

Generation of Replacement Vehicle Speed Cycles Based on Extensive Customer Data by Means of Markov Models and Threshold Accepting

Roman Liessner, Ansgar Dietermann, and Bernard Bäker
TU Dresden

Klaus Lüpkes
Daimler AG

ABSTRACT

The reduction of fuel consumption as well as the rising demands of customers regarding a vehicle's driving dynamic and the legislator's continually rising demands are a current issue in vehicle development. Hybrid vehicles offer a possibility to rise to this challenge. Realistic driving cycles are of utmost importance for the calibration of a hybrid vehicle's operational strategy. Deriving replacement speed cycles from extensive customer data sets seems to be an approach for solving these problems. The contribution at hand describes the derivation of replacement cycles by using stochastic models, probabilistic (weighted) drawings and a combinatorial optimisation. The novelty value is that the characteristic influences of all drivers are being considered in the generation due to the stochastic modelling. The newly developed algorithm extracts frequently reoccurring patterns from the stochastic model and then assembles several generated velocity progressions to one replacement cycle which combines characteristics which are important for consumption and are also customer-oriented. The contained combinatorial optimisation is based on an optimisation algorithm called "threshold accepting" and is an innovation for this usage scenario. Studies show positive properties for the combination of different driving patterns with the result that realistic replacement cycles can be extracted in a short time from extensive customer data. The ensuing replacement cycles provide the opportunity to attune a hybrid vehicle's operational strategy to the market and to perform sensitivity examinations and consumption forecasts.

CITATION: Liessner, R., Dietermann, A., Bäker, B., and Lüpkes, K., "Generation of Replacement Vehicle Speed Cycles Based on Extensive Customer Data by Means of Markov Models and Threshold Accepting," *SAE Int. J. Alt. Power*. 6(1):2017, doi:10.4271/2017-26-0256.

INTRODUCTION

Besides realising a low fuel consumption and high vehicle dynamics, another important goal of Europe's automobile manufacturers is to fulfil the new emission regulations. The until now employed New European Driving Cycle (NEDC) test procedure is to be replaced by the new Worldwide Harmonized Light-Duty Vehicles Test Cycle (WLTC) test procedure in the next years. In comparison to the NEDC, the WLTC test shows significantly more dynamic proportions and higher load areas. Additionally, there is the intention to introduce a so-called Real Drive Emissions (RDE) test. This test, which was performed in regular traffic and not on a test bench, offers new challenges. It examines if the vehicle emissions are complied with in various real driving situations [1]. These changing requirements encourage new methods for drafting and calibrating vehicles. An important part is the generation of customer-oriented replacement cycles.

According to [2, 3], the methods for generating replacement cycles reach from arbitrary to statistically demanding attempts. Test cycles as for example the NEDC and the 10-50 mode (Japan) have a strongly synthetic course being characterised by various constant velocity and acceleration proportions which are rather rare in a drive. Then again, the EPA Federal Test Procedure 72 (FTP-72) & FTP-75 (U.S.) are based on a real measurement drive; however, the underlying route was not methodologically deduced [4]. Besides recording own drives for example in [3], do [2, 5, 6, 7, 8] examine attempts to derive replacement cycles from larger sets of recorded data. Lee chooses a version of modelling by making use of Markov models [5]. A similar approach chosen by Reiser [2] differs mainly in the generation of new data sets [9]. Yet, a generation based on the approach introduced by him is not always successful. Based on the successive removing of the respective classes' elements, the generation can be terminated as soon as there are no more elements in a class and hence no followers can be determined. Marotta [7] shows an interest in the combination of single drive proportions to one

replacement cycle. Among others, he sets the focus on retaining important characteristics for fuel consumption [9]. However, Nyberg's results in [8] and the approach for generating by Marotta [7] contradict each other. In [7], Marotta points out that there is a similarity of driving cycles regarding the consumption if the distributions (as for example the velocity and acceleration distributions) correspond. The NEDC equivalent cycles presented by Nyberg in [8] do not fulfil this criterion. It would be expected to find constant velocity and acceleration phases in the replacement cycle as in the NEDC.

