genetic operators are applied and each generation subjected to a selection of the fittest individuals. The same author infers that evolutionary algorithms are approximations and that the objective is not to find an exact solution or a good numerical approximation, but the find solutions that satisfy a set of criteria (bounds) that are usually contradictory.

The goal of this work is to apply stochastic method of evolutionary algorithms namely differential evolution to fit the parameters described by the Wiebe and Woschni correlations to a specific engine dataset, leading to more accurate simulations results and furthermore perform a sensibility analysis specifically for the Woschni correlation parameters in function of engine operation conditions.

2. MATHEMATICAL MODELING

2.1 Wiebe Correlation

The Wiebe correlation is a formulae that according to Velasquez, (1993) takes into account that the combustion rate is proportional to the formation of active chemical radicals considering that the rate of generation of those radicals per unit of fuel mass is proportional to the duration of the combustion powered to a exponent do be determined. Taking the form of Equation (1), where x_b is the burned mass fraction, θ is the crankshaft angle θ_d is the combustion duration, θ_s is the beginning of combustion and ‘a’ and ‘m’ are the adjustable parameters of efficiency and form with standard values of 5 and 2 respectively, according to Caton, (2016).

$$x_b = \frac{m_{f,burned}}{m_{f,total}} = 1 - \exp\left(-a\left(\frac{\theta-\theta_s}{\theta_d}\right)^{n+1}\right) \tag{1}$$

Unfortunately, this equation was unable to describe the two-stage combustion that occurs in Diesel engines. Realizing that fact Watson *et al.*, (1980) and Miyamoto *et al.*, (1985), proposed the use of two Wiebe functions to describe Diesel combustion, one for premixed phase and another for the diffusive phase reaching good results when compared to experimental data, thus obtaining Equation (2), where X_p is the total fraction of fuel burned during the premixed combustion and subscripts ‘p’ and ‘d’ refers to the premixed and diffusive phases respectively while maintaining the same variables meaning of Eq (1). Inferring that the proposed double Wiebe equation has eight adjustable parameters, to a specific engine and operation conditions, and are a subject of continued studies as several authors such as Hu, *et al.*, (2018) analyze how these parameters can be obtained.

$$x_b = X_p\left(1 - \exp\left(-a_p\left(\frac{\theta-\theta_s}{\theta_{d,p}}\right)^{n_p+1}\right)\right) + (1 - X_p)\left(1 - \exp\left(-a_p\left(\frac{\theta-\theta_s}{\theta_{d,p}}\right)^{n_p+1}\right)\right) \tag{2}$$

2.2 Woschni Correlation

As pointed by Junior, (2002) due to the great variation in cylinder temperature and pressure, considering that the heat flow consists in a three-dimensional turbulent unsteady flow, the heat transferred to the cylinder wall is an extremely complex phenomenon. Therefore, determination of the rate of heat transfer inside the cylinder surfaces is made using empirical models found in the literature, being the Woschni model one of the most used in engine simulations. In his work Woschni, (1967) performed a series of experiments with both Diesel engines and constant volume pumps, concluding that experimental data of local wall temperature were inappropriate, since data was extremely dispersed. Instead analyzing the problem trough of thermal balances, Woschni obtained a correlation for the heat transfer coefficient (h), according to Equation (3), where A is a constant based on the engine, Dc is the cylinder diameter, T is the fluid temperature, P is the pressure and ω is the fluid characteristic velocity.

$$h = AD_c P^{0,8} \omega^{0,8} T^{-0,53} \tag{3}$$

As observed by Rakapoulos (2009), the correlation proposed by Woschni utilizes different expressions for the characteristic velocity (ω) of the work fluid during the periods of gas exchange (compression, combustion-expansion), taking into account the different levels of turbulence that occurs during the cycle, as expressed in Equation (4), where c_1 and c_2 are adjustable constants whose the standard values are bases on the engine tested by Woschni, ω_p is the piston velocity, V_h is the volume displaced, P is the cylinder pressure, P_0 is the cylinder pressure in motoring mode and V_1, P_1 and T_1 are volume, pressure and temperature of in-cylinder gas. Concluding that the Woschni correlation has three adjustable parameters, based on the characteristics of the engine used for testing and still remains relevant as its use is frequent in papers dealing with engines operation, such as the work of Czarneski, (2019).

