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Calibration of the VISSIM truck performance model using GPS data

Luan Guilherme Staichak Carvalho[1], **José Reynaldo Setti**[2]

[1]Departamento de Engenharia de Transportes, EESC-USP, lgscarvalho@usp.br
[2]Departamento de Engenharia de Transportes, EESC-USP, jrasetti@usp.br

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ABSTRACT
Traffic simulators can be used to perform safe, low cost scenario evaluation. However, their mathematical models are calibrated to scenarios commonly found in the simulators' country of origin. VISSIM truck acceleration functions were created for trucks with better power/mass ratios than typical Brazilian trucks. This paper presents the calibration of VISSIM truck acceleration functions using the difference between real and simulated speed profiles as goodness-of-fit measures. Using GPS, speed profiles were obtained for 57 trucks travelling over a segment of 18 km, four-lane freeway situated on rolling terrain, under low traffic flow. The calibration procedure was automated and based on a genetic algorithm. Several calibration runs were performed using different numbers of generations and population size. The resulting acceleration functions are presented and discussed.

RESUMO
Simuladores de tráfego permitem avaliar cenários de maneira segura e com baixo custo. Todavia, os modelos matemáticos que os regem são ajustados para cenários frequentes no país de origem do simulador. No VISSIM, os modelos referentes ao deslocamento de caminhões simulam veículos com melhor desempenho, se comparados aos caminhões brasileiros. Este trabalho apresenta a calibração das funções de aceleração para caminhões do VISSIM, utilizando a diferença entre perfis de velocidade simulados e reais como medidas de ajuste. Usando GPS, foram obtidos perfis individuais para 57 caminhões que trafegaram por cerca de 18 km ao longo de uma rodovia de pista dupla em relevo ondulado, sob baixo fluxo de tráfego. A calibração foi automatizada por meio de um algoritmo genético. Diversas execuções do algoritmo foram realizadas, variando número de gerações e tamanho populacional. As funções de aceleração obtidas são apresentadas e discutidas.

1. INTRODUCTION

Computional simulation models are used in different areas of science because they can predict, reproduce and assess real and hypothetical scenarios. In traffic studies, widespread use of these tools can be explained by the low cost, the fact that they are risk-free and the speed in which data are obtained (Park and Qi, 2005). By combining different mathematical models, simulators are able to reproduce real phenomena of great complexity. This ability leads to the study and evaluation of the theories behind these phenomena by comparing them with simulated scenarios (Heermann, 1990).

Simulators present one or more default setting sets for each of their mathematical models. Each set is made in such a way that the reproduction of specific traffic scenarios – usually consistent with the fleet and the drivers of the simulator's country of origin – reproduces the real traffic flow with a satisfactory degree of fidelity. However, the vehicles' characteristics and behavior can vary not only from one country to another, but also between regions within the same country. Therefore, simulators should be calibrated according to the conditions of the place of study in order to ensure the reliability of the simulated data (Hourdakis *et al.*, 2003).

In Brazil, most efforts made to calibrate simulators focus on models that govern interactions among vehicles (Egami *et al.*, 2004; Medeiros *et al.*, 2013; Bethonico *et al.*, 2016), and there are few studies actually addressing vehicle performance calibration (Cunha *et al.*, 2009). Therefore, the aim of this paper is to calibrate the VISSIM vehicle performance model for Brazilian trucks. To do this, a real freeway segment of rolling terrain, approximately 18 km long, was used. The calibration was carried out by comparing the speed profiles of real and simulated trucks travelling along the segment under study, where the real instantaneous speeds were obtained from GPS data processing. The calibration was automated using a genetic algorithm as this technique is widely cited in the literature concerning traffic simulator calibration (Kim & Rilett, 2001; Ma & Abulhai, 2002; Egami *et al.*, 2004; Cunha *et al.*, 2009; Medeiros *et al.*, 2013; Chiappone *et al.*, 2016).

2. TRAFFIC SIMULATORS AND THE NEED TO CALIBRATE THEM

Computational simulators are often cited in the literature and have appeared as both objects and tools for studies in different areas of science for over 50 years (Shumate and Dirksen, 1965). Despite the long history of studies on traffic simulators, the need to calibrate them has become a recurrent topic only since the late 1990s. The 30-year time lag of this topic in relation to the beginning of when these tools were used in the transport sector can be explained by the way these programs were developed. The first traffic simulators were created and validated to simulate one or a few specific scenarios, whereas their successors were designed to reproduce increasingly broader conditions (Kotusevski and Hawick, 2009). As current simulators are created and validated to simulate generic networks, calibration has become necessary to better represent behaviors observed in local scenarios (Jayakrishnan *et al.*, 2001; Hourdakis *et al.*, 2003).

Among the various attempts to calibrate simulator models, the most frequent ones are the car-following and lane-change models (Chu *et al.*, 2003). However, the large number of variables and the high computational costs required for calibration mean that, generally, models are not calibrated regularly. Therefore, the frequent use of simulators occurs only by adjusting the origin-destination matrices and changing a few behavioral variables based on the user's experience (Balakrishna *et al.*, 2007).

In traffic microsimulators, the models involved recreate the traffic flow by generating vehicles with individual behaviors. Thus, using aggregate traffic measurements to calibrate these models is not appropriate since aggregate measurements are affected by the combination of several models simultaneously (Toledo *et al.*, 2004). On the other hand, disaggregate data is difficult to collect and costly (Balakrishna *et al.*, 2007), making it complex to calibrate simulators. Despite this difficulty, Li *et al.* (2015) carried out the calibration of the VISSIM desired acceleration function for passenger cars using GPS data obtained for individual vehicles travelling on urban roads. Hence, it is expected that this approach can be applied for freeway segments.

