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Calibration of Gipps' car-following model for trucks and the impacts on fuel consumption estimation

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Abstract

Calibration of car-following models plays an important role in traffic simulation but also in the estimation of the traffic-related energy consumption. However, the majority of calibration studies only focus on errors on position or speed whereas these models are used to evaluate environmental parameters associated to road traffic (e.g. pollutant emissions, energy consumption). Then, this study focuses on the ability of Gipps' car-following model calibrated on trajectory parameters to estimate properly the fuel consumption of a heavy vehicle. First, the shape of one of the most used Goodness-of-Fit (GoF) function, Theil's inequality coefficient, is investigated. It will be demonstrated that optimal domains are flat and large, and so, many combinations of parameters could accurately reproduce the vehicle trajectory. Then, we found that Gipps model, calibrated via a Multi-Objective Particle Swarm Optimization is relevant to simulate the trajectory of a heavy vehicle but fuel consumption estimation resulting of these trajectories exhibits large discrepancies. To solve this issue it is proposed to add the fuel consumption estimation directly in the calibration process as a further dimension. The results show an improvement in the value of energy consumption estimation without increasing too much the error on the trajectory.

Keywords: Mutli-Objective Calibration; Gipps' car-following model; Truck's behaviour; Energy consumption

1. Introduction

The reduction of fuel consumption, and more generally pollutant emissions, is one of the major challenges of vehicle manufacturers. With the increase of communicating systems, new technologies: Intelligent Transportation Systems (ITS) and Advanced Driver Assistance System (ADAS), play now an important role in the reduction of pollutant emissions. In order to reduce prototyping costs, it is important to have powerful and relevant simulation tools for project development phases.

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There are different ways to estimate fuel consumption of a vehicle. If we consider an individual vehicle, the calculation of its energy consumption requires only the knowledge of its own kinematics. This can be done on real data but for prototyping new solutions on doing test at large scale it is very useful to boost the simulation. However, to estimate it in a road traffic environment, in order to assess for example the benefit of new driving strategies, it is necessary to assess how vehicle kinematics derived from traffic simulation model is accurate enough for such an application.

The study of car-following models calibration has already a long history, but very few studies focus specifically on Heavy Duty Vehicles (HDVs) behaviour (Aghabayk et al. (2015), Nodine et al. (2017)) although trucks reactions to traffic are different from those of cars as shown in Aghabayk et al. (2016),Sarvi and Ejtemai (2011) and Aghabayk et al. (2012). For the trucks trajectory one can observe that spacing would be larger, acceleration capabilities are smaller, speed profiles are more complex due to more complex engine chains. Inertia also modifies the driving behaviour of HDVs due to the important weights of vehicles. The main studies taking into account truck following behaviour focus on the differences in following reactions (Nodine et al. (2017), Aghabayk et al. (2016), Aghabayk et al. (2012), Sarvi (2011)) depending of the follower and the leader type (passenger car or HDV). Some other studies describe the influence of heterogeneous vehicle flow on traffic instabilities (Yang et al. (2014), Liu et al. (2016), Chen et al. (2016)).

To model the heterogeneity of real road traffic, several modified car-following models were previously developed. Previous studies about truck-following rule where either based on specific mode formulation (Aghabayk et al. (2016), Liu et al. (2016)), on quite complex existing car-following rules (Aghabayk et al. (2016)) or on new developped models based on the local linear mode tree approach, LOLIMOT (Aghabayk et al. (2013), Aghabayk (2013)). All of these studies used data from the Next Generation Simulation (NGSIM) project. The trajectories used were collected on the Hollywood freeway (U.S.101) and on the Berkeley Highway (I-80) in California. They are respectively $640m$ long and $503m$ long. Here, we want to assess if a simpler expression, the Gipps' model, with dedicated parameter settings can accurately reproduce truck behaviour under different applications: urban or regional. This would be very useful in practice as the Gipps model is widely used in traffic simulation because it is a good compromise between accuracy and the number of parameters for calibration.

A second contribution of this paper is about the connection with fuel consumption. First, we want to know if a calibration based on traffic objective function provided accurate results when calculating the fuel consumption. This is important because it is a common practice to calibrate the model for traffic applications and then determinate the fuel consumption as an output. Second, we will determine the improvements related to a direct integration of fuel consumption in the calibration process through multi-objective optimization.

