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Statistic Method for Extraction of Synthetic Load Cycles for Cycle life Tests of HEV Li-ion Batteries

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Abstract

Despite rapid development, the battery is still the single most expensive component in a HEV drivetrain. Consequently, its durability is critical to the overall feasibility of the vehicle. The battery ageing mechanisms and the resulting cycle life of HEV-optimised batteries are highly non-linear and difficult to test. In addition, the selection of load cycle profile is of great significance when battery cycle life is to be verified experimentally. This paper presents a statistic method for evaluation and simplification of dynamic load profiles based on measured load profiles from heavy-duty HEV applications. The presented method has been used to extract simplified synthetic load cycles with configurable energy throughput as well as different strategies for state-of-charge control. These cycles were also compared with reference cycles and evaluated regarding power distribution, energy distribution, energy window and energy throughput. The presented method was found to be a usable tool for creating new battery load cycles for cyclelife tests. In addition, it may be a useful to evaluate and compare statistical properties of measured cycles before initiating laboratory battery tests.

Keywords: battery model, battery SoH (State of Health), cycle life, lithium battery, energy storage

1 Introduction

The energy storage in a HEV, often a battery or a supercapacitor, is the single most expensive component in a HEV-powertrain. Hence, its cycle life and reliability is of fundamental importance for the feasibility of the complete HEV.

Batteries are continuously improved for first and foremost higher energy and power density with prolonged life, increased safety and lower production cost. The battery life is nonlinearly dependent on several parameters such as voltage range, operating temperature, current rate and energy throughput.

While some other applications using Li-ion batteries, such as consumer electronics and communication satellites, may have a predictive and representative usage patterns which easily can be converted into a typical load cycle suitable for cycle life testing, HEV energy storages are used in diverse conditions with a wide range of climate profiles, drive patterns, duty cycles, average power etc. Hence, a uniform and representative load cycle is normally not possible to extract.

Furthermore, the HEV powertrain control system needs to be complex and dependent on a large number of variables in order to obtain high performance and good drivability. As a consequence, measured battery load cycles are typically characterized by fast dynamics, few rest periods and short power transients combined with slower variations in power level. Also, batteries used in heavy-duty HEVs are often cycled at drive cycles that cannot be divided into short, uniform segments to simplify testing.

Generally, the total battery life time in a specific application is estimated from a combination of field test experiences and a limited number of cycle life tests of batteries at cell level with load cycles carefully selected to correspond to the actual usage as good as possible to provide valid information on actual battery lifetime. Different applications and different drive patterns result in different load cycles. Consequently, a complete test matrix covering the full range of possible load profiles would require extensive testing over several years and expand the test matrix beyond practical limits. An additional complication to this process is the fact that even small changes in the vehicle control system may change the battery load cycle in vital aspects, thus requiring a new set of cycle life tests to revalidate the battery lifetime.

Battery manufacturers often test battery cycle life according to standardized load cycles such as the widely spread profiles developed by EUCAR, USABC, ISO/IEC and other organizations and OEMs. Even if detailed case studies and measurements are used to select a suitable reference case, the load cycle used in cycle life tests must often be simplified to increase test stability and to reduce the dynamic requirements on the battery test equipment.

Simplified load cycles might not be representative to the actual battery usage even though the average current, RMS power and energy throughput are identical. Nevertheless, simplified test cycles would greatly simplify the set-up and evaluation of cycle life tests as well as enabling a comparison between different cycles tested by different OEMs. Furthermore, there is a need for a method to compare, evaluate and combine different load cycles for different conditions to enable the usage of existing test results from other applications, projects, test objects and load cycles in the current development by OEMs and battery developers.

2 Scope

The method proposed in this paper suggests a statistic approach for analyzing measured battery load cycles in terms of a number of key properties such as power distribution and energy throughput.
These statistic cycle properties are then used to compare cycles and to generate new synthetic load cycles where key parameters such as average power and current rate can be adjusted while keeping other properties of the cycle constant. In addition, the method can be used to reduce the total load cycle length to a minimum which further simplifies the test setup.

The primary target for the work performed is to find an objective, reliable method for reducing the setup time for battery tests. In addition, the method should be a tool for evaluating how applicable results from different load cycle tests are to a particular application.

First and foremost this method is developed for use in cycle life tests of Li-ion batteries optimized for heavy-duty HEVs. There are however no direct restriction to the usage of the method to the testing of other secondary batteries.