In order to calibrate vehicle performance models, common procedures include simulating segments comprising a long ramp preceeded by a flat section in which the truck's speed stabilizes (Cunha *et al.*, 2009). Although this approach makes it possible to compare the equilibrium speed, such a combination of ramps rarely occurs since the rolling terrain, characterized by the constant alternation between up grades and down grades, is the most common scenario.

In this research, these shortcomings were avoided by collecting data in a more realistic way, using a GPS device installed on a sample of trucks that travelled along a divided multilane highway during periods of low traffic flow. With the set of instantaneous speed profiles thus obtained, the truck performance model used by VISSIM was recalibrated using a genetic algorithm.

3. VISSIM TRUCK PERFORMANCE MODEL

In VISSIM, vehicles can change speed through acceleration functions, which in turn are created for each vehicle based on their category from pre-configured functions, as shown in Figure 1. These functions represent a region of possible acceleration values in relation to the vehicle's instantaneous speed. For heavy vehicles, these regions are delimited by acceleration functions that correspond to the limits for the power/mass ratio. For the VISSIM default setting, the upper and lower limits are 7 and 30 kW/t, respectively (PTV, 2016).

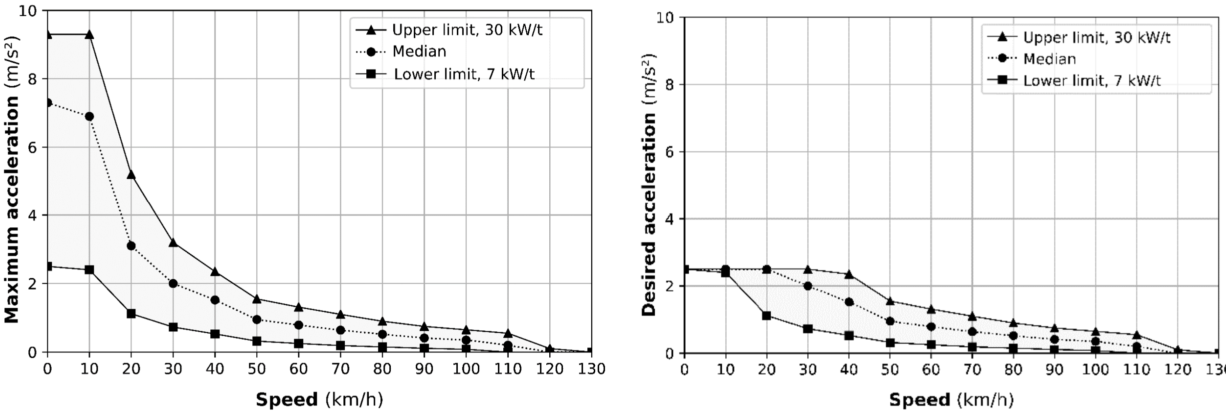


Figure 1. Default maximum acceleration and desired acceleration functions for heavy vehicles in VISSIM 9 [Adapted from PTV (2016)].

In order to define the acceleration versus the available speed values for a simulated truck, VISSIM calculates the power/mass ratio of that vehicle the moment it is generated. The obtained value is then compared with the upper and lower limits of the power/mass ratio set for the simulation. If the truck's power/mass ratio is not within the limits, the calculated value is replaced by the nearest limit; for example, in the setting shown in Figure 1, the power/mass ratio of a truck with 4 kW/t will be rounded up to 7 kW/t as that is the limit closest to the calculated value. In this case, the vehicle's maximum acceleration and desired acceleration values will be equal to the respective limit-curves for its new power/mass value.

If the truck's power/mass is within the limits, its acceleration values will be obtained by linear interpolation between the limit-curves, using the truck's power/mass as a measure of distance for interpolation. In Figure 1, the "median" curves correspond to the interpolated accelerations for a truck with 18.5 kW/t, whereas the limit-curves are the accelerations used by trucks outside the stipulated power/mass range.

Apart from the differences in mass and power among trucks, VISSIM also varies the possible acceleration based on the slope of the ramps. Whenever a vehicle is travelling on steep grades, its maximum acceleration curve is displaced vertically, changing each point through the relation $a_{v,G} = (a_v - 0.1G)$, where a_v is the acceleration (in m/s^2) at speed v on a flat stretch; and $a_{v,G}$ is the acceleration (in m/s^2) at speed v in an ascending grade of magnitude G (in m/100 m).

Another important aspect of this simulator is that all the vehicles receive a desired speed value when they are created. The desired speed determines the highest speed the vehicle will reach, even when the interpolated acceleration curves allow it to reach higher speeds.

4. THE APPROACH USED

The VISSIM default setting provides only one category for trucks. However, the Brazilian fleet is heterogeneous, and each vehicle can present quite varied combinations of characteristics (power, mass, number of axles, age, maintenance conditions, and so on). Therefore, calibrating acceleration functions for more than one category of trucks is a way of obtaining more appropriate results for subgroups that share common characteristics. This work follows the classification of Brazilian trucks as proposed by Cunha *et al.* (2008), dividing them into four types: light (2 axles); medium (3 axles); heavy (4 and 5 axles) and extra-heavy trucks (6 or more axles).