$$\omega = c_1 \omega_p + c_2 \frac{V_h T_1}{p_1 V_1} (P - P_0) \tag{4}$$

2.3 Differential Evolution (DE)

Evolutionary algorithms are inspired by the Darwinian natural evolution and stochastic in nature as stated by Och *et al.*, (2016). The Darwinian theory states that only the best adapted individual will survive natural selection and have descendants from one generation to another. This evolution is reflected by the search of an optimal point in a given domain. The process of evolutionary optimization as stated by Och *et al.*, (2016) begins with the initialization step: individual's finite amount x_i, usually randomly picked within the domain of variables, form the initial population P_0. Followed by the variation operator (mutation and crossover) are applied in order to create a new set of individuals, called children population. These children will be evaluated and combined with their parents in order to decide which ones will replace certain parents and will be part of the next generation (selection). One important fact to consider is that is most cases the computational cost of the evolutionary algorithms is associated with evaluation of the objective function.

The evolutionary method used in this paper proposed by Storn and Price, (1997) is denominated differential evolution that creates new candidate solutions by combining the parent individual and several other individuals of the same population, therefore the method is divided in three steps: mutation, crossover and selection.

Since the computational cost of the method is associated with the evaluation of the objective function one important step is to define which function will be used. The problem proposed by this work is to identify the adjustable parameters of the Wiebe and Woschni equation. Therefore, two objective functions will be required. For the Wiebe parameters identification, the sum of squared errors will be used, comparing burned mass fraction obtained from a tested engine with the Wiebe correlation values, as expressed in Equation (5), where xb_mes is the burned mass fraction from experimental data and xb_calc is the double Wiebe function with eight identifiable parameters. This function will be minimized through de algorithm in order to identify these parameters.

$$S = \sum (xb\_mes - xb\_calc)^2 \tag{5}$$

As for the Woschni parameters a predictive model needs to be used in order to compare values in the quadratic sum of error function, since the heat flow of the cylinder cannot be directly compared to the measured cylinder pressure, for that a zero dimensional single zone model developed by Velasquez, (1993) used by Bueno, (2006) , Och, (2009) and more recently by Germano, (2020) will be used, as showed in Equation (6) where P_mes is the measured cylinder pressure and P_calc is the single zone model with three identifiable parameters. The minimization of this function via the algorithm is needed to identify the parameters mentioned.

$$S = \sum (P\_mes - P\_calc)^2 \tag{6}$$

With the objective functions defined, a domain of search needs to be established. For this work the values denominated as standard literature for the Woschni and Wiebe correlations are the ones used by Velasquez, (1993). From these values is possible to establish the range of search used by the differential evolution algorithm. Table 1, shows the upper and lower bounds used at the Wiebe identification, while Table 2, displays the values used at the Woschni correlation identification. It is important to emphasize that the ranges used represent the best bound values archived throughout several iterations, based on the value reached by the objective function used.

Table 1 – Literature data used, and search range upper and lower bounds used by the algorithm for the Wiebe correlation.

Parameters	Unit	Standard from literature	Upper Bound	Lower Bound
A_p	[-]	6.908	6.700	7.000
n_p	[-]	2.500	2.450	2.7500
θ s	[degrees]	-12.000	-13.500	-11.000
$\Theta_{d,p}$	[degrees]	25.000	23.000	26.000
A_d	[-]	6.908	6.700	7.000
N_d	[-]	1.500	1.300	1.700
$\Theta_{d,p}+\Theta_{d,d}$	[degrees]	95.000	92.000	97.000
X_p	[$m_{burned,gas\ premixed\ phase}/m_{total}$]	0.450	0.430	0.470

Table 2 – Literature data used, and search range upper and lower bounds used by the algorithm for the Woschni correlation.