In the context of this work, we introduce a new method which differs in two central features from the previously published. Building on the studies in [5], first the data basis is transferred to a Markov model. Nevertheless, for the subsequent generation not only a large number of replacement cycles is created and the best is chosen on the basis of its entire length and vehicle-related statistical criteria. In contrast to this, the introduced method aims to create vehicle independent replacement cycles. Initially an extensive complex data set with new mixed stochastically weighted progressions is constructed. For the following processing, this complex data set is separated in microtrips. A microtrip defines itself as a drive between two vehicle standstills [6]. Following up, the challenge is to choose the most suitable microtrips and to combine them fittingly into one replacement cycle. Because a brute force approach cannot be done in a feasible time, a new algorithm based on threshold accepting was implemented. This algorithm offers the possibility to assemble microtrips into one replacement cycle in a relatively short time if they have similar properties as the data basis regarding the consumption.

In the following, the single steps for generating replacement cycles will be introduced. The flow chart in Figure 1 illustrates the different steps.

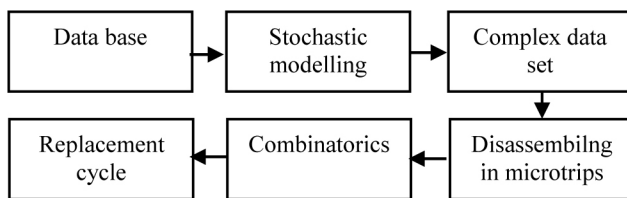


Figure 1. Schedule for generating replacement cycles from extensive base data.

The steps mentioned in Figure 1 will be explained in detail in the following subchapters.

METHOD

Data Basis

Real measured drives of an arbitrary number of drivers and vehicles serve as the basis for generating replacement cycles. These can be customer data, endurance runs and other drives. The resulting velocity and acceleration progressions form the basis for generation. The amount of data should be chosen as extensive as possible.

Stochastic Modelling

The method begins with the modelling of the data basis. When comparing possible ways, Markov models proved to be especially suitable. It is a stochastic process model that describes unknown systems on their states and their transitions. The Markov model takes simplification through a so-called Markov assumption as a basis (memorylessness). Thus a system's following state only depends on the current one. States being further in the past have no effect on the change of states. This correlation is described by formula 1: x_n stands for the current state and x_{n+1} for the following. States further in the past as well as their influence (in Formula x_1, x_2) are neglected [9]. For further information on the functionality of Markov models, see [10].

$$\begin{aligned} P(X_{n+1} = x_{n+1} | X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) \\ = P(X_{n+1} = x_{n+1} | X_n = x_n) \end{aligned} \quad (1)$$

Where,

$P()$ = probability function

X_n = Markov variable

x_n = current state

X_{n+1} = Markov variable

x_{n+1} = following state

A state x_k in this proposed application contains a discrete value of velocity and acceleration as seen in Formula (2).

$$x_k = \begin{cases} v_k \\ a_k \end{cases} \quad (2)$$

Where,

x_k = state

v_k = velocity value

a_k = acceleration value

To transfer the data basis into the Markov model, a simple iterative transfer of the single state transitions, from one point in time to the next, is sufficient. The assumption for further processing is that the saved state transitions in the Markov model contain all relevant information of this relationship. Because after all, the Markov model contains all recorded data of the drives in a condensed and anonymised form. The challenge is to choose and combine fitting parts of the complex data set in such a way so that representative replacement cycles with similar properties regarding the consumption can be derived.

Generation of the Complex Data Set

The following strategy is suitable to derive newly mixed velocity progressions from the Markov model. Based on an initially set velocity and acceleration combination, a generation is done by a query of the saved state transition in the Markov model. Through a weighted drawing according to the probabilities, the next velocity and acceleration combination is chosen. This procedure is repeated until the desired scope of the complex data set is reached. Thus an arbitrarily large complex data set is created which contains newly mixed stochastically weighted progressions. In the following, it is difficult to identify the elements in the complex data set which finally represent the customers' behaviour in the replacement cycle best. For this a separation of the complex data set into smaller units, which can be separately processed, is expedient.