The first part of the article presents the data used for the study. Then, Gipps' car-following model is detailed and its parameters to calibrate are highlighted. The following section is about calibration method and a particular attention is given to the Goodness-of-Fit function and indicators on which computing the error between measured and simulated data. Then, the results of the calibration of the Gipps' car-following model are presented and resulting trajectories are used to estimate the fuel consumption of the vehicle. Finally, a solution is proposed to improve the calibration results and particularly the results on fuel consumption estimation.

2. Data description

Data were recorded in Lyon (France), with a vehicle weighted at 19 tons and equipped with sensors measuring the spacing to the vehicle ahead. The route driven by the vehicle is about 80km.

Over the all route, the outputs of sensors measuring spacing are processed to extract sub-cycles with a situation of following. The data processing is out of the scope of this paper. The data is sampled with a time step of $0.1s$. For each sub-cycle, a lot of information is available at each time step: the position of the vehicle, its speed, its acceleration, the fuel injected (the instantaneous fuel consumption) and the slope. The instantaneous fuel consumption is used to compute the cumulated fuel consumption along the sub-cycles, and the fuel consumption expressed in $L/100km$ which will be respectively used in calibration and for comparison between the measure and the simulation. Among the extracted sub-cycles, ten cycles are presented in this article. Five of the cycles are located in urban areas; the five others are regional cycles. The characteristics of those cycles: length, average and legal speeds in km/h, are presented in the Table 1.

Table 1. Characteristics of the selected sub-cycles

	Urban					Regional				
N°	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
Length $[m]$	409	866	350	210	306	2634	1777	1771	1717	962
Average Speed $[km/h]$	12	38	38	23	29	58	63	66	60	48
Legal speed $[km/h]$	50	50	50	50	50	90	90	90	90-70	90-70

3. Calibration of Gipps' car-following model

The calibration of car-following models aims at finding the set of parameters which would minimize the errors between the simulated trajectory of the truck and the measured one. The function computing the errors between the measure and the simulation will be named Goodness-of-Fit (GoF) function in the rest of the paper. Besides, the trajectory of a vehicle can be described by different parameters: its position, the spacing to the vehicle ahead, its speed or its acceleration. The errors can be computed on each of these indicators, called Measure-of-Performance (MoP) in the rest of the paper.

3.1. Gipps' car-following model

Gipps' model was first introduced in 1981 (Gipps (1981)). This model is defined as a safe distance model because it is based on the choice of a safe following distance to avoid possible collision with the leader vehicle. The empirical model developed by Gipps consists of two components. The first represents the intention of a driver to achieve a certain desired speed, while the second reproduces the limitations imposed by the leader when trying to drive at the desired speed. The output of Gipps' car-following model is the speed. In the rest of the article, index n refers to the studied truck (the following vehicle), index $n-1$ refers to its leading vehicle.

Gipps' car-following model has six parameters to calibrate: a_n is the maximum acceleration rate of the Follower, $S_{n-1} = L_{n-1} + SafetyMargin$ represents the length of the Leader vehicle including a minimum safe distance, τ_n is the reaction time of the Follower, V_n^{des} is its desired speed, b_n is its maximum braking rate and $\hat{b}_{n-1}$ is the assumed braking rate of the Leader.

3.2. Investigations on the Theil's inequality coefficient function shape

Before calibrating Gipps' car-following model, a particular focus will be done on GoF function and MoPs. In the literature on car-following calibration, many different GoF functions are used (Ciuffo et al. (2012), Punzo and Simonelli (2005), Kesting and Treiber (2008), Ciuffo and Punzo (2009) and Treiber and Kesting (2013)): the *Root Mean Squared Error* (RMSE), the *Root Mean Squared Percentage Error* (RMSPE), the *Squared Error* (SE) or the Theil's inequality coefficient to mention the most used. This article will focus on Theil's inequality coefficient, described in equation (1).

