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Optimization of a vehicle's electric fan parameters through evolutionary algorithms aiming a higher energy efficiency

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Abstract. In current automotive projects, the presence of new technologies aimed to maintain a better energy efficiency and, consequently, a reduction in fuel consumption is very common. Most of these technologies need a specific calibration, in order to increase the efficiency of the component, keeping its performance within acceptable limits. Regarding cooling system components, the electric fan driven by Pulse Width Modulation (PWM) is an example of technology used to enhance the vehicle's energy efficiency with less demand from the alternator and, consequently, less engine torque. Its calibration, however, is often performed in an experimental way, and many tests are performed until satisfying values are found for the calibrated parameters. The present work aims to use a computational model of the cooling system to adjust the fan control parameters of a vehicle controlled by a Fuzzy Logic based strategy. The optimization of the control parameters is performed through three different genetic algorithms - Standard Genetic Algorithm (SGA), Differential Evolution (DE) and Particle Swarm Optimization (PSO) - which are compared with each other and with the Nelder Mead algorithm (considered as a reference for comparison, since it is the algorithm used in previous works). The main purpose is to show a comparison of the coolant temperature, the percentage of the Duty Cycle and the energy spent by the electric fan, using the computational model, with each of the optimization algorithms discussed, being the energy the main parameter to be considered in the comparison. The results demonstrate a reduction of energy spent by the electric fan in relation to the reference for all the studied genetic algorithms, being the PSO and DE algorithms presenting the better results, with an energy reduction percentage of the order of 15%, followed by SGA algorithm, that presents an energy reduction percentage of the order of 12%.

Keywords: Genetic Algorithms, Cooling System Simulation, Electric Fan Control

1 Introduction

After the radiator dimensioning in the new cooling systems, it is necessary the definition of the control parameters of the vehicle's electric fan, in a way that it shows the necessary performance to cool the engine, but spending the minimum amount of energy from the vehicle's battery and alternator. Various forms of control are known and used in the industry, including the use of a lookup table or a PID (proportional-integral-derivative) control.

Direct control, performed by a lookup table is commonly used in the industry due to low cost and ease of implementation, understanding and control process. PID control is also used, but on a smaller scale. In other hand several control logic, applied in many systems use Fuzzy logic, which presents a control based on qualitative classifications of a given event or situation.

It is proposed in this work, to present a comparison of a vehicle's cooling system behavior with different calibration parameters to control the electric fan speed, as well as the comparison of the energy spent by the component when being controlled by each control strategy. Most of the electric fan control strategies are related to only one input variable. In the case of the cooling system, the main parameter that drives the fan is the vehicle's coolant temperature. For the present work, however, a proposed control strategy is applied that takes into account, in addition to the coolant temperature, the current state of thermal rejection, both of the engine and the radiator. The control parameters of the electric fan used for the aforementioned logic were calibrated in order to find a smaller amount of energy required by the component during a given cycle. The optimization and calibration of these parameters are carried out in four different ways. In the present work, a comparison of the energy spent by the fan is presented, using each of the optimization algorithms discussed later.

Thermal system modeling in general is present in several studies, and the models and equations presented by some of them served as the basis for the vehicle's cooling system model developed and presented in Silva [1]. In Yoo et al. [2], a simple model is presented, used for modeling the cooling system of a vehicle, in which it is understood as an energy storage, composed of coolant fluid, oil, engine block and head cylinder, such that the energy level of the system can be expressed as its temperature.

In a simple way, the vehicle's cooling system has a heat source, from the fuel combustion in the engine, and several sources of energy loss, shown in general in Fig. 1.

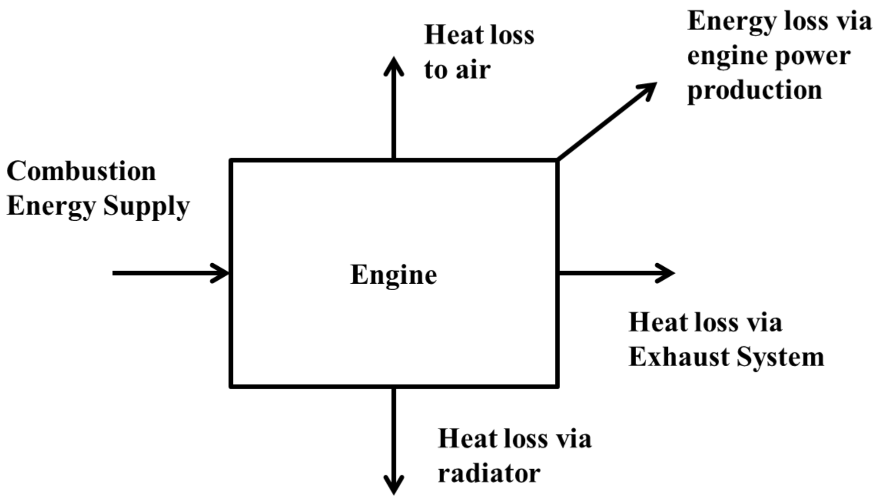

Figure 1. Energy sources associated with the internal combustion engine. SOURCE: Adapted from Yoo et al. [2]

The source of energy loss treated in the present study is the loss of heat to the coolant, rejected in the radiator. After combustion, part of the heat generated inside the cylinders is transferred to the coolant, heating it up. When leaving the engine, the thermostatic valve distributes this liquid to the components of the vehicle's cooling and air conditioning system. When the coolant has a temperature higher than the opening of the thermostatic valve, part of it goes to the radiator and is then cooled, Yoo et al. [2]. In most passenger vehicles, the cooling module is composed, in addition to the radiator, by the heat exchanger of the air conditioning system (condenser) and by the electric fan.

The electric fan of the cooling system is the component responsible for forced ventilation in the vehicle's radiator when it is stopped in operation or at low speeds, since even in these conditions the engine still needs to be cooled, Bosch [3]. The majority of the electric fan are made on plastic and its power depends on the vehicle's cooling system dimensioning. This component can have discrete control, in which it is activated at certain speeds depending on the vehicle's coolant temperature or the pressure of the air conditioning system. By the other hand, the component activated speeds can also be continuous, in such a way that the electric fan can perform numerous rotation speeds, being gradually controlled, Vasca and Ianelli [4]. This component has high importance in the vehicle's thermal management and recently, studies have focused on the optimization of the fan speed, minimizing power usage while rejecting sufficient heat by the radiator, Tao and Wagner [5]. Wang and Wagner [6], created a mathematical model to describe the cooling system transient thermal behavior. The thermal management system is composed by a smart valve, a variable speed coolant pump, a radiator fan matrix and sensors. Based on the thermal model, the authors developed a Lyapunov based nonlinear control system to activate the electric fan matrix, aiming the engine temperature tracking. Aiming a higher energy efficiency, the new automotive projects are more frequently applying variable speed controlled electric fans, activated by Pulse Width Modulation (PWM), Paparrizos [7]. Besides the advantages found in the conventional electric fans, the PWM controlled fans have a higher mechanical reliability, Rodrigues [8].

Regarding thermal management optimization, developed studies also concern all components of the cooling system as a whole. Tao and Wagner [5] propose a work to examine the thermal management system for a military ground vehicle, synchronously regulating the radiator fan, coolant pump and smart valve operations. The goal is to control the components in order to track a prescribed reference temperature, considering the components power consumption. Kalelı et al. [9] proposed a thermal management system for internal combustion engines aiming an optimal distribution of the heat transfer. They compared the proposed thermal management system with a traditional internal combustion engine cooling system, regarding exhaust emission values. An electrical coolant pump and control valve are the control inputs for the model proposed by the authors.