Parameters	Unit	Standard from literature	Upper Bound	Lower Bound
A	[-]	820	830	810
c_1	[-]	2.28	2.35	2.20
c_2	[m/s degree K]	$3.24\text{x}10^{-3}$	$3.50\ \text{x}10^{-3}$	$3.00\ \text{x}10^{-3}$

2.4 Sensitivity analysis

Its important to several engineering problems to evaluate how a single or multiple input parameters affects the final output of a given function or model, in order to measure this influence, sensitivity analysis models are used. Usually according to Saltelli, (2004) until recent sensitivity analysis was conceived and often defined as a local measure of the effect of a given input on a given output, even with the existence of more complex global methods of analysis. This was archived by computing via direct or indirect approach the system derivatives, described in Equation (7), where η is the output of interest and β an input factor.

$$S = \frac{\partial \eta}{\partial \beta} \tag{7}$$

From Eq (7) is possible to construct system of numerical partial derivatives showed in Equation 8, displaying the matrix used for the sensitivity analysis where β1, β2, β3 represent the Woschni parameters and η represents que simulation results at a given engine operating condition. With the matrix of Equation (8) is possible to determine its condition number. According to Williams, (1986) the condition number can be used to evaluate the accuracy of the solution of a system of equations, by accessing if changes in the parameter matrix result in a great variation in the model output, being very useful to estimate the sensibility of the models at several conditions.

$$\begin{bmatrix} \sum_{i=1}^{N}\left(\frac{\partial \eta_i}{\partial \beta_1}\right)^2 & \sum_{i=1}^{N}\frac{\partial \eta_i}{\partial \beta_1}\frac{\partial \eta_i}{\partial \beta_2} & \sum_{i=1}^{N}\frac{\partial \eta_i}{\partial \beta_1}\frac{\partial \eta_i}{\partial \beta_3} \\ \sum_{i=1}^{N}\frac{\partial \eta_i}{\partial \beta_2} & \sum_{i=1}^{N}\left(\frac{\partial \eta_i}{\partial \beta_2}\right)^2 & \sum_{i=1}^{N}\frac{\partial \eta_i}{\partial \beta_2}\frac{\partial \eta_i}{\partial \beta_3} \\ \sum_{i=1}^{N}\frac{\partial \eta_i}{\partial \beta_3}\frac{\partial \eta_i}{\partial \beta_1} & \sum_{i=1}^{N}\frac{\partial \eta_i}{\partial \beta_3}\frac{\partial \eta_i}{\partial \beta_2} & \sum_{i=1}^{N}\left(\frac{\partial \eta_i}{\partial \beta_3}\right)^2 \end{bmatrix} \begin{bmatrix} \Delta\beta_1 \\ \Delta\beta_2 \\ \Delta\beta_3 \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{N}(Y_i - \eta_i)\frac{\partial \eta_i}{\partial \beta_1} \\ \sum_{i=1}^{N}(Y_i - \eta_i)\frac{\partial \eta_i}{\partial \beta_2} \\ \sum_{i=1}^{N}(Y_i - \eta_i)\frac{\partial \eta_i}{\partial \beta_2} \end{bmatrix} \tag{8}$$

3. RESULTS

Identification of the parameters described by Wiebe and Woschni were carried using the engine testing results described by Velasquez, (1993), where the author informs the engine operational conditions used and the values used in correlations mentioned for the simulation, therefore providing the standard literature data displayed in the results.

The Wiebe parameters identification settings used for algorithm were initial population of 80 individuals with maximum of 100 iterations and mutation of .2. The results of the simulation are displayed in Table (3), where the value of the objective function S shows a small error and R^2 is close to 1 revealing that the parameters calculated by the algorithm are within a good approximation of the tested data used. Table (4) shows the Wiebe parameters used by Velasquez, (1993), and the parameter values calculated by the algorithm for the eight adjustable variables. Figure (1a) displays the resulting double Wiebe function result using the parameters found compared with the compared to test data, while Figure (1b) shows the module of error between standard values and this work.