Specifically, this paper investigates the suitability of using a Markov chain as a model for the battery load cycle in heavy-duty HEV applications. Firstly, the theoretical background the method is presented together with the battery model. Secondly, a simplified charge sustaining algorithm is added to the system to control the state-of-charge (SOC) of the battery during longer load cycles. Thirdly, the method is used to generate a number of synthetic load cycles to be compared with a reference cycle from a HEV city-bus. Additionally, the simulation results are compared to test results on Li-ion cells cycled at both measured and synthetic load cycles.

3 Stochastic Model

The use of a Markov chain has been suggested for load cycle simulation in several papers [1], [2], [3] and [4].
This method can easily be adapted to HEV load cycles by converting the power into discrete power levels in a state-vector S in which each level represents a unique state. A probability matrix Q, called the *Markov* matrix, can then be formed where the probability for transition from state i to state j is equal to element Q_{ij}:

$$Q_{ij} = P(S_{n+1} = i \mid S_n = j) \quad (1)$$

$$Q_{ij} = \begin{bmatrix} S_1 \to S_1 & S_2 \to S_1 & \cdots & S_n \to S_1 \\ S_1 \to S_2 & S_2 \to S_2 & \cdots & S_n \to S_2 \\ \vdots & \vdots & \vdots & \vdots \\ S_1 \to S_m & S_2 \to S_m & \cdots & S_m \to S_m \end{bmatrix} \quad (2)$$

where S_{n+1} is the next state (power level), S_n is the current state and P is the probability for a transition from S_n to S_{n+1}.

The m x m matrix, Q, is typically a sparse matrix with the greatest elements around the diagonal $Q_{1,1}$ to $Q_{m,m}$. Each column sum must be equal to 1, since the probability for transition to any possible new state must be one for each current state. This is however only true if all states in the state vector is entered in the real load cycle. If not, numeric problems might occur depending on the implementation. The Q matrix is "trained" with one or several load cycle to populate each element with the corresponding probability.

A new, synthetic cycle of any length can then be calculated using a minimum of tools, which will be further described in section 3.1:

1. an initial state in the S-vector for which the corresponding column sum $\neq 0$
2. a random number generator

Changes and adaptations to the probabilities in the Q matrix should be avoided to preserve stability. Instead, power levels can either be adjusted according to an independent weight function before the population of the Q matrix or the output state can be adjusted by selecting either a higher or lower power level than the one generated by the random function. Even though such modifications to the cycle are in conflict to the stochastic approach, it will in practice be necessary to include them to first and foremost keep the SOC within the admissible range.

There is a specific issue related to the selection of states to include in the S-vector. Depending on the choice and the cycle properties the S-vector and the Q-matrix may contain empty states / empty column. These states might in turn cause instabilities to the cycle generation. There are two obvious solutions to this issue:

1. The corresponding column in Q can be populated as the linear interpolation between adjacent columns. This method will generate a stable output but may cause the output synthetic cycle to consist of power levels never observed in the real cycle.
2. The SOC-algorithm can be changed to avoid selecting states (power levels) not observed in the real cycle.

In theory, this may not be an issue, but in practice when using standard random number generators in for example Matlab® it may be relevant as described further in section *Implementation*. The second method was selected in this project to ensure that the procedure can work with a large variety of load cycles in combination with a comparably large Q-matrix.

3.1 Implementation

Firstly, the S-vector of length m is selected to correspond to the reference load cycle properties. The m x m-matrix Q is then formed by stepping through the reference load cycle and incrementing the corresponding state $Q_{n,x}$ for each step, followed by the normalization of the columns by the total column sum. The first step in this learning process can be repeated for every measured (or simulated) load cycle that should be included in the synthesis as long as the sample rate is the same for all cycles and the total number of cycle steps for all cycles are used to normalize the columns in the second step.

At this stage it is also possible to introduce limitations, weight functions, or in other ways change the properties of Q and any generated synthetic cycles compared to the input cycle(s).