An important issue regarding thermal management is finding the optimal control parameters of the applied components in order to guarantee both the thermal performance and the energy consumption reduction of the analyzed components. A powerful tool regarding optimization problems is the Evolutionary Computation, which according to Gosselin et al. [10], although the Genetic Algorithms have been developed in the 70s decade, their utilization in heat transfer problems is recent. In his work, Gosselin et al. [10] presents a review survey about the application of Genetic Algorithms in heat transfer problems. In order to perform the task of finding the best control parameters of the thermal management system maintaining the minimum energy consumption as possible, the Evolutionary Computation can be applied.

The present work uses computer simulation to estimate the thermal behavior and the energy spent by an electric fan controlled by PWM, using different control parameters, as it presents a better control possibility and a gain in load consumption in relation to the electric fan controlled by discrete voltages. The work proposes to present a comparison of a vehicle's cooling system behavior when the electric fan is controlled by a Fuzzy logic based control strategy, presented in the subsection: Electric Fan Controlling. It is also showed a comparison of the energy spent by this component when the Duty Cycle control parameters are optimized by three different Evolutionary based algorithms. The three algorithms used to optimize the control parameters are Standard Genetic Algorithm (SGA), Differential Evolution (DE) and Particle Swarm Optimization (PSO). All the three optimization algorithms studied are going to be compared with each other and also with a reference algorithm, the Nelder-Mead (present in the function *fminearch* from Software Matlab), already studied in Silva [1].

Firstly, the work addresses the methodology of thermal and radiator modeling, to estimate the behavior of the cooling system as a whole, necessary for the simulation of each one of the control algorithms. The strategy used to control the electric fan is presented in the topic: Electric Fan Controlling. After discussing the strategy used to control the component, the optimization algorithms used to adjust the control parameters of the component through the strategy discussed are presented. The cycle used for the optimization of the parameters, as well as analysis of the cooling system behavior is discussed in the computational simulation section. Finally, the results obtained and the conclusions of the work are presented, as well as further suggestions for future works.

2 Methodology

The present study utilizes a simulation model of the liquid/air cooling system, widely used in automotive vehicles, with the purpose of estimating the behavior of the coolant temperature over a speed cycle through the use of an electric fan control strategy, previously defined. The thermal modeling as well as the liquid model in the radiator, were developed through the interaction between several studies and formulations found in the literature and discussed with more details in Silva [1]. With the cooling system model, the energy spent by the electric fan is estimated using four different control tables, which are compared with each other, aiming at greater energy efficiency and, at the same time, being able to maintain the system temperature in optimal operating levels (between 90 and 105 ° C).

The developed modelling and simulation procedure of the vehicle's engine cooling system is illustrated in the flowcharts presented in Fig. 2 and Fig. 3.

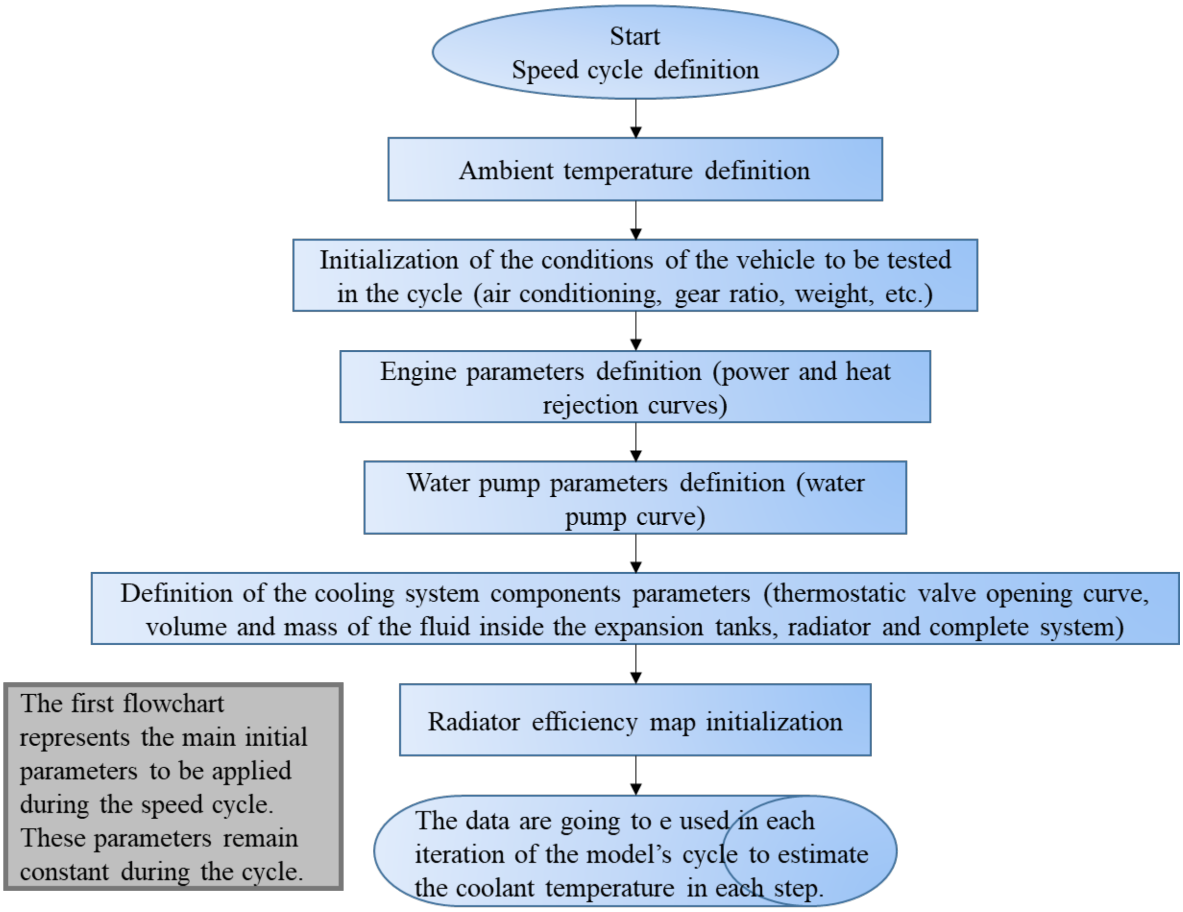

Figure 2. Flowchart of the parameters initialization steps in the model.