Table 3 - Results for the Wiebe correlation parameter identification

Function	Unit	Result
S	$[(m_{burned,gas}/m_{total})^2]$	0.0255
R^2	[-]	0.9995

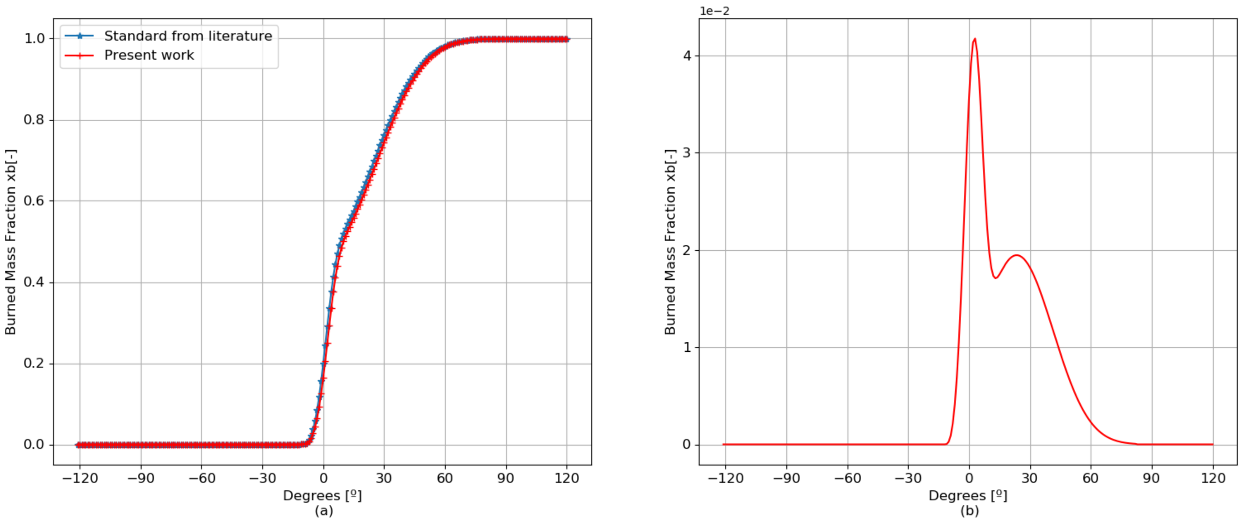

Figure 1 –(a) Comparison of the standard literature test data and present work results for the Wiebe correlation, (b) module of error between the standard literature and present work results.

Table 4 – Comparison of Wiebe correlation parameters with test data.

Parameters	Unit	Standard from literature	Present work
Ap	[-]	6.908	6.852
np	[-]	2.500	2.521
θ s	[degrees]	-12.000	-11.625

Table 4 Continuation – Comparison of Wiebe correlation parameters with test data.

Parameters	Unit	Standard from literature	Present work
$\Theta_{d,p}$	[degrees]	25.000	25,694
A_d	[-]	6.908	6.859
N_d	[-]	1.500	1.566
$\Theta_{d,p}+\Theta_{d,d}$	[degrees]	95.000	94.728
X_p	[$m_{burned,gas\ premixed\ phase}/m_{total}$]	0.450	0.444

Parameter identification for the Woschni correlation also used the same test data. Since the objective function used for the Woschni correlation has higher computational cost, test were conducted with the following settings for the algorithm: initial population of 30 individuals, maximum of 5 iterations and mutation of .2. The conducted simulation results are showed in Table (5), where the objective function S is small and R^2 is close to 1, therefore, the adjustable parameters calculated by the differential evolution algorithm are within a good approximation of the test used. Table (6), displays a comparison between the test data values and the values found, and Figure (2a) offers a graphical representation of the cylinder pressure evolution of the test data and when the found parameters are used, and Figure (2b) represents the module of error between the literature values and this work.

Table 5 - Results for the Woschni correlation parameter identification

Function	Unit	Result
S	[bar²]	$6.38\text{x}10^{-9}$
R^2	[-]	0.99999999999994

Table 6 – Comparison of Wiebe correlation parameters with test data.