Following the calculation of the Q-matrix, a synthetic cycle can easily be generated step-wise using a general random number generator. In Matlab®, this can be done by creating a support matrix Qs consisting of the cumulative column sum of Q and the random generator **rand**; the column in Qs corresponding to the current state is compared by a random number [0..1] and the element closest to the random number is selected as the next state. That is, the output state is the first row index n of $Q_{s(n,x)}$ that satisfies the relation $Q_{s(n,x)}>$ **rand** where x is the current state and n is the next state. Simplified examples of Q and Qs are shown in Figure 1 and Figure 2. These examples are however not representative to HEV-cycles.

This short algorithm is repeated for each step in the cycle starting the initial state x_0 corresponding to the initial power level. The output state n of each iteration is used as input state x for the next calculation. There is no theoretical limit to the total length of the synthetic cycle. In practice the length will however be limited by a lower limit determined by the requirements on correspondence with the reference cycle (see section 3.2).

$$Q=\begin{bmatrix} 0.9 & 0.05 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.05 & 0.8 & 0.2 & 0.1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.04 & 0.05 & 0.7 & 0.2 & 0.08 & 0 & 0 & 0 & 0 & 0 \\ 0.01 & 0.05 & 0.1 & 0.6 & 0.02 & 0.06 & 0 & 0 & 0 & 0 \\ 0 & 0.03 & 0 & 0.05 & 0.9 & 0.04 & 0.03 & 0 & 0 & 0 \\ 0 & 0.02 & 0 & 0.05 & 0 & 0.8 & 0.17 & 0.01 & 0.04 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.1 & 0.5 & 0.03 & 0.06 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.2 & 0.95 & 0.1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.1 & 0.01 & 0.7 & 0.2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1 & 0.8 \end{bmatrix} \quad (3)$$

Figure 1 Example of 10 x 10 Markov matrix Q

$$Q_s=\begin{bmatrix} 0.9 & 0.05 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.95 & 0.85 & 0.2 & 0.1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.99 & 0.9 & 0.9 & 0.3 & 0.08 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0.95 & 1 & 0.9 & 0.1 & 0.06 & 0 & 0 & 0 & 0 \\ 1 & 0.98 & 1 & 0.95 & 1 & 0.1 & 0.03 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0.9 & 0.2 & 0.01 & 0.04 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0.7 & 0.04 & 0.1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0.9 & 0.99 & 0.2 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0.9 & 0.2 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \quad (4)$$

Figure 2 Example of cumulative sum matrix Q_s of Q

As mentioned in the previous section, a problem with SOC exceeding the maximum limits might occur when battery load cycles from charge-sustaining HEVs are studied, especially if the cycles are comparably long and the energy throughput is in the range of the usable energy content of the battery. In such cases the SOC of the target battery must be calculated for each time step and then, *via* a predefined SOC control strategy, be used to adjust the output power for the next step to limit the required SOC-range. Thus, the battery load cycle cannot be treated as a purely stochastic process from a strictly fundamental standpoint unless the battery capacity is infinitely large or the load cycles are very short in duration. Nevertheless, this limitation of the proposed method is still viable since it replicates the situation in a real HEV where the drive pattern and road profile may be considered as stochastic whereas the actual battery current is limited and controlled by a control unit based on a non-stochastic strategy.

If, in addition, the S-vector is composed by representative levels with a high number of levels, the SOC-strategy will only have a minor impact on cycle properties in terms of power and energy. This issue and a proposed solution are presented in detail in the following sections, where the first part presents the definition of SOC and the associated battery model, followed by an example of a simple SOC-preserving control strategy.

3.1.1 Battery model used for SOC-estimation

The state-of-charge (SOC) of a battery is typically defined as the ratio between the available discharge capacity and the maximum discharge capacity at a specific temperature and age (state-of-health – SOH). While the SOC in a HEV is carefully controlled to ensure the performance and durability of the battery throughout the design lifetime, this is not the case for the generated stochastic cycle according to the Markov-process. However, the average SOC for any truly stochastic cycle will be equal to the initial SOC for an infinitely long cycle if the total probability for charge is equal to the probability for discharge, capacity wise. This is naturally not the case for real cycles of finite length, especially not for HEV batteries with a comparably high energy throughput. Hence, the resulting SOC of the synthetic cycle must be controlled according to a pre-defined strategy using a similar method as is implemented in a real HEV.