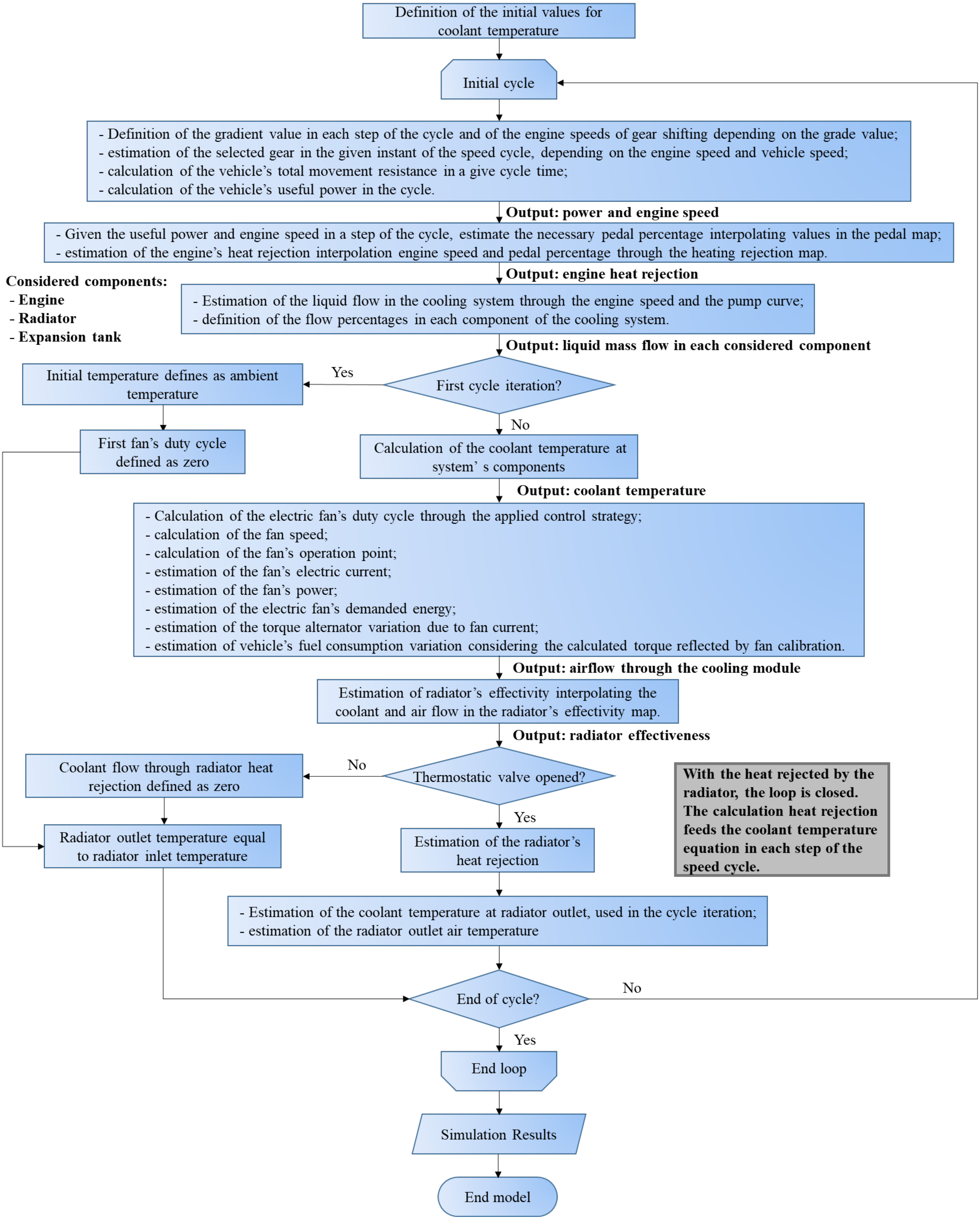

Figure 3. Flowchart of the parameters initialization steps in the model.

2.1 Radiator Modeling

According to Bosch [3], the radiator is a heat exchanger responsible for removing the heat from the liquid that exits the engine at a high temperature so it can continue dissipating the heat derived from the combustion inside the engine. This component has fins that promote a higher heat exchange between the air and the liquid flowing inside the component.

The present study uses the effectiveness method to develop the model of the cooling system radiator. The estimation process of each one of the parameters and procedures are showed on the flowchart of Fig. 2 and Fig. 3, but they are not going to be deeply discussed in the present work. More details about the applied model to estimate these parameters and the formulation used to model the cooling system as a whole can be found in Silva [1].

The effectiveness method is a method that uses the effectiveness of a heat exchanger in removing certain amount of heat in order to estimate the liquid temperature at inlet and outlet of the component Barros [11]. The effectiveness of a heat exchanger can be defined as showed in eq. (1).

$$\varepsilon = \frac{Real\ heat\ exchange}{Maximum\ heat\ exchange} \tag{1}$$

By definition, the effectiveness, a dimensionless parameter, must be in the range $0 \leq \varepsilon \leq 1$. In the model applied in the present study, the effectiveness of the heat exchanger is obtained from a bench test in which its value is calculated as a function of different values of coolant and air flow in the component. Once the effectiveness values for each heat exchanger operating situation are estimated, and the coolant and air inlet temperatures in the radiator are known, the actual heat transfer rate can be determined by the expression of eq. (2):

$$q = \varepsilon \cdot C_min \cdot (T_{liq_{in}} - T_{air_{in}}) \tag{2}$$

Where C_min is the minimum thermal capacity between the liquid and air thermal capacities; $T_{liq_{in}}$ and $T_{air_{in}}$ are the liquid and air inlet temperatures respectively in the heat exchanger. Finally, it is possible to calculate the water and air outlet temperatures through the energy balance of eq. (3):

$$\Delta T = \frac{q}{m \cdot c_p} \tag{3}$$

At the end of all calculations, the radiator inlet and outlet temperatures are found. These results are compared with the experimental results obtained from test cell, and analyzed so that the appropriate conclusions about the procedure can be drawn. Table 1 shows the calibration results of the model in the stabilized cycles. During this phases the main objective is the correlation between the coolant temperature after reaching steady state, found in physical test, performed in a controlled test cell and computational simulation. Finally, after calibrating the model in stable phases, the thermal masses were finally adjusted with an unstable cycle correlation with physical tests, as shown in Fig. 4. The curve corresponds to a situation with high variation of heat rejection and electric fan duty cycle. More details about the model calibration and correlation can be found in Silva [1].

2.2 Electric fan controlling

Through a computational model capable of simulating a vehicle's cooling system temperature it is possible to perform the study of different control parameters of the fan speed. With the electric fan control parameters modification, it is possible to compare the energy spent by the component, looking for a higher energy efficiency.

The following sections present a description of the strategy applied in the electric fan controlling studied in the model as well as the respective possible adjusts are going to be discussed, aiming a lesser energy spent by the electric fan. The different optimization algorithms used to adjust the control parameters of the presented strategy are also going to be explained.

2.2.1 Electric fan control logic

For the control of the electric fan in the present work, a strategy similar to a lookup table control strategy was used, but unlike this strategy, the target temperature is no longer a single defined value, but a range of values. In

Table 1. Comparison between the results obtained with test cell physical tests and computational simulation, during the model calibration.

Phase	Speed $[km/h]$	Grade $[\%]$	Air Conditioning	Measured Temperature $[C]$	Simulated Temperature $[C]$	Percentage Error $[\frac{(TM-TS)}{TM}]$
Phase 1	23	9	Off	65.9	65.6	0.45%
Phase 2	42	6	Off	66.0	67.4	-2.12%
Phase 3	42	6	On	70.5	74	-4.96%
Phase 4	42	9	Off	67.8	69.6	-2.65%
Phase 5	42	9	On	72.5	76.1	-4.96%
Phase 6	140	0	On	70.7	73.2	-3.54%
Phase 7	0	NA	On	53.7	55.5	-3.35%