As the acceleration functions govern the independent displacement of the vehicles, i.e. as if they did not suffer interaction from traffic, in order to calibrate the simulator, real data from trucks travelling under these conditions need to be obtained. Carvalho and Setti (2017) present a method for collecting, treating and obtaining speed profiles of individual vehicles, which can be used as a measure for adjusting the functions.

However, VISSIM is a stochastic simulator, in which the mass, power and desired speed (MPdS) values of each vehicle are random variables, generated from cumulative frequency distributions for that truck's class. Consequently, cross-checking the real and simulated speed profiles under these conditions would not produce a satisfactory calibration, as the MPdS properties of the trucks being compared would be different from each other. Thus, a non-stochastic configuration of the simulator needs to be obtained for the calibration.

By default, VISSIM vehicle types correspond to vehicle categories (for ex.: Type 1 – passenger cars, Type 2 – trucks). At the beginning of a simulation run, three cumulative frequency distributions (one for each MPdS characteristic) and one set of acceleration functions are assigned to each vehicle type.

In order to make it possible to compare real and simulated vehicles with equal MPdS values, the concept of VISSIM vehicle types was modified, making each type correspond to an observed truck, i.e. with known and constant MPdS values. Trucks from the same category use the same set of acceleration functions, allowing these functions to be calibrated simulating all trucks that belong to this category.

Therefore, the MPdS distributions still need to be configured for each truck so that they use fixed values, preventing the generation of random vehicles. The distributions were configured as two pairs of values: Y (0%), for the cumulative frequency 0%; and Y (100%), for the cumulative frequency of 100%. As VISSIM does not allow Y (0%) = Y (100%), it was assumed that Y (0%) = Y (100%) − 0.001, so that the MPdS property value is constant, regardless of the value selected by the distribution.

5. PROPOSED METHOD

Briefly, the calibration was obtained using a genetic algorithm whereby each individual is a possible combination of values for the limit-curves that comprise the maximum and desired acceleration functions. The presentation of the method begins by addressing two important aspects of the genetic algorithm: the real data and the fitness function, calculated at the end of the evaluation function. Afterwards, the procedure to create the four networks (one for each truck category) in the simulator is described. Then, the implementation of the genetic algorithm is discussed. Finally, the validation of the acceleration functions is addressed.

5.1. Input data

Speed profiles are used to assess the acceleration function fitness. The sample consisted of 57 trucks travelling on a divided, multilane highway, with a posted speed limit of 90 km/h for trucks. The road segment chosen for the data collection is located in rolling terrain and its vertical alignment consists of a sucession of crest and sag vertical curves connected by grades of varied lengths and magnitudes. The horizontal alignment of this road segment is straight, without any horizontal curves.

Truck drivers were approached at a mobile weigh station and, upon their agreement in participating in the data collection, a researcher would board the truck and install the GPS unit and antenna. The drivers were asked to drive as they usually would do in that segment. The GPS unit recorded the vehicle location at 1-second intervals. The data collection was conducted during periods when the traffic flow was low, to prevent speed reductions due to the traffic. Truck mass was obtained from the weigh station scale; the engine power and number of axles were obtained from a short interview with the driver. Figure 2 shows the power/mass ratio for the trucks in the sample, according to their category. The grey area in the graph shows the upper and lower limits of VISSIM's default power/mass ratio.

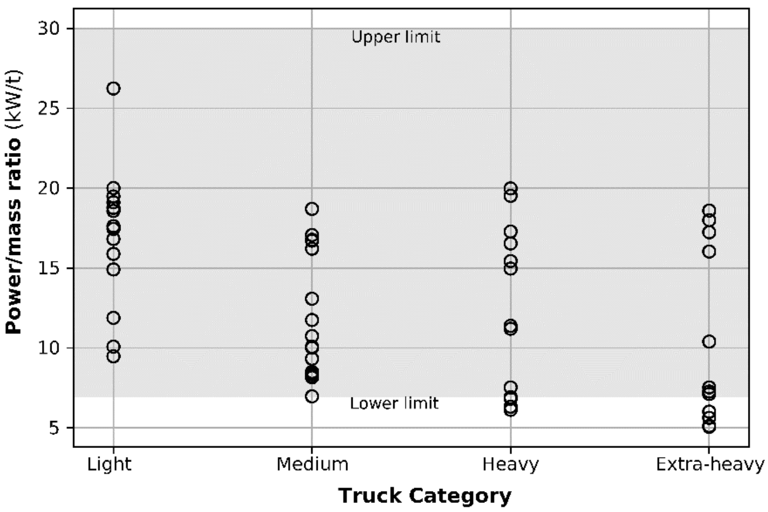


Figure 2. Power/mass ratio for trucks in the sample. The grey area shows VISSIM's default range for power/mass ratios (7–30 kW/t).

The method used for constructing the speed profiles was adapted from Carvalho and Setti (2017), using code written in Python 3.6. Two different speed profiles were derived for each truck. The first one characterizes the initial phase of the movement, when the truck is starting from a complete stop and accelerates to reach the desired speed. It was assumed that this initial phase comprised the first 1.5 km travelled. It describes the instantaneous speed of the vehicle at predetermined points.

The second profile represents the movement of the truck after it reached its desired speed and accelerates or decelerates because of the effect of grades on its path. This speed profile was built using the GPS data collected over the 16.5 km segment after the initial 1.5 km section and consists of the instantaneous speeds at 100-m stations along the segment.