$$U = \frac{\sqrt{\frac{1}{N}\sum_i \left(Y_i^{obs} - Y_i^{sim}\right)^2}}{\sqrt{\frac{1}{N}\sum_i \left(Y_i^{obs}\right)^2} + \sqrt{\frac{1}{N}\sum_i \left(Y_i^{sim}\right)^2}}, \text{ With: } \begin{cases} Y_i^{obs}, \text{ the measured MoP} \\ Y_i^{sim}, \text{ the simulated MoP} \end{cases} \tag{1}$$

The different studies comparing the calibration of car-following models mainly focus on error on position or speed. It has been previously shown (Punzo and Montanino (2016)) that it is better to use as MoP the spacing (or the position) instead of the speed when we want to minimize error on both spacing (or position) and speed. However, these studies were done by using a single MoP (Punzo and Simonelli (2005), Kesting and Treiber (2008), Punzo and Montanino (2016)) or combined MoPs (Ossen and Hoogendoorn (2008), Kim and Mahmassani (2011)),

Table 2. Range of variation of Gipps' car-following model

Parameter	τ_n $[s]$	V_n^{des} $[km/h]$ - Urban	V_n^{des} $[km/h]$ - Regional	a_n $[m/s^2]$	$SafetyMargin$ $[m]$	$\hat{b}_{n-1}$ $[m/s^2]$	b_n $[m/s^2]$
Min	0.2	40	70	0.5	0.1	-6.1	-4.1
Step	0.3	2	3	0.4	0.5	0.5	0.5
Max	3.8	50	85	2.9	4.6	-0.1	-0.1

but not using a Multi-Objective (MO) calibration. Because we want to estimate the energy consumption of a heavy vehicle, both trajectory and dynamics of the vehicle are important, therefore the solution of the MO calibration is investigated here.

Prior to looking for optimal parameters values, we investigate the response of the GoF function to a large range of parameter values. Actually, if this function is flat, the optimal domain is large and so the calibration process will not lead to a narrow definition of optimal parameters. Moreover, because we want to focus on multiple objectives when calibrating the model, it is interesting to evaluate the intersection of optimal domains obtained independently for position, spacing, speed and acceleration. If this intersection is close to the union, it means that all independent processes converge to the same consistent region for optimal parameters. If this intersection is void it means that a single but multi-objective calibration process is mandatory to determine a relevant set of optimal parameter values.

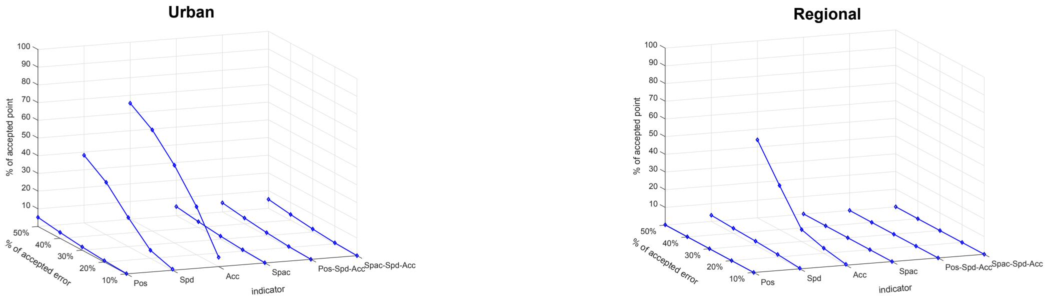
First, a surface grid of the Theil's inequality coefficient is done. For Gipps' car-following model, a range of variation of the parameters to calibrate is defined (Table 2). Then, trajectories are simulated for each possible combination of parameters and the error between the simulated trajectory and the measured one is computed with Theil's inequality coefficient. To study the shape of this function, the sizes of optimal domains are compared.

Optimal domains are defined for each of the variables that we want to optimize error on. Those variables are, as mentioned in previous paragraphs, the position of the follower, the spacing between the follower and the leader, the speed of the follower and its acceleration. The optimal domains are defined as follows: we search for the point which provides the minimum error on the variable, then, five optimal domains are defined per variable we want to optimize error on. The first one contains the points for which the error is between the minimum error and the minimum error plus 10%. The second domain contains points for which the error is between the minimum error and the minimum error plus 20%, and so on until the minimum error plus 50%.
The number of points in each optimal domain, expressed as a percentage of the total number of tested points, is compared. First the evolution of the optimal domains size is studied. If the size of the domain increases a lot with the percentage of the accepted error, it means that the optimal domain is quite flat, so a large range of parameters are acceptable.