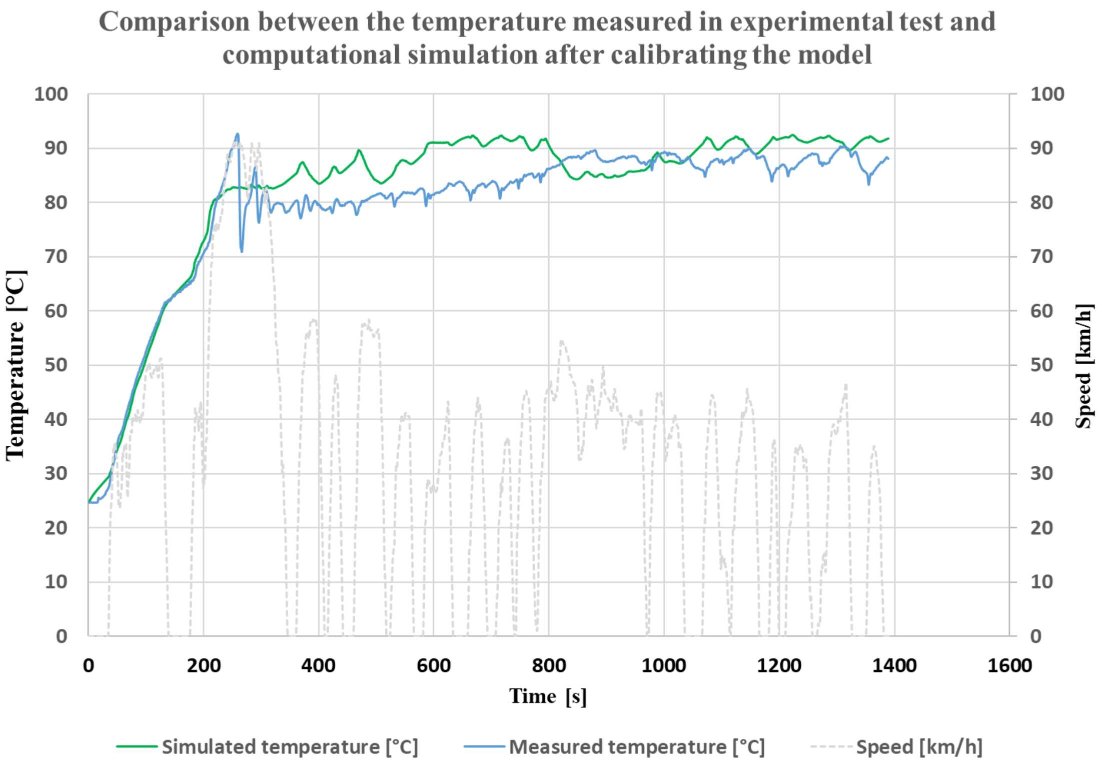

Figure 4. Calibration of the cooling system model in transient situation, through the comparison of the simulated coolant temperature with test cell experimental result.

addition, the duty cycle increment of the electric fan depends on both a range in which the temperature is located and the thermal rejection of the battery and the radiator. Table 2 shows the parameter used to perform the Duty Cycle increment. The values of the first column on the left refer to the current coolant temperature, which can be in a certain range of values, defined as described below:

Low: Temperature below 30°C
Warm: Over 30°C and below 35°C;
Ideal: Above 35°C and below 40°C;
Attention: Above 40°C and below 50°C;
Critical: Above 50°C.

Similarly, the first line of the table refers to values of the difference between the heat rejected by the battery and the heat rejected by the radiator of the vehicle. They are defined as:

Very positive: the difference is greater than one tenth of the heat rejected by the battery;
Ideal: the absolute value of the difference is less than one tenth of the heat rejected by the battery;
Very negative: the heat rejected by the radiator is at least one-tenth greater than the heat rejected by the battery.

The other values in the table refer to the Duty Cycle increment of the fan, depending on the situation of the coolant temperature and the difference between the heat rejected by the battery to the coolant and from the coolant to the air in the radiator. Table 2 shows the Duty Cycle increment parameters used to control the fan speed during the speed cycle.

Table 2. Reference duty cycle increment control parameters of the electric fan speed

	Very Positive	Ideal	Very Negative
Low	-9.06	-8.64	-9.05
Warm	-0.22	-1.74	-4.25
Ideal	0.739	-0.492	-10.3
Attention	2.51	1.33	-1.58
Critical	10.3	3.37	-2.45

The first values used for the control of the electric fan, were obtained from an optimization algorithm, which used the *fminsearch* function of the software Matlab to find the optimized control parameters. The energy spent by the electric fan using this first control logic and optimized by the specific Matlab function will be compared with the control parameters optimized by evolutionary algorithms, presented in later in this work. The table with the reference control parameters is shown in table 2.

Fuzzy logic concepts

A concept widely used in controllers, which uses artificial intelligence, is the concept of Fuzzy logic. In the present work, this concept was used to define the temperature range in which the coolant is found, and the logic defined for the membership of each of the temperature levels is illustrated in Fig. 5. After calculating the membership of each temperature level for a given coolant temperature value and a given radiator and engine thermal rejection value, the *defuzzification* to the temperature level of the coolant and consequently to electric fan duty cycle is done according to the maximum or minimum membership value, depending on the thermal rejection of the engine and radiator. Figure 5 shows the membership curves and the *defuzzification* for each one of the radiator and engine thermal rejection situations.

Optimization of the control parameters of the Fuzzy logic based strategy

Two different optimization algorithms performed the control parameters adjustment. Each one of them are going to be discussed in the next sessions. The optimization algorithms modified only the duty cycle breakpoints column, in such a way that all the values of temperature breakpoint remained the same. The following algorithm can represent the optimization process performed:

- minimize the energy spent by the electric fan, knowing: the coolant temperature, the engine heat rejection, the radiator and engine heat rejections, the duty cycle increment values depending on the coolant temperature and the difference between thermal rejection of the engine and radiator, the electric fan power as a function of the duty cycle;
- determine: the duty cycle increment values from table 2, minimizing the energy spent by the vehicle's electric fan during a certain speed cycle;
- variables: duty cycle increment values;
- subject to: coolant temperature cannot overpass an established limit, defined as 105ºC.