Figure 3 shows the speed profile for one of the trucks in the sample. The speeds from filtered data at each station were adopted as the real speeds in the calibration of the truck performance model.

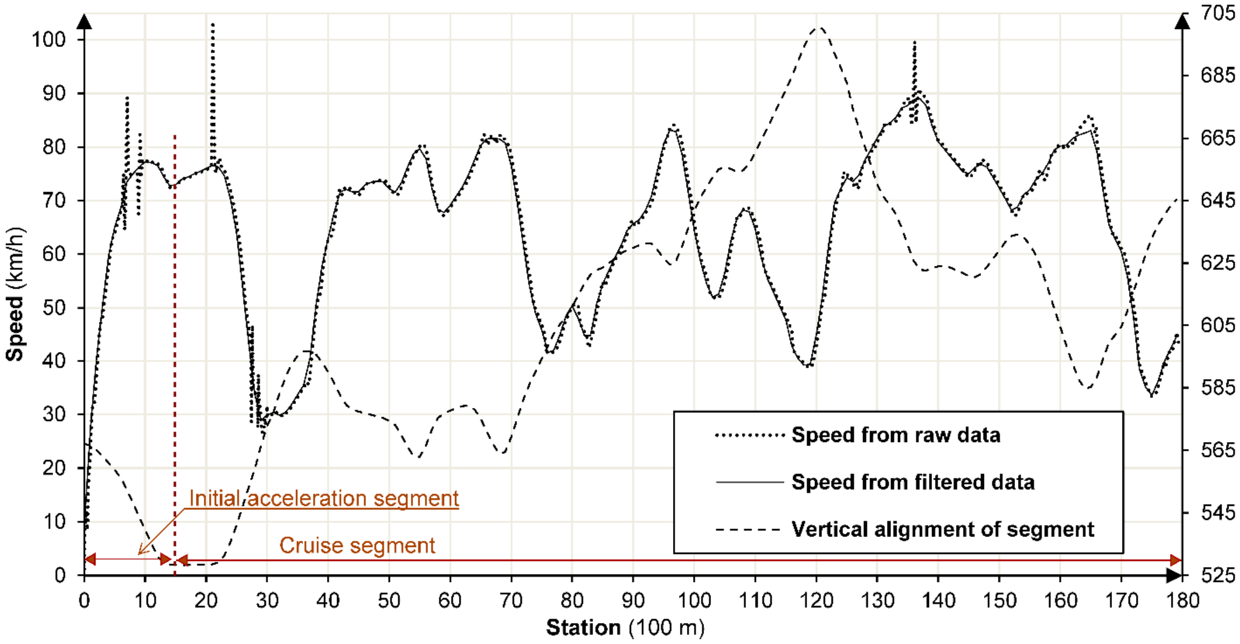


Figure 3. Speed profile representing the observed speeds during the initial acceleration and cruise phases for one of the trucks used for the data collection (Truck 53).

The desired speed for each truck was defined as the 90th percentile of the cruise speed of the respective vehicle. This threshold was adopted after identifying that, despite the observed trucks being able to reach high speeds, they were unable to maintain these high speeds for long distances. Speeds near the 90th percentile, however, were more easily sustained by most trucks and thus considered more representative of the truck's desired speed.

5.2. Creating simulation networks

The simulation network was created using the path of a randomly chosen truck as the reference for the horizontal and vertical alignments of the highway. This highway segment was reproduced in the simulation by one 18-km link with one single traffic lane. To optimize the simulation runs, the network used comprised two identical 18-km links, one that was used to analyze the initial acceleration phase of the trip and the other for the cruise phase of the trip. To collect the data to characterize the performance of the simulated trucks, dual-loops detectors measured the speed of the truck at predetermined points along the network links. In the link representing the initial acceleration phase, the detectors were placed at variable distances; in the link used to simulate the cruise phase of the trip, the detectors were placed at 100-m stations. Figure 4 illustrates the network used for the simulation.

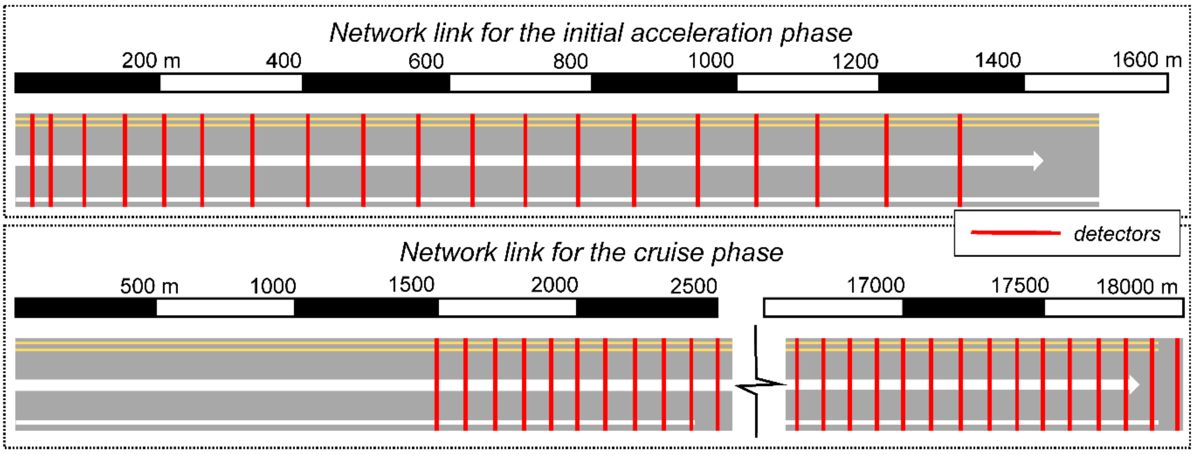


Figure 4. Schematic diagram of start and cruise default links.