Separation in Microtrips

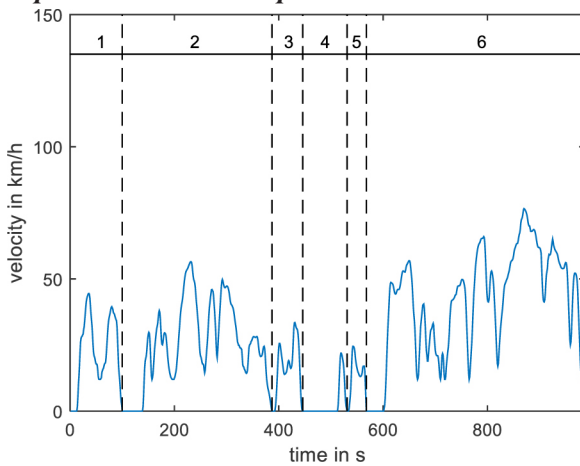


Figure 2. Separation of a drive in microtrips at the example of the WLTC.

For disassembling the complex data set, a fragmentation into so-called "microtrips" showed to be useful. A microtrip is a journey from one vehicle standstill to the next [6]. Figure 2 depicts a microtrip segmentation in six sections at the example of a part of the WLTC. Such a segmentation done for the complex data set creates a very high number of microtrips¹.

Finally, the main difficulty is to choose and combine fitting parts. Approaches like [5] pursue the goal to create vehicle-specific replacement cycles by analysing the energy at the wheels and to create a selection of statistical key figures. In contrast to this, it is this contribution's goal to introduce a vehicle-independent combinatorics which by means of distributions (velocity, acceleration, velocity multiplied by acceleration and standstill) and the Relative Positive Acceleration (RPA) index contains properties in the replacement cycle which are relevant for consumption. Single microtrips have to be combined into one replacement cycle with the goal that the resulting distributions agree in the best way possible with the data basis. For this, the following procedure is suitable.

Combinatorics

The number of microtrips which are necessary for combinatorics can be easily determined by means of few specific values. Since a microtrip is defined as a drive between two vehicle standstills, there is, per definition, one stop per microtrip. Thus the number of stops matches the number of microtrips. By means of the desired cycle length T_{cycle} (e.g. the duration of a usual customer drive), the mean velocity $\bar{v}$ of the data basis, and the stops per kilometre N_{Stp} of the data basis, it is possible to calculate the number of the necessary microtrips $N_{microtrip}$ needed for the replacement cycle as in Formula (3).

$$N_{microtrip} = T_{cycle} \cdot \bar{v} \cdot N_{Stp} \quad (3)$$

Where,

$N_{microtrip}$ = amount of needed microtrips

T_{cycle} = desired cycle length

$\bar{v}$ = mean velocity of the data basis

N_{Stp} = stops per kilometre N_{Stp} of the data basis

As it was explained before, the number of necessary pauses (stops) stands in direct proportion to the number of microtrips. However, the duration of the single pauses has to be calculated to reach similar distributions as in the data basis. The generation of the pauses is similar but easier in contrast to the generation of the velocity progressions because for this only the duration and its frequency have to be determined (the velocity is 0 km/h).

Given that there is a variety of microtrips and suitable pauses, we have to combine them in such a way so that the replacement cycle agrees with the relevant specific values for the consumption² in the data basis. Theoretically, it would be possible to try out all variants (brute force method). Yet it becomes clear that in a complex data set with K microtrips and for the replacement cycle E necessary ones, K^E combinations emerge. For example, $K=1000$ available and $E=5$ for the replacement cycle necessary microtrips as well as the assumption that an evaluation takes 0.1 seconds, a duration of $2.7 \cdot 10^{10}$ hours for the generation of the replacement cycle would be set. Thus a brute force approach for combination is not suitable. To counteract this problem³, a reduction of the complex data set K would be conceivable. Yet in most cases a reduction of the complex data set would be reflected negatively in the quality of results. To circumvent this compromise, a new algorithm for combining microtrips was implemented which is based on the idea of Threshold Accepting (TA). This is an algorithm introduced by Prof. Dueck to solve combinatorial problems [11]. This algorithm is a further development of the wide used Simulated Annealing (SA) approach which in comparison to the SA reaches better results in a shorter time [11]. The combination of the microtrips originating from the complex data set solves the threshold accepting approximately in a relatively short time. The pseudo code for the generation of replacement cycles is depicted in the following.