Parameters	Unit	Standard from literature	Present work
A	[-]	820	813
c_1	[-]	2.28	2.30
c_2	[m/s degree K]	$3.24\text{x}10^{-3}$	$3.27\ \text{x}10^{-3}$

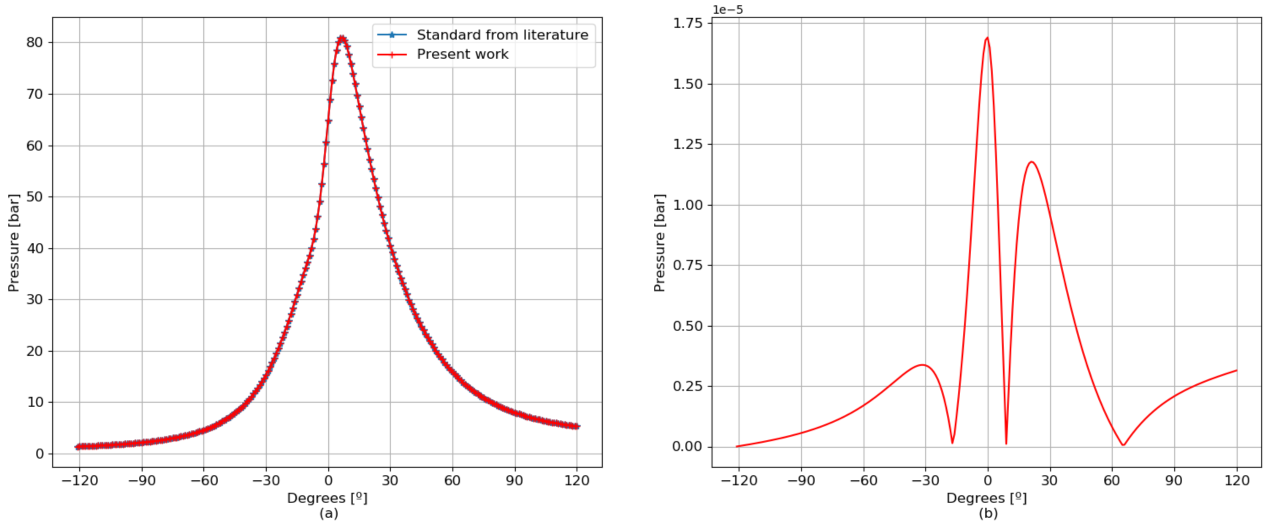

Figure 2 – (a) Comparison of the standard literature test data and present work results for the Woschni correlation, (b) module of error between the standard literature and present work results.

Results show that the parameters of both Wiebe and Woschni correlation can be accurately identified using a stochastic method of differential evolution. These can improve engine simulations to provide betters calculation results such as an more accurate value for tailpipe emissions or fuel consumption at different engine operational conditions, since both correlations play a major role at the temperature and pressure values obtained by the simulation.

The sensibility analysis performed, analyzed only the Woschni correlation parameters, as showed at Figure (3) where the curve represents the condition number of the coefficient matrix at different engine rotations used in common engine operation. The lowest engine speeds have the highest condition number, while at high speeds the condition number decreases, this represents that the capability of identifiability of the parameters increases with engine speed leading to a decrease of the number of iterations required for a successful result.

Nevertheless, this logic can only be applied when dealing with linear methods of optimization, and not being true for non-linear stochastic methods such as the differential evolution algorithm used in this paper. This fact is represented in Figure (4) where the algorithm was used with an initial population of 30 individuals and a limit of iterations of 100 per engine operation speed. Results displayed at Figure (4), show the number of iterations necessary to archive a good convergence and the computational time associated with each simulation, its important to emphasize that, the results are a mean of 5 simulations at each condition.