The simulations used a flow of 60 veh/h during the first minute of the simulation, followed by no additional input flows, ensuring that only one truck per link were simulated, with a total absence of traffic interaction.

In VISSIM, vehicles whose power/mass ratio is not within the predefined limits (7 to 30 kW/t) receive an acceleration curve that is equal to the nearest limit. As can be observed in Figure 2, a significant part of the power/mass values of the sample are not within VISSIM standard limits. In order to prevent the simulator from disregarding the difference of the vehicles' performance not included in this range, the decision was to change the power/mass ratio limits to 2.3 and 23.2 kW/t.

Finally, the simulation time was set to 40 minutes, which is approximately double what is required for the real trucks to complete the route along the segment.

5.3. Fitness function

The fitness function, i.e. the function that returns the quality measure of the calibrated acceleration functions was a combination of two error measures, calculated for the two speed profiles (the initial acceleration phase and the cruise phase).

The first error measure uses the average error between real (observed) and simulated speeds in order to obtain an average error close to zero. This measure is represented by:

$$\mu = \frac{1}{N}\sum_{c=1}^{N}\left\{\frac{1}{M(c)}\sum_{i=1}^{M(c)}\left[V_c^s(i) - V_c^r(i)\right]\right\}, \quad (1)$$

where μ: the mean average of the simple errors for the speed of each truck;

c: the index that represents the trucks belonging to the category (light, medium, heavy or extra-heavy);

N: the total number of trucks for that category;

i: the index that represents the station along the way;

$M(c)$: the number of stations through which the c-th vehicle travelled;

$V_c^s(i)$: the simulated speed of the c-th truck at the i-th station along the segment; and

$V_c^r(i)$: the observed speed of the c-th truck at the i-th station along the segment.

The second measure uses square errors to penalize the larger differences between real and simulated speeds at each station:

$$\varepsilon = \sqrt{\frac{1}{N}\sum_{c=1}^{N}\left\{\frac{1}{M(c)}\sum_{i=1}^{M(c)}[V_c^s(i) - V_c^r(i)]^2\right\}}, \tag{2}$$

where ε is the square root of the mean average of the squared errors in the speed observation of each truck and all the other parameters were defined in Eq. 1.

Finally, the fitness function, which measures the quality of the calibration, is calculated through the function:

$$F = \frac{\mu_a + \mu_c + p\varepsilon_a + \varepsilon_c}{4} \tag{3}$$

where F is the fitness for an individual (i.e. a given set of calibration parameters from the performance model) in the population which comprises the current generation; a and c indicate the acceleration and cruise segments, respectively, for which the measurements μ and ε are calculated; and p is the penalty factor for measurement ε in the accelerating segment (where the initial acceleration occurs). The p value was empirically fixed at 0.2 because it was detected that this measurement could represent about 80% of the fitness, which would virtually eliminate the contribution of the other measures in the total value of F, hindering the calibration of the acceleration functions.

5.4. Implementing the Genetic Algorithm

A genetic algorithm is a search heuristic based on the process of natural selection. The genetic algorithm used to search for the best values for the acceleration functions was coded in Python v. 3.6 using the Spyder v. 3.2.6 development environment. Figure 5 shows a flowchart of the general structure of the genetic algorithm (GA) used.

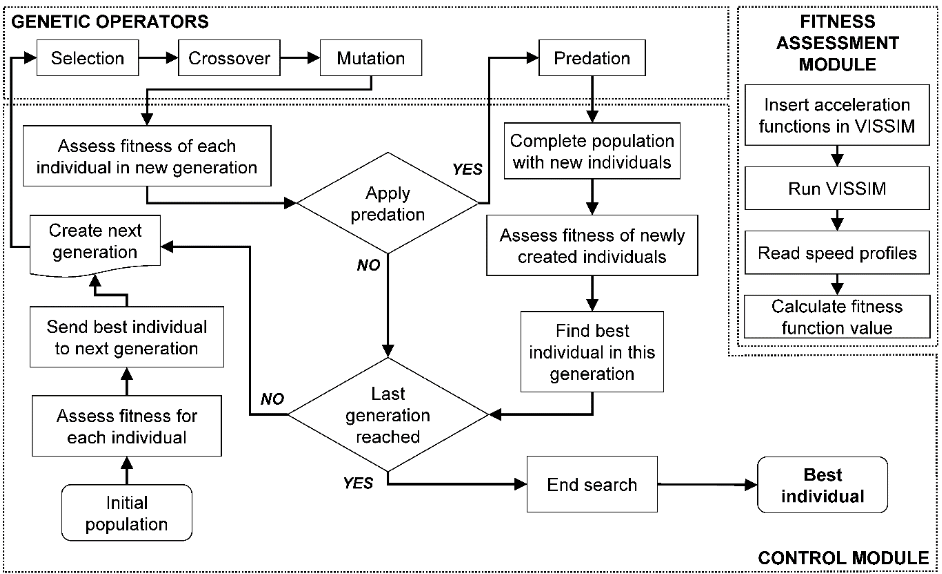


Figure 5. General flowchart of the genetic algorithm used to recalibrate the truck performance model.