The evolution of the size of the optimal domain is similar whatever the cycle of the category (urban or regional). This evolution is presented in Fig.1. Figure 1.a illustrates the evolution for urban cycles and figure 1.b illustrates the evolution for regional cycles of the size of optimal domains. The first axis represents the optimal domains for the four variables (position, speed, acceleration and spacing) and two intersection domains. The first intersection domain represents the common points of optimal domains in position, speed, and acceleration. The second is for common points for optimal domains in spacing, speed and acceleration. The second axis corresponds to the percentage of accepted error, from 10% to 50%. And the last axis (vertical) represents the percentage of points in the optimal domain.

For the optimal domains in position and spacing, the results are quite identical. The sizes of the optimal domains increase only slightly when the percentage of error is increasing. Moreover, these two domains are really close to each other even if the optimal domain for spacing is a bit larger. The optimal domains, in speed and acceleration for urban areas, and in acceleration for regional cycles, are really sensitive to the percentage of accepted error. From 20%, their sizes increase quickly, so the GoF function is quite flat for these two variables.

It was previously demonstrated that it is preferable to use spacing or position as MoP (Punzo and Simonelli (2005), Kesting and Treiber (2008), Punzo and Montanino (2016)). This result is consistent with the preceding conclusion. As illustrated in Fig.1, the optimal domain for spacing is really less flat than speed or acceleration optimal domains, that ensure to find a minimum more easily than for the other MoPs. Calibrating the car-following model according to the error on speed or on acceleration could lead to many sets of parameters that could be considered as optimal. However,



(a) (b)

Fig. 1. Evolution of optimal domains for Gipps' car-following model for Theil's inequality coefficient - (a) urban cycle, (b) regional cycle

the final objective of the calibration method developed in this paper is to have a car-following model well calibrated to compute the fuel consumption of industrial vehicles: the error on speeds and accelerations must be minimized too. Moreover, we can observe on Fig.1 that the intersection domains are small. That means that very few points are optimal for all MoPs. Then, multi-objective calibration is needed for the application considered in this study.

Two intersections of optimal domains were defined. The second intersection domain (spacing, speed and acceleration) is generally bigger than the first one (position, speed and acceleration) because the optimal domain for position is a little smaller than the optimal domain for spacing. To ensure that the multi-objective calibration algorithm will find the maximum of possible optimal points, it will be run with the three variables which allow the biggest intersection domain: spacing, speed and acceleration.

3.3. The Multi-Objective Particle Swarm Optimization (MOPSO)

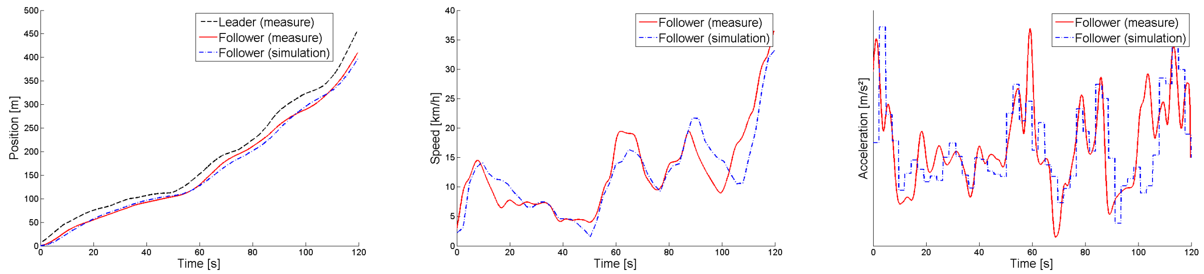
The Gipps' model is calibrated using a method based on the Particle Swarm Optimization (PSO) algorithm. This global optimization method was proposed in Kennedy and Eberhart (1995). The method used here is the standard GBEST model (Eberhart and Kennedy (1995)). As demonstrated previously, the optimal domains are different depending on the MoP. Then, a multi-objective calibration is mandatory to try reducing errors on spacing, speed and acceleration. This approach is interesting because new driving strategies are mainly used to reduce fuel consumption, and it is necessary in this way to simulate accurately not only position or spacing but also speed and acceleration.