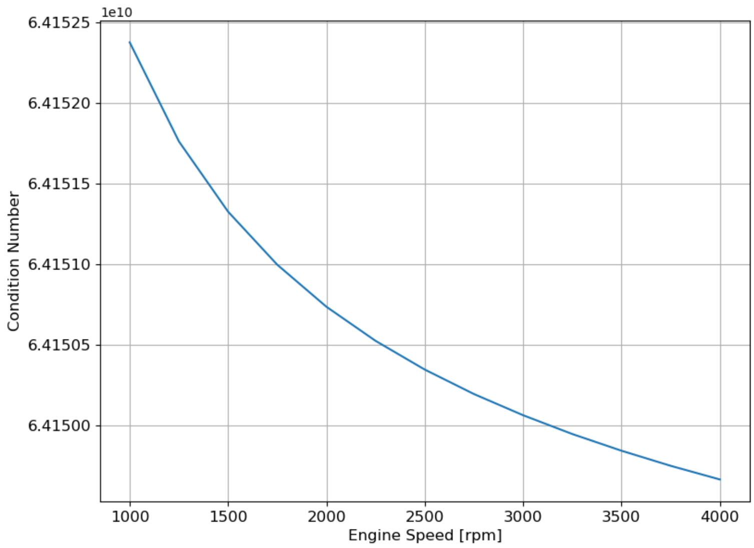

Figure 3 – Condition number for different engine speeds

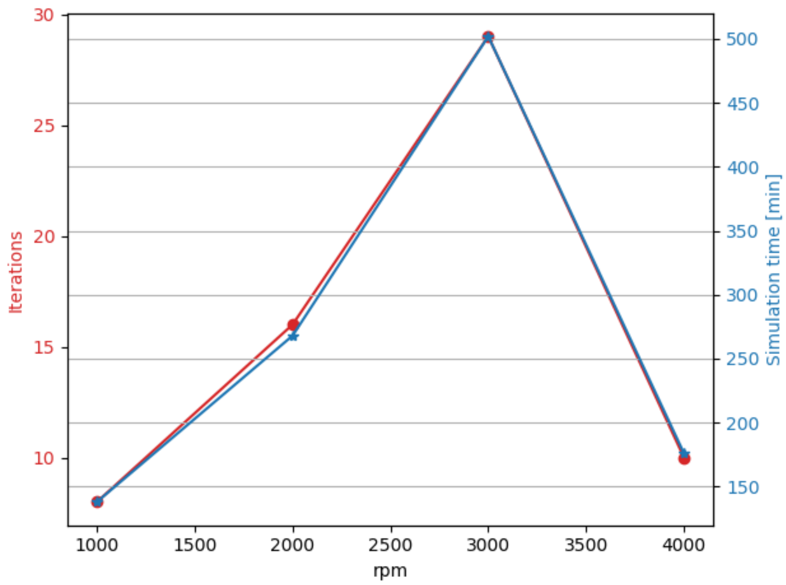

Figure 4 – Iterations and simulation time needed for convergence at different engine speeds.

4. CONCLUSIONS

The results obtained in this work showed that the use of the stochastic method of differential evolution can provide highly accurate values within few iterations when compared with the standard literature test data used, leading to a few conclusions and suggestions for future works, as follows:

- Parameters identification of the Wiebe correlation variables using the differential evolution method was reached with a low number of iterations and great accuracy, displaying the potential of being a valuable tool in engine simulations projects, since at each specific engine test condition these parameters need to be reevaluated to improve the accuracy of the simulation results.
- Identification of the Woschni correlations provided good results within few iterations, leading to accurate results when compared to test data. The close results obtained show the value of the method to better describe engine simulations heat transfer, and its results, ranging from tailpipe emissions to fuel consumption.
- The sensibility analysis performed with the Woschni correlations, revealed that identification of its parameters becomes more feasible at higher engine speed, for linear method of identification, not being true for nonlinear stochastic methods, such as the one used in this work.
- For future works is recommended that this analysis be performed with more engine test data to further explore the relations of the Wiebe and Woschni correlation with others engine variables. Currently the acquiring of further test data is impaired due to the COVID-19 pandemic.

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