The program contains three modules. The control module contains the routines to control the search and call the other two modules when needed. The second module is used to apply the genetic operators (selection, crossover, mutation and predation) used to create new individuals from the current population. The third module is used to calculate the fitness function value of an individual, a process that requires running VISSIM with new values for the maximum and desired acceleration functions to produce a simulated speed profile.

Selection of individuals for crossover assumes that all individuals in the previous generation are able to reproduce; best fitted individuals, however, have a greater chance to be selected, as the selection is based on the individual's fitness value. Routines for crossover, mutation and creating new individuals include a series of constraints, because VISSIM requires the acceleration functions to have the characteristic format shown in Figure 1. Those constraints also prevent the GA from creating acceleration values that would represent unrealistic operating conditions for the trucks. The best individual in each generation is always preserved, so the fitness value of the best individual in every generation is either maintained or improved and never worsens.

The creation and modification of individuals considered only the upper and lower limits of the acceleration functions. This decision reduced the constraints on the application of genetic operators when creating a new generation and increased the genetic variability of the populations. When needed, the median function is obtained from the average between the lower and upper acceleration limits for a given speed.

In each generation, 30% of the population (excepting the best individual) were randomly selected for mutation. Once an individual is selected for mutation, each of its genes had a 20% chance of being mutated. Mutation was carried out by attempting to add a random number between ±0.2 m/s^2 to the gene selected for mutation. If the new value was not valid, a new random value was selected, and the new sum was verified. The procedure is repeated up to five times and if none of the attempts resulted in a valid new gene, the original gene value was kept.

Predation was applied at every generation corresponding to 1/10 of the number of generations chosen for the GA run. At each predation, individuals were ranked according to their fitness function value and the individuals in the lower quartile were replace by new, randomly generated individuals.

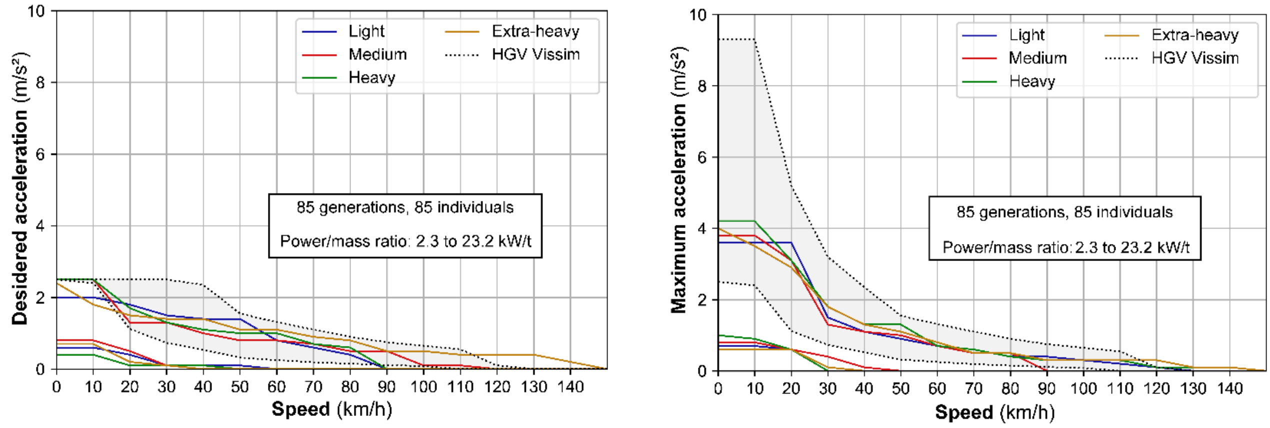
The fitness function evaluation consists of the following stages: inserting the acceleration functions' parameters into VISSIM, simulating the network with the configuration of the individual's acceleration functions; reading the simulation outputs; extracting detector speeds from the report; and calculating the individual's fitness.

The criterion for stopping the search was the number of generations, as the overall objective was to obtain the best fitness possible. At the end of its execution, the genetic algorithm issues two reports. The first one contains the configurations of the algorithm, the maximum and desired acceleration functions for the best individual, the measurement of its fitness and the metrics concerning the crossover and mutation operations. The second report contains the best and worst individuals of each generation, as well as the maximum, average, minimum and standard deviation of the fitness of each population.

To validate the calibration, 12 out of the 57 trucks were removed from the calibration phase, 3 from each category. The performance models for each truck category were calibrated separately from each other. Several combinations of population size and number of generations were analyzed to find the one that delivered a good level of fitness with an acceptable processing time. The combinations chosen for this study were: (1) population size of 85 individuals and 85 generations, which required 7423 evaluations of the fitness function; and (2) population of 105 individuals and 105 generations, demanding 11268 calculations of the fitness function value.