$$SOC(t) = \frac{C_{reference}[As] - C_{discharged}(t)[As]}{C_{reference}[As]} = \quad (5)$$

$$= \frac{C_{reference}[As] - \int_0^t I\,dt}{C_{reference}[As]}$$

Firstly, a method for a step-wise calculating SOC during the extraction of the synthetic cycle is selected. Using the relation in (5) and a fixed value for the reference capacity $C_{reference}$, the $SOC(t)$ is numerically calculated as the Euler approximation of the integrated current in each step. If the load cycle is characterized by constant power levels rather than current levels, a separate algorithm for estimation of current must be added. Any battery model able to calculate current from a power input is possible to use at this stage. For simplicity, a rudimental *Thevénin* equivalent circuit is used here:

$$U(t) = U_{OCV}(t) + R(t)I(t) \quad (6)$$

Assuming the typically narrow SOC-range of most Li-ion batteries designed for HEV's, the average open circuit voltage U_{OCV} may be regarded as a constant. Similarly, the internal resistance can be simplified using a single value or a limited set of values to further simplify the equation.
Starting from the input power to the battery, the power – current relation in (7) must be satisfied for all time steps.

$$P(t) = U(t) \cdot I(t) = U_{OCV}(t) \cdot I(t) + R(t) \cdot (I(t))^2 \qquad (7)$$

Solving this equation for each time instant yields a time-varying current vector to be used in SOC-estimation.

Secondly, an appropriate SOC strategy is added to keep the SOC of the battery within the acceptable range throughout the duration of the synthetic cycle. This approach, or any other SOC-preserving method, is absolutely essential when extracting synthetic cycles in which the energy throughput is comparable to the maximum usable energy of the battery.

3.1.2 SOC Control Strategy

Naturally, there are countless ways to control the SOC in a HEV. That is especially challenging for cycles with an energy throughput that is comparable to or exceeding the usable battery energy. A synthetic load cycle could either be designed to replicate the SOC-trends of the target load cycle as accurately as possible, or to reflect the statistical properties of the load cycle using an additional weight function that will control the SOC to stay within the acceptable range. One approach to control SOC is to limit the charge power close to the upper SOC-limit and the discharge power close to the lower limit. Rutquist *et al* [5] suggested the tangent function as the optimal control function *u=f(soc)* for a simplified system with a supercapacitor energy storage. This strategy may be expanded to batteries, at least within a narrow SOC-range, and was therefore used in this paper.

Regardless of which strategy that is chosen, a stable weight function that limits the maximum SOC-swing of the synthetic load cycle is needed. The reference for this function could either be a static target (SOC_{target}), a dynamic SOC signal according to measured properties or a simulated signal assuming a constant average efficiency of the battery cell.

Since the generated cycle is stochastic, no change made to the *Q*-matrix will be efficient to keep SOC within the admissible range. Even small changes in the Q-matrix defining the Markov process might cause severe stability problems in the cycle generation. Hence, the Q-matrix must be left un-changed and the output power levels used to control SOC instead.

The inverse tangent function according to [5] was used to generate a limit function for SOC. This function can be configured with different steepness at the edges (see Figure 3). For each step generated according to the method described in the previous section, the output power level is weighed with this limit function. If the SOC is close to the target SOC no change is made to the output power. In contrast, when the SOC is close to the limits the target function gradually limits the charge power (at high SOC) and the discharge power (at low SOC). The calculated new power level is then adjusted to fit the pre-defined power levels (states) in the *S*-vector. The adjustment factor 0..1 is based on the Matlab® tangent function **tan** according to equations 8 and 9.

$$SOC_{\mathrm{LimitFcn}} = 1 - \left| \tan\left(\left(\frac{SOC - SOC_{\mathrm{target}}}{SOC_{\mathrm{max}} - SOC_{\mathrm{target}}} \right)^{SOC_{\mathrm{slope}}} \right) \right| \qquad (8)$$

where
SOC_{target} is the centerpoint of the admissible SOC-range,
SOC_{max} is the maximum admissible SOC,
SOC_{min} is the minimum admissible SOC, and
SOC_{slope} is a control parameter typically between 1 and 10 that determines the steepness of the limit function close to the boundaries.