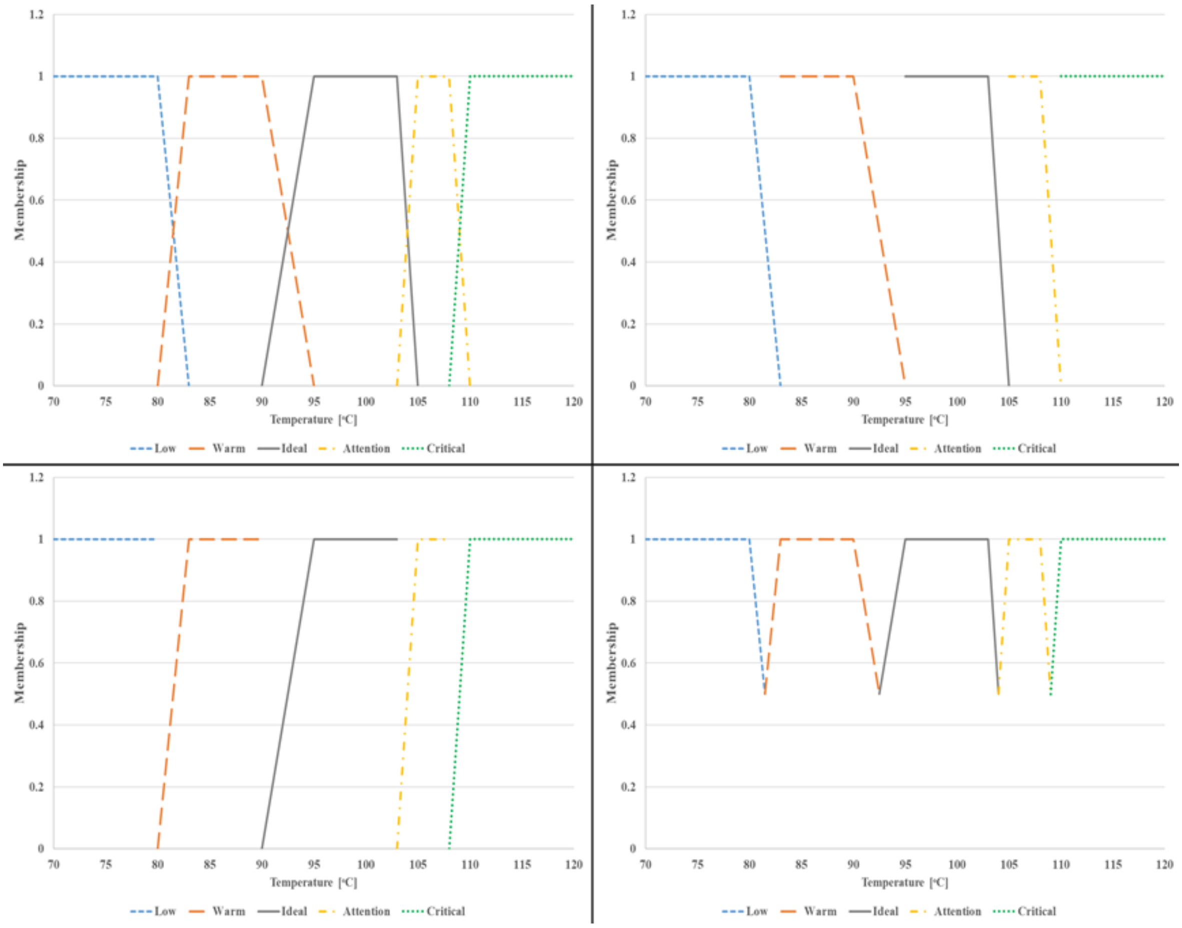

Figure 5. Membership curves applied in each temperature range. Up Left: trapezoidal membership functions representing each temperature range. Up Right: prioritized membership groups in the case of negative heat rejection difference. Down Left: prioritized membership groups in the case of positive heat rejection difference. prioritized membership groups in the case of ideal heat rejection difference.

2.3 Control parameters calibration

The calibration of the control parameters was performed in four different ways. The first has already been carried out previously for the generation of reference parameters, whose results are compared with the other forms of calibration. These parameters were generated using the *fminsearch* function of the Software Matlab, which uses the Nelder-mead optimization algorithm. The values generated by this algorithm are shown in table 2.

The next procedures used for the optimization of the electric fan control parameters use evolutionary algorithms in order to find the optimal values. For all of them, as well as the reference calibration, the the cooling system limit temperature is set as 105°C, defined due to lessons learned during the system calibration and design. Three evolutionary algorithms were used, presented below.

2.3.1 Standard Genetic Algorithm

In this algorithm, the standard approach of genetic algorithms was used to calculate the control parameters, with the presence of crossover, mutation and selection. Initially a random population is defined, containing 35 individuals. Each individual has 15 real variables, representing the duty cycle increment values from table 2, and each one is optimized in order to obtain the lowest energy spent by the electric fan.

The parent selection for crossover is carried out by tournament, where the tournament size is defined as 80% of the total population. Within the tournament, elitism is carried out in order to reduce the likelihood of premature convergence. After selecting adults, two parents are randomly selected to perform the crossover. The population was defined as generational, and each pair of adults can generate two children with a certain probability of crossing over, if the probability of crossover is not reached, the parents are selected for the next generation.

After the crossover process, the next procedure performed by the algorithm is the mutation, which occurs with a certain probability previously calculated, depending on the diversity of the population. The mutation occurs in such a way that, at each iteration of the cycle, a mutation probability value is calculated, and, if this value is reached, the mutation process will occur in the defined number of individuals. Two types of mutation process were implemented, a first less aggressive type, performed by a process, similar to Swap Mutation. In this process two values from the Duty Cycle increment table are randomly selected, and their allele values are swapped. The other mutation process, a more aggressive type, called Reset Population, occurs according to specifics diversity criteria defined in the algorithm.

Before the crossover and mutation processes are carried out, it is necessary to define the probability that these processes will occur. Both the crossover and mutation probabilities are calculated in the algorithm at each iteration, taking into account the diversity of the current population. Given a population, the diversity is calculated by eq. (4)

$$d = \frac{\sum_{i=1}^{N} |f(x)_i - \overline{f(x)}|}{N} \tag{4}$$

where $f(x)$ is the value of the energy calculated for the electric fan with the i-th individual; $\overline{f(x)}$ is the electric fan average energy calculated for all individuals; N is the size of the population.

Maximum and minimum values of population diversity is also defined, in such a way that these values also influence the probabilities of crossover and mutation. The maximum crossover probability and minimum mutation probability are defined when the diversity is greater than an upper limit while the minimum crossover probability and maximum mutation probability values are defined when the diversity is less than a certain value. If the diversity is between its maximum and minimum value, the probabilities are calculated dynamically as a linear function between the maximum and minimum values, for each of the probabilities. Figure 6 illustrates the procedure for calculating the crossover and mutation probabilities, in relation to the electric fan spent energy diversity.

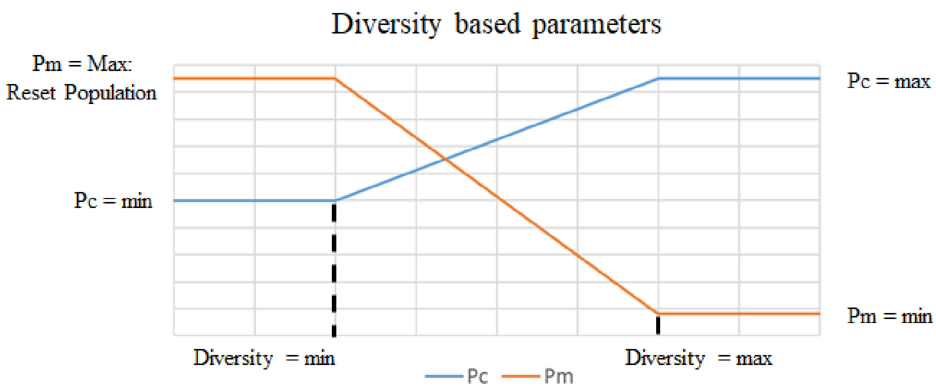

Figure 6. Hiperparameters dynamically adjusted during SGA algorithm, based on the diversity.

The results obtained for the energy spent by the electric fan in the simulated cycle with the parameters optimized by the standard genetic algorithm, as well as the new table generated with this algorithm are presented later in the results section.

2.3.2 Differential Evolution

The next algorithm used for the electric fan control parameters optimization uses a differential evolution algorithm. Initially, a random population is defined, and each individual is composed of a vector of 15 variables, representing each one of the duty cycle increment values from table 2, from which the process of differential evolution is carried out. During the optimization process with this algorithm, the diversity variable is also used to assist in the search for the global optimum, reducing the probability of being attracted to local optimums. The population diversity acts on two variables: the crossover probability the scale factor (F) applied to the difference vector. Figure 7 and table 3 illustrate the crossover probability and Scale Factor adjustment related to the diversity of the electric fan spent energy found for each population. The values applied for each hyper parameter were adjusted and defined during the model development.