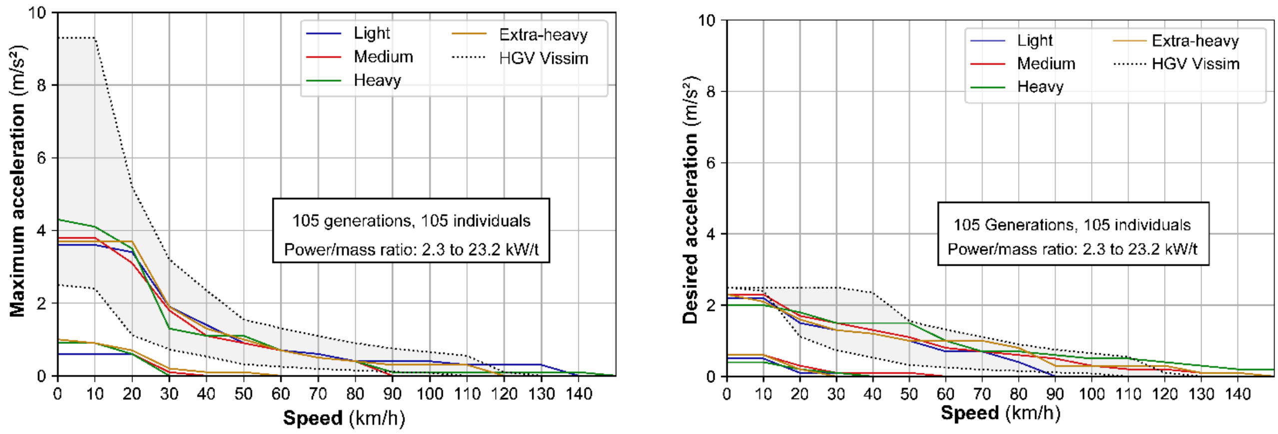
6. RESULTS ANALYSIS

Figures 6 and 7 show the default values for the maximum and desired acceleration functions (shown as HGV Vissim), as well as the best configurations for the four categories of trucks obtained for two combinations of numbers of generations and population size. The limits of the calibrated acceleration functions refer to power/mass ratios ranging between 2.3 and 23.2 kW/t, whereas the VISSIM default functions assume power/mass ratios from 7 to 30 kW/t.



(a) Maximum acceleration functions (b) Desired acceleration functions

Figure 6. Maximum and desired acceleration functions obtained from 85 generations and 85 individuals.



(a) Maximum acceleration functions (b) Desired acceleration functions

Figure 7. Maximum and desired acceleration functions obtained from 105 generations and 105 individuals.

It can be observed that, in general, the calibrated maximum acceleration functions are similar in format to the originals for speeds between 30 and 80 km/h. However, the calibrated values are slightly lower. Two hypotheses are raised to explain this phenomenon. First, it is likely that lower values are caused because the sampled trucks did not use all the engine power. As the drivers were not asked to drive in a specific way, they probably did not use all the power provided by the engines. Therefore, the obtained acceleration values refer to the use of the power desired by the drivers rather than the maximum possible power. Furthermore, the maximum power depends on the engine's conditions (maintenance, age, etc.) and, therefore, the resulting functions are affected by the difference between nominal and real power. This hypothesis is corroborated by the maximum acceleration functions presented in Figure 6 and Figure 7, which are always lower than the original ones.

The calibrated desired acceleration function presented upper limits with a similar format to the original, between 0 and 80 km/h. At the lower limits, the accelerations between 0 and 60 km/h are significantly lower than the default configuration, which suggests that the drivers were not using the maximum power.

It was observed that, in general, the different combinations of the number of generations/ population size generated calibrated functions with formats similar to each other for the range from 0 to 90 km/h. However, the acceleration values for speeds above 90 km/h differed significantly between the algorithm alternatives (number of generations, population size, among other issues), for the same category of trucks. This can be observed by comparing the functions in Figure 6 with those in Figure 7. This is probably because there are few observations of real speeds above 90 km/h.

Figure 8 shows the real and simulated speed profiles for the same truck. It can be observed that the simulated speed profiles are limited by the desired speed. It can also be noticed that the default performance model tends to overestimate the speed in a significant part of the trip, whereas the calibrated model tends to the observed speed. It is also important to notice that VISSIM does not replicate illogical driver behavior, such as the speed reduction applied to the truck between stations 40 and 50 and between stations 155 and 160. Figure 9 also shows that the effect of having a greater population and a greater number of generations is not very noticeable on the recalibrated performance model.

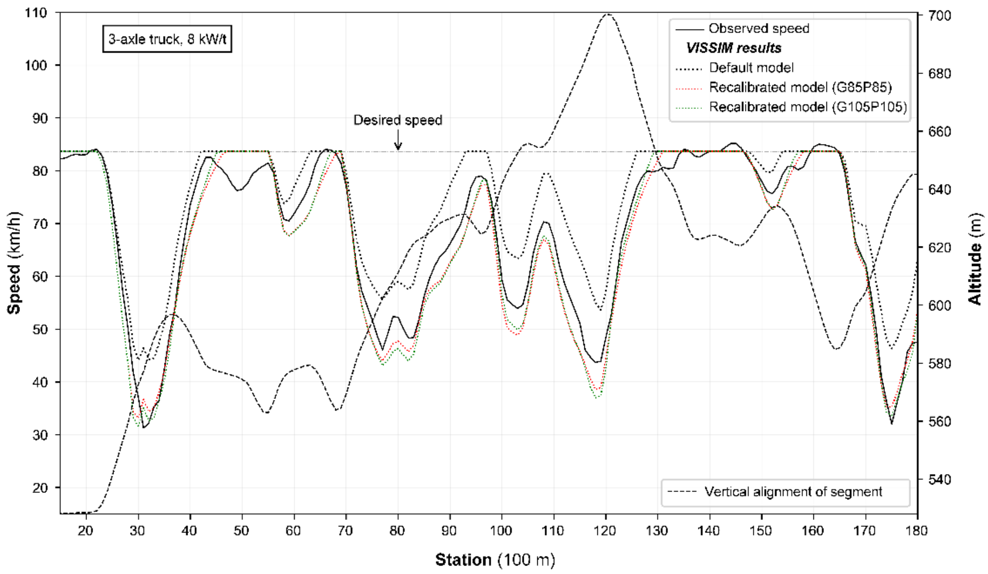


Figure 8. Speed profiles for the same truck showing real and simulated data (Truck 44).