The PSO algorithm is modified into a Multi-Objective PSO (MOPSO) allowing the calibration of several variables: spacing, speed and acceleration. The MOPSO algorithm provides a set of optimal parameters for Gipps' model which dominate other possible parameters according to the dominance definition of Pareto (Coello Coello and Lechuga (2002)).

3.4. Results: Ability of Gipps model to reproduce truck's behaviour

The Gipps' car-following model has been calibrated using the MOPSO algorithm presented in the previous section. The results of the calibration of the cycles presented in this article are summarized in Table 3.

One can see that the calibration has provided good results. The errors on position and speed are very low for all of the cycles. The errors on acceleration are higher than on the other variables, they fluctuate around 26%. Acceleration profiles are more difficult to model and heavy vehicle kinematics are more complex than the one of light vehicles, moreover Gipps' output is the speed of the vehicle and not its acceleration; these points can explain that the errors on acceleration are greater than the other errors. However, contrary to what was found in Rakha and Wang (2009), Gipps' model does not overestimate the acceleration value of the truck. An example (cycle 1u) of the simulated trajectories compared to the measured ones is presented on Fig.2, respectively for the position, the speed and the acceleration. Moreover, Gipps' model can be said to be a robust model in the sense where we can use an average of the optimal parameters per category of cycles, without losing the ability of Gipps' model to reproduce trucks behaviour and dynamics. Using average parameters instead of optimal ones leads to a small increase of the value of the error. For position, errors are less than 6% for urban cycles and less than 2% for regional ones. For speed, for urban and regional



(a) (b) (c)

Fig. 2. Measured and simulated trajectories for Cycle 1u - (a) Position, (b) Speed, (c) Acceleration

cycles, errors are respectiveley below 10% and 4.5%. For the acceleration, the error is a bit higher than with optimal parameters, around 35% in average instead of 26%.

3.5. Results: Application to fuel consumption

The previous sections have allowed to demonstrate that Gipps car-following model could be relevant to simulate the behaviour of a heavy vehicle. However, we would like now to assess whether these simulated trajectories are precise enough to estimate fuel consumption. To answer this question, the generated trajectories will be used as input of a fuel consumption estimation tool. The fuel consumption estimation tool is an internal tool used within Volvo Group.

The results of the simulations are presented in Table 3. It presents the error in percentage between the total fuel consumption measured and the simulation expressed in L/100km.

The results of the fuel consumption estimation are not so good because they represent a huge gap for the total consumption over the cycles. The error values are closer to each other for regional cycles than for urban cycles where error goes from -14% to +21%.

As shown in Vieira da Rocha et al. (2015) for passenger vehicles, we can say that a car-following model can be well calibrated for a traffic point of view but not good from an energy consumption estimation point of view. However, car-following models or traffic models are always calibrated regarding traffic indicators, and they are used to estimate energy consumption or pollutant emissions. As we can see in this study, this method can lead to bias in the energy consumption value, particularly for HDVs.

To solve this problem, we propose to add the fuel consumption estimation into the calibration process as a fourth MoP.

4. Calibration of Gipps' car-following model taking into account fuel consumption evaluation

The calibration of Gipps' car-following model is done again but with four MoPs this time. Results are presented in Table 4. We observe that the errors on position, spacing, speed or acceleration are really close to the errors presented

Table 3. Errors (Theil's inequality in %), for the 10 cycles, on position, spacing, speed, acceleration and fuel consumption (computed in L/100km) relative error between simulation and measure (in %)

	Urban					Regional				
N°	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
Position	1.43	0.51	0.47	1.90	1.15	0.59	0.22	0.56	0.45	0.63
Spacing	12.16	10.93	4.71	3.10	6.62	13.70	6.98	8.30	11.75	8.76
Speed	10.43	3.10	1.96	6.04	2.13	2.65	2.32	3.30	3.01	3.66
Acceleration	40.83	30.47	13.19	24.23	26.46	32.60	21.50	24.88	23.22	25.53
Fuel consumption	-14.22	21.13	-8.09	-9.58	-1.04	3.24	4.07	4.34	9.87	-3.67