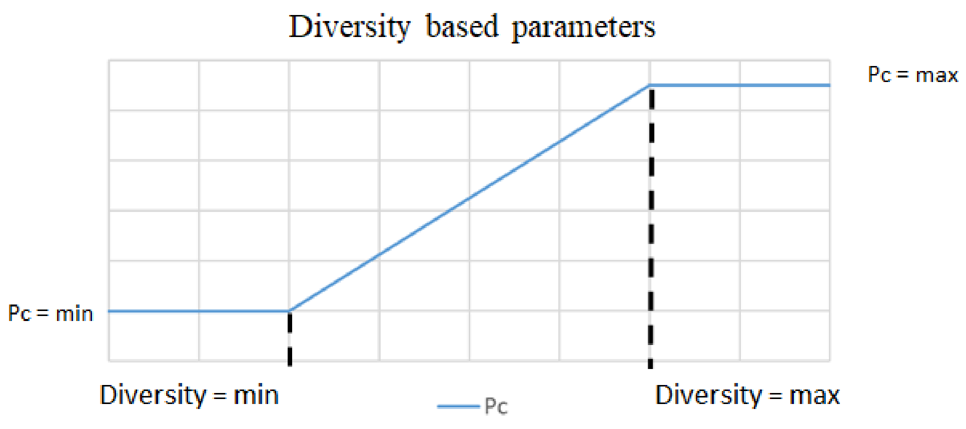

Figure 7. Dynamic adjustment of the crossover probability applied on the differential evolution algorithm

Table 3. Scale Factor adjustment applied on the differential evolution algorithm

	$F(x) < Div_{min}$	$Div_{min} < F(x) < Div_{max}$	$F(x) > Div_{max}$
Scale Factor	$F = U[0.5, 2]$	$F = U[0.5, 0.9]$	$F = U[0.1, 0.4]$

The remaining processes of the algorithm occur normally, according to the classic version of the differential evolution algorithm theory, represented by eq. (5) to eq. (7)

$$\mathbf{v}_(t,i) = x_{t,r1} + F(x_{t,r2} - x_{t,r3}) \tag{5}$$

Where $x_{t,rN}$ are individuals represented by the control parameters vectors, chosen randomly from the population, $r1, r2andr3 \in [1, 2, ..., N]$.

$$u_{t,i,j} = \begin{cases} \mathbf{v}_{t,i} & \text{if } U_{[0,1]} \leq p_c \wedge j = \delta_i \\ x_{t,i,j} & otherwise \end{cases} \tag{6}$$

$$x_{t+1,i} = \begin{cases} \mathbf{u}_{t,i} & \text{if } U_{[0,1]} \leq p_c \wedge j = \delta_i \\ x_{t,i,j} & otherwise \end{cases} \tag{7}$$

Where $u_{t,i,j}$ and $x_{t+1,i}$ are the test population and the survival population chosen by next generation respectively.

2.3.3 Particle Swarm Optimization

The evolutionary based algorithm used, Particle Swarm Optimization (PSO), is also applied in the Duty Cycle breakpoints of the lookup table strategy. The type of PSO algorithm used is the Global Best Constricted PSO, in its synchronous form. Initially it is created a random population (Swarm) and the model calculates the cost for each created particle, represented by the total energy spent by the electric fan at the end of the defined cycle. In this moment it is also defined an initial speed equal to zero and the initial personal cost is calculated for each particle. The next step is defining a better global cost, represented by the best cost among all the particles. Each particle speed in the next iteration is defined by eq. (8).

$$\mathbf{v}_i(t+1) = \chi\{w\mathbf{v}_i(t) + \phi_1[\mathbf{p}_i(t) - x_i(t)] + \phi_2[g(t) - \mathbf{x}(t)]\} \tag{8}$$

Where $\phi_1 = c_1 * r_1$ and $\phi_2 = c_2 * r_1$, being defined $c_1 = c_2 = 2$ and $r_1 andr_2$ real numbers randomly chosen in the interval $[0, 1]$. The variable $\chi = 1$ and w randomly defined in the interval $[0, 1]$, during all the optimization process in each iteration and for each particle.

After the speed calculation for the next iteration, a possible position for each particle is given by eq. (9).

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \tag{9}$$

After this step, the model calculates the cost for each particle and if the cost is lesser than the personal cost of the respective particle, the position is updated. This process repeats until the total number of iterations is reached, returning the lowest personal cost (global minimum among all particles).

2.3.4 Evolutionary algorithm simulation parameters

The evolutionary algorithm is simulated with the following parameters defined for population, variables and iterations:

- Population Size: 35 individuals/particles
- Optimizing variables number: 15
- Total iterations number: 200
- Total evaluations number: 700

2.4 Computational Simulation

To perform the computational simulation it is used a vehicle's cooling system simulation model, whose previous calibration and correlation are described in Silva [1]. In the present work, all parameters concerning the model were used as described in Silva [1], except during Fuzzy control table parameters optimization, in which the duty cycle increment parameters are calculated and optimized by the proposed algorithms.

The simulated cycle consists of a simple speed cycle in such a way that the cooling system temperature is estimated as well as the required energy by the electric fan during the cycle. The objective of the computational simulation is to compare the total spent energy by the electric fan at the end of the speed cycle, controlled by the adjusted strategy calibrated by the fminsearch function from the software Matlab [12] and by the evolutionary algorithms discussed. Figure 8 represents an illustration of the developed cycle used to compare the optimization algorithms.

3 Results

Table 4 present the control parameters values, optimized with each one of the evolutionary algorithms previously presented. Subsequently, the results showing the vehicle's cooling system behavior will be presented with each of the control tables tables presented, as well as the energy spent by the electric fan and its duty cycle. The control table presented in table 2, found with Nelder Mead algorithm, is considered as the reference to be compared with the evolutionary algorithms results.

Table 4. Control table parameters adjusted by Evolutionary Algorithms

	Standard Genetic Algorithm			Differential Evolution			Particle Swarm Optimization		
	Very Positive	Ideal	Very Negative	Very Positive	Ideal	Very Negative	Very Positive	Ideal	Very Negative
Low	0	0	0	-2.45	-0.65	-5.13	-10.5	-4.35	-8.16
Warm	-7.99	0	0	-0.163	-6.76	-0.685	-15.3	-27.4	-14.1
Ideal	-3.80	-8.5	-9.12	-4.16	-2.81	-9.07	-27.7	-3.95	-7.03
Attention	5.99	-2.33	9.86	6.96	-11.2	-1.08	7.37	-10.5	-6.93
Critical	4.91	0.728	9.40	-19.7	-5.05	-10.8	4.42	0.79	9.86

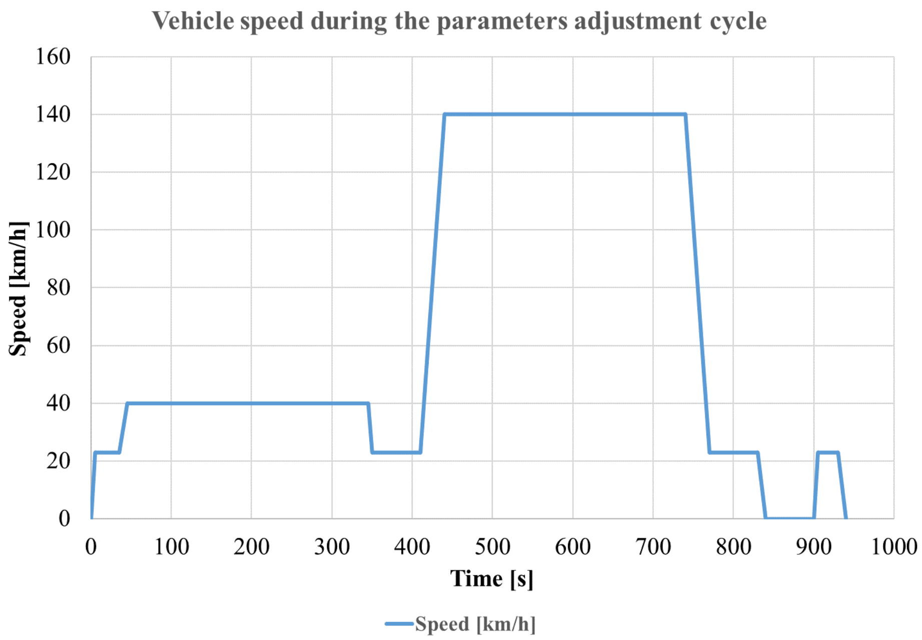

Figure 8. Illustration of the control parameters optimization speed cycle, composed by consecutive stable speeds

3.1 Results of cooling system behavior

Initially, a comparison of the cooling system temperature behavior is presented with each one of the control table parameters, discussed in the previous sections. Figure 9 presents the curve comparing the simulated temperature with the four control parameters presented.