7. VALIDATION OF THE RECALIBRATED MODEL

Figure 9 summarizes the validation of the recalibrated truck performance model. The validation consisted in comparing observed and simulated speed profiles for trucks whose speed data were not used in the model calibration.

The recalibrated models used in the simulations whose results are shown in Figure 9 were derived from the average acceleration values found for the trucks in each category, thus supposed to represent a typical truck of that particular type. Consequently, it is normal to find greater differences in speed during the validation of the model.

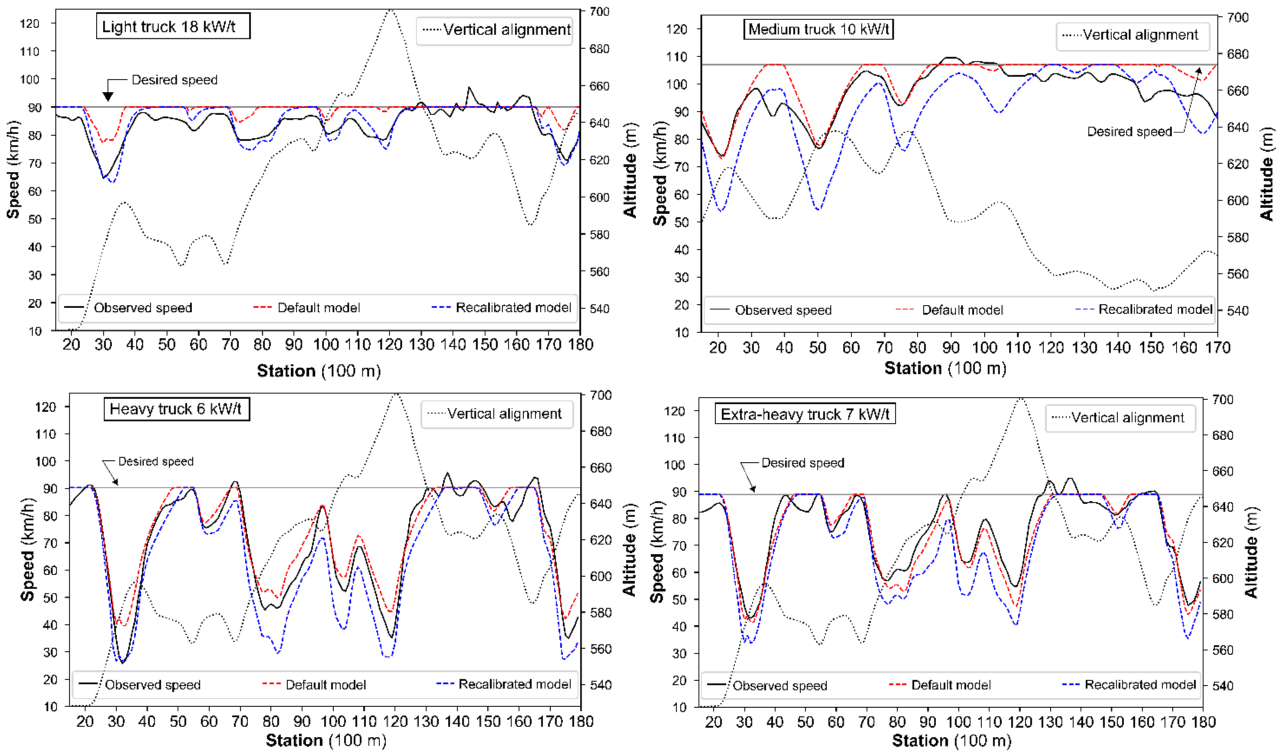


Figure 9. Comparison of observed speed profile vs. speed profile obtained with the default model and the recalibrated model, for four different trucks not included in the sample used for the calibration of the truck performance model.

Figure 9 shows that the behavior of all four trucks is consistent with the observed speed profile, except for the illogical speed reductions that VISSIM cannot reproduce well – e.g., between stations 30 and 40 for the medium truck; and between stations 40 and 50 for the extra-heavy, the medium and the light trucks.

8. FINAL CONSIDERATIONS

By using the proposed method, the maximum and desired VISSIM acceleration functions for Brazilian trucks could be calibrated. Based on the considerations adopted, it can be observed that the functions have satisfactory values for speeds between 0 and 90 km/h. Moreover, it should be highlighted that the limits for the power/mass ratio should be adjusted when using the calibrated functions.

A suggestion for future calibrations is to conduct an in-depth analysis to adopt the desired speed, given its importance not only for the VISSIM operation, but also for the evaluation of the functions' adjustment.

Finally, we recommend analyzing the importance of calibrating different functions for each truck category. Increasing the number of executions of the algorithm would enable one to evaluate how significant the differences are between categories. A second implication would be to obtain maximum and desired acceleration functions for a single truck category from the mean values obtained for the segregated truck categories.

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