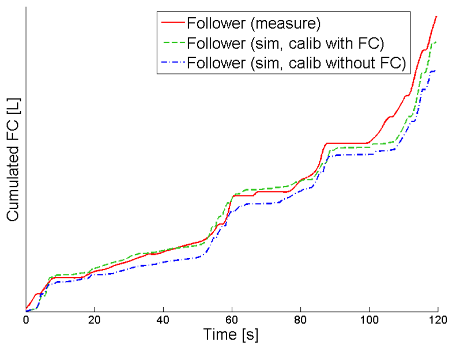
Table 4. Errors (Errors (Theil's inequality in %), for the 10 cycles, on position, spacing, speed, acceleration and fuel consumption (computed in L/100km) relative error between simulation and measure (in %) after calibration of the model with the fuel consumption esitmation as the 4th MoP

	Urban					Regional				
N°	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
Position	1.49	0.70	0.45	1.26	1.05	0.54	0.19	0.62	0.48	0.67
Spacing	13.82	13.82	4.78	2.05	6.12	12.71	6.48	9.44	13.22	9.27
Speed	11.27	3.49	2.02	3.39	2.10	2.59	2.27	2.95	1.99	3.50
Acceleration	41.29	31.56	14.30	25.58	26.75	31.56	21.69	24.16	23.25	24.79
Fuel consumption	-6.90	9.82	4.43	1.56	0.22	2.50	2.58	0.71	7.91	3.13

in previous sections. However, the errors on fuel consumption estimations are reduced significantly.

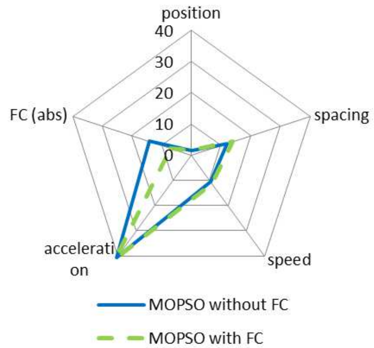
It means that we can reduce the error on the fuel consumption estimation without deteriorating the error on trajectory indicators. The optimal parameters domain from a traffic point of view is large and including another indicator in the calibration process helps to narrow it.

Fig.3 presents the improvement of the fuel consumption estimation after the calibration in four dimensions. Fig.4 illustrates the fact that the improvement of the fuel consumption estimation does not affect the other MoPs.



(a)

Fig. 3. Measured and simulated fuel consumption for Cycle 1u



(b)

Fig. 4. Error evolution between calibration without and with fuel consumption estimation in MoPs

5. Conclusion and discussion

Gipps' car- following model was first calibrated with a MOPSO algorithm on spacing, speed and acceleration, and the calibration has provided good results with small error values. However, the simulated trajectories were not good to estimate the energy consumption of the vehicle. This is why the energy consumption estimation was added to the calibration process. The trajectories resulting from this second calibration were really better than the previous ones to estimate the fuel consumption of the vehicle. Moreover, it has been shown that the errors on position, speed and acceleration were not affected by adding the energy consumption as a fourth MoP. This study demonstrated, as in Vieira da Rocha et al. (2015), that car-following models could be well calibrated from a traffic point of view but not from an energy consumption point of view. A solution is proposed to solve this problem.

This work points out an important issue in the way traffic simulation tools are used. At the moment, car-following models are calibrated based on traffic data (macroscopic or microscopic) and they were originally used to evaluate road construction, new control strategies or to predict traffic evolution. Their validity was mainly validated in this context. However, these models are now more and more used to estimate environmental parameters such as energy consumption, fine particles or CO_2 emissions and the effects of new driving strategies such as ITS and ADAS on the environment. Because the simulation tools are calibrated for traffic purposes, a bias can be observed between real emissions and simulated emissions. It is important to notice this phenomenon to calibrate the models in a proper way for emission estimations.

This study was done considering only the case where the leading vehicle is a car and the following vehicle is a truck. However, the same results were demonstrated in the case of a car following a car in Vieira da Rocha et al. (2015), and we can assume that it will be true for the two other following situations. Gipps' car-following model was here calibrated for a particular vehicle. The optimal parameters found could not be optimal for another vehicle but the methodology of the calibration could be used for any other vehicle. The values of the parameters have not been discussed here, the small number of cycles don't allow to conclude, similarities and differences between parameters values seem dependant of the cycle.

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