The temperatures remains similar for almost the whole cycle, however, at the end, a lower temperature value is noticed for the electric fan controlled by the fminsearch function optimized table, this fact is probably due to the presence of a higher percentage of duty cycle by the electric fan, what is confirmed in Fig. 10, which shows the duty cycle percentage of the component throughout the simulation.

The analysis of Fig. 10 shows that at different time intervals, when the other strategies were still with duty cycle equal to zero, the Nelder-Mead algorithm already starts the component's operation, which means more energy spent by the fan. In addition, at several other points, it can be seen that on average, the Nelder-Mead algorithm remains above the other evolutionary algorithms. These, by the other hand, presents percentages of duty cycle very similar throughout the cycle, with in some points a little more presence of electric fan in one of them, mainly in the time interval between 400 and 500 seconds, when there is a small difference between the duty cycle speed decreasing from 100% to 0% in relation to the SGA and the other evolutionary algorithms, DE and PSO. This behavior can be demonstrated in Fig. 11, which shows the energy spent by the electric fan throughout the cycle. From this graph, it can be seen that all strategies remains with a similar energy behavior, with the genetic algorithm having the total energy spent slightly lesser than all the other algorithms, until the time of 400 seconds. From that moment on, however, coinciding with the moment in which there is a difference in the the duty cycle reduction, mentioned above, the total energies of the Nelder-Mead and SGA (Standard Genetic Algorithm) algorithms present higher values than the other algorithms: Differential Evolution and Particle Swarm Optimization. This fact shows the better performance of the PSO and DE optimization algorithms to find parameters for the electric fan control table, capable of more efficiently activating the component when needed. With the control table generated by these two algorithms, the speed of Duty Cycle decreasing in the high speed phase, beginning after 400 seconds, happens in a faster way compared with SGA and Nelder-Mead. That is, the energy spent by PSO and DE in this phase reached lower levels faster than the remaining algorithms, what demonstrated to be crucial to the results achieved. It can be also noticed, in 800 seconds similar results, where Nelder-Mead algorithm increase its Duty Cycle percentage earlier comparing with other algorithms, while Differential Evolution and Particle Swarm Optimization activate later.

Table 5 presents a summary of the results obtained for the total energies spent by the electric fan with each of the discussed algorithms. It is evident that the Differential Evolution and Particle Swarm Optimization algorithms

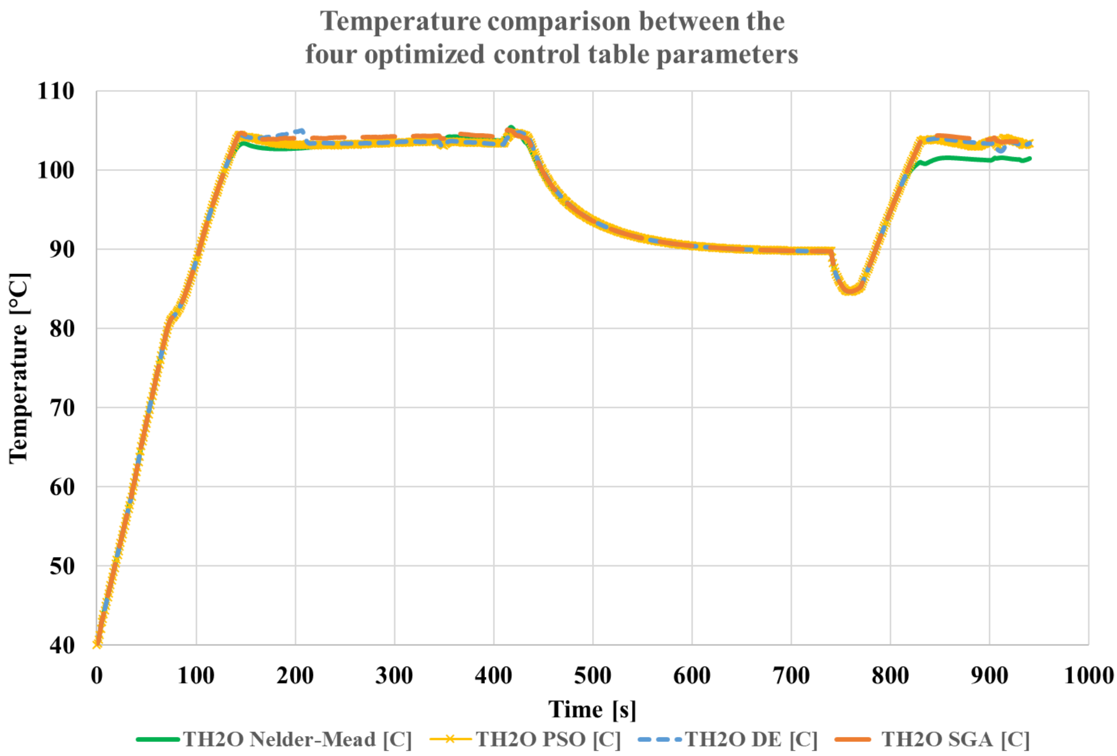

Figure 9. Comparison of the cooling system temperature behavior for each one of the control tables

shows the greatest percentage of energy reduction in relation to the reference (Nelder-Mead). The classical genetic algorithm (GA) showed a considerable reduction, but less than the two mentioned above.

Table 5. Summary of the energy spent results compared with reference (Nelder-Mead), where EA is the correspondent evolutionary algorithm and NM is the Nerder-Mead algorithm

Optimization Algorithm	Adjusted Parameters $[kJ]$	Reduction Percentage $(1 - \frac{EA}{NM})$
Nelder-Mead	31.39	Reference
GA	27.70	11.8%
DE	26.81	14.6%
PSO	26.79	14.7%

The higher the energy spent from the electric fan the higher is the demand from the vehicle's alternator, leading to more power from the engine to this component, and consequently, increasing the vehicle's fuel consumption. The energy reduction due to the electric fan calibration can represent a relevant gain for the vehicle as a whole, regarding its fuel consumption and energy efficiency. As the control parameters adjustment is frequently performed manually in field, optimization algorithms and new control strategies are very important to be studied and applied.

4 Comments and Conclusions

In the present study, two main subjects were addressed:

i Optimization of the electric fan control parameters through four different optimization algorithms, in order to reduce the energy spent by the component;

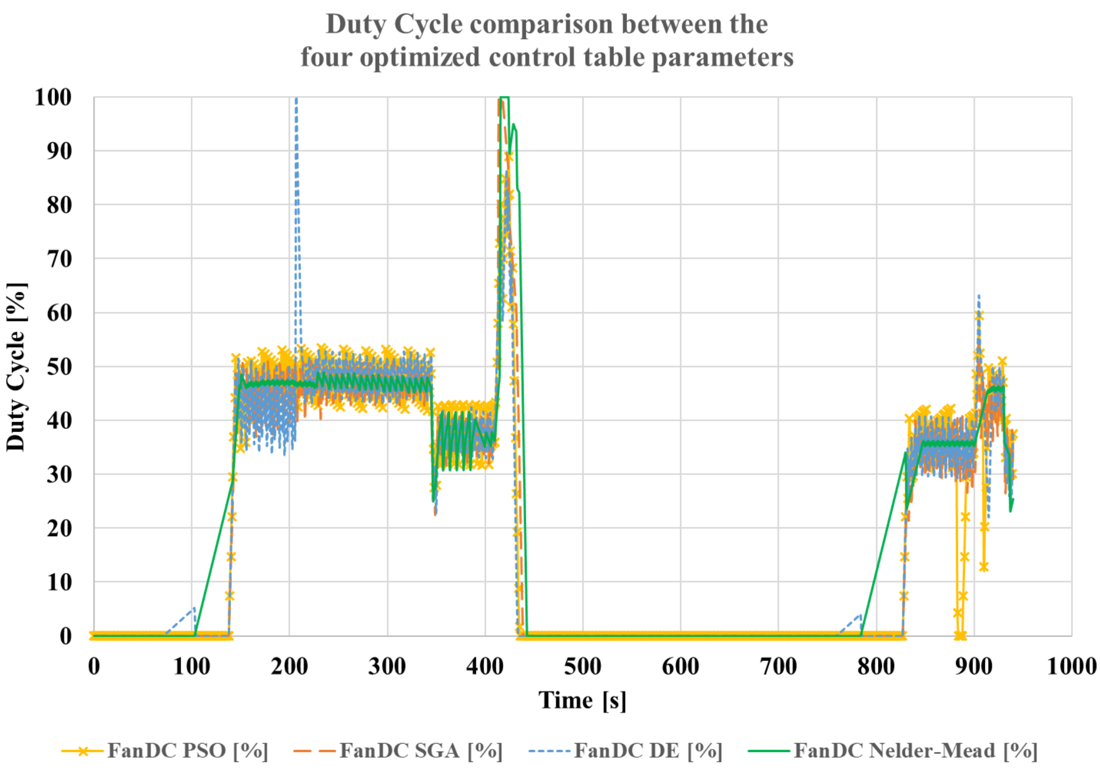

Figure 10. Comparison of the electric fan duty cycle behavior for each one of the control tables

ii The use of each of the control tables obtained with its parameters optimized by each of the different optimization algorithms to simulate the behavior of the vehicle's cooling system in a given speed cycle.

Regarding the first item, all control algorithms used were able to be optimized by the proposed model of the cooling system, in such a way that the evolutionary algorithms discussed showed reduction in the energy spent by the electric fan when compared with the reference. In addition, the application of the membership functions from Fuzzy logic were improvements that showed an enhancement of the results obtained by all the control tables, when this artificial intelligence tool is not considered.

Regarding the results obtained with each of the control algorithms in the behavior of the cooling system, it can be seen that the temperature of the system remains similar for all algorithms, which implies that the percentage of duty cycle used by them is also similar. Because of this, the energy differences between these algorithms were due to small energy differences during the cycle, mainly due to small time intervals where a certain algorithm maintains the fan activated by a greater duty cycle than another, or even average of the duty cycle in a given time interval. Anyway, it can be stated that all algorithms that use evolutionary computation presents better results compared to the reference algorithm, Nelder-Mead. This algorithm had already been used previously in Silva [1], for the optimization of the control parameters of a similar strategy, achieving significant energy reductions. The procedure with evolutionary algorithms, however, was able reduce even more the energy spent by the electric fan. This fact demonstrates the great ability of this tool to avoid premature convergence at local minimums. It can be said that even though the values found are still local minimums, they were able to find minimum values smaller than the fminsearch function, especially the DE and PSO algorithms, which showed the lesser energies spent by the electric fan.

4.1 Suggestions for future works

After using a vehicle's cooling system model to optimize the control parameters of the electric fan of the control strategy discussed, some improvement suggestions can be mentioned:

i the complexity of the cooling system model can be increased, including other parameters and components, for example, cabin air heater, as well as modeling its thermal rejection; inclusion of pressure loss on the liquid side, in order to increase the correlation with reality. It is still possible to carry out further studies aimed at determining thermal masses, as well as including the analysis of the engine temperature, directly influenced

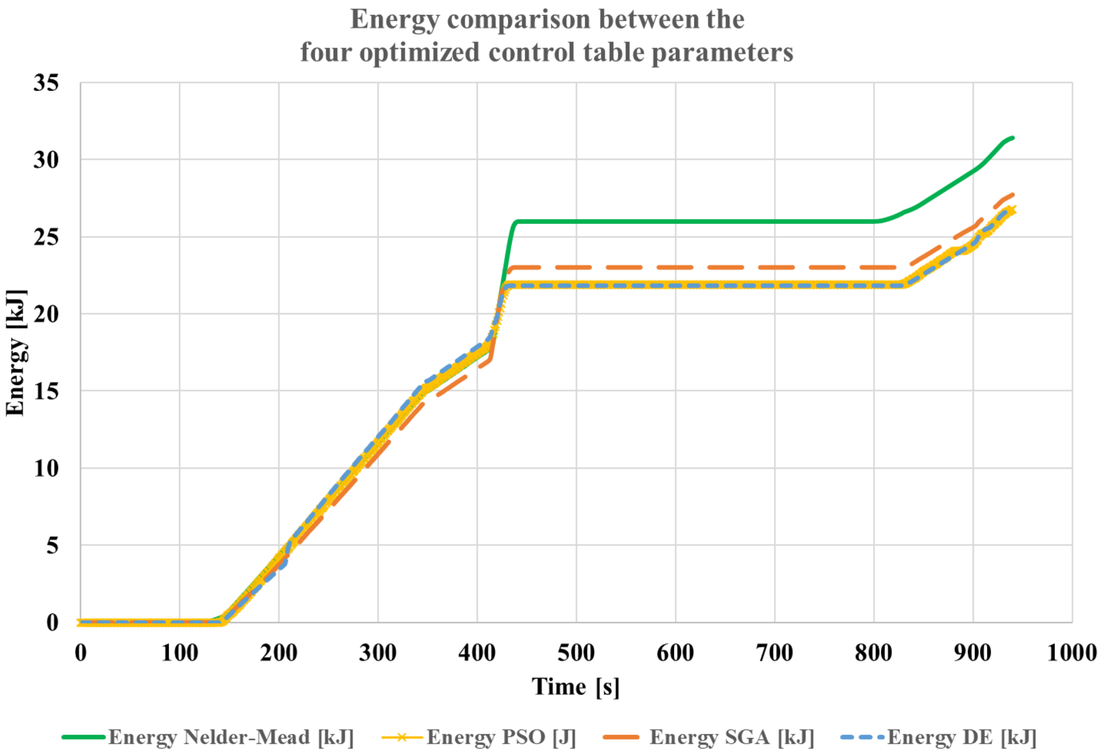

Figure 11. Comparison of the electric fan spent energy for each one of the control tables

and controlled by the temperature of the coolant;

ii regarding the control strategy used, it is possible to increase its complexity, including new input parameters in order to develop an even more versatile control strategy, being able to reduce the energy spent by the component to lower levels, in a smoother and less unstable manner;

iii another improvement opportunity related to the Fuzzy logic strategy is the optimization of its temperature parameters, which were kept constant in the present study. By modifying these parameters, even smaller values of energy could be found, however, it is advisable to pay attention with the temperature of the cooling system liquid, which must remain within the engine functional limits;

iv the complexity of the Fuzzy Logic is also an improvement point, in such a way that its complexity can be enhanced, using other ways to define the groups membership, or even in the manner that each membership is prioritized in the Defuzzification process.

v the effect of new electric fan control strategies and parameters optimization on the vehicle's fuel consumption and energy efficiency needs to be explored. Improvements in the model can be done in order to estimate the vehicle's fuel consumption variation, due to electric fan spent energy.

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