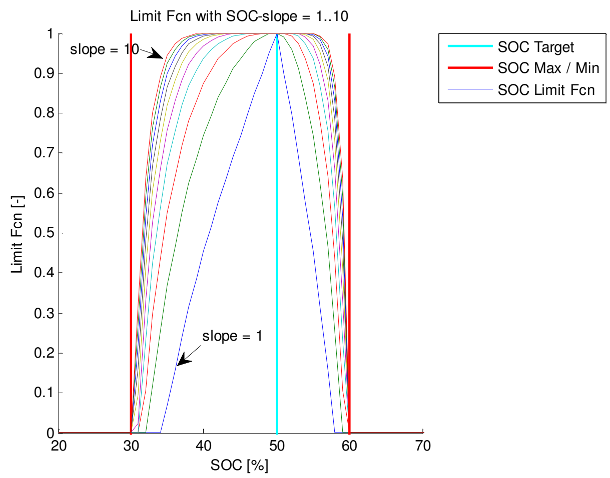

Figure 3 Limit function using tangent function and SOCslope between 1 and 10

The limit function $SOC_{Limit\ Fcn}$ varies between 0..1 for SOC between [SOC_{min} … SOC_{max}] and can be used directly as a multiplication factor for the output power level in each step of the cycle generation:

$$P_{output} = SOC_{LimitFcn} S_{n+1} \quad (9)$$

The corrected output state corresponding to P_{output} in (9) must then be selected as the power level that best corresponds to the discrete levels in the state vector S for which the probability is larger than zero.

3.1.3 Optimisation

Any cycle generated according to the proposed method will reflect the fundamental properties of the reference cycle. However, the actual SOC-characteristics as well as other cycle properties will differ significantly between different synthetic cycles. To find and evaluate solutions / versions of the synthetic cycle with good, objective correspondence to the reference cycle, an optimisation process was run where key aspects of the cycle were compared to the reference cycle by means of weighted error functions, (10) to (14). A large number of cycles were generated, each according to the same *Markov* process and with the same settings, presented in Table 1.

1.
Difference in SOC over the complete cycle:

$$ERR_{SOC} = K_{SOC} \cdot \frac{1}{n_2 - n_1} \cdot \sum_{n_1}^{n_2} \left| SOC_{synthetic} - SOC_{reference} \right| \quad (10)$$

2.
Difference in RMS-power, scaled to kW:

$$ERR_{P_{RMS}} = K_P \cdot \left| P_{RMS,\,synthetic}[kW] - P_{RMS,\,reference}[kW] \right| \quad (11)$$

3.
Difference in maximum energy window:

$$ERR_{W_{window}} = K_W \cdot \left| W_{window,\,synthetic}[Wh] - W_{window,\,reference}[Wh] \right| \quad (12)$$

4.
Difference in power distribution:

$$ERR_{P_{dist}} = K_{P,dist} \cdot \sum_S \left| \frac{hist(P_{synthetic}, S)}{N} - \frac{hist(P_{reference}, S)}{N} \right| \quad (13)$$

where
N = number of elements
S = discrete power vector
hist(Y,X) = the histogram (distribution) of Y over X

5.
Difference in energy distribution:

$$ERR_{W_{dist}} = K_{W,dist} \cdot \sum_S \left| \frac{hist(W_{synthetic}, S)}{N} - \frac{hist(W_{reference}, S)}{N} \right| \quad (14)$$

where
N = number of elements
S = discrete power vector
hist(Y,X) = the histogram (distribution) of Y(X)

The weight factors K_{SOC}, K_P and K_W are set for the specific application to set internal priority between the evaluation measures.

For sufficiently long synthetic cycles the power distribution and energy distribution over the discrete power vector are expected to be similar to that of the reference cycle. However, this is only the case if the reference cycle can be modelled as a truly stochastic *Markov* process. Consequently, the shape of the power and energy distribution can be compared to the reference cycle to determine

a) the validity of the *Markov* process to model the load cycle

b) the minimum length of the synthetic output cycle to cover the full spectrum of the reference cycle

Previous sections described the SOC-strategy as a necessary perturbation to the true *Markov* cycle since it affects the power levels in the synthetic cycle when the estimated SOC-level is close to the limits.

The method in this paper uses the five presented error functions above, with weight factors according to Table 1 set to address specific properties. If the synthetic cycle should be similar to the reference cycle in SOC-variations, a larger value should be assigned to the factor K_{SOC}, and similar for the other properties. Naturally it is also viable to use a combination of the K-factors to generate cycles that in average corresponds well to the reference cycle. Nevertheless, the fourth and fifth error function should be used to determine the minimum cycle time or minimum cycle length which has the fundamental properties of the reference cycle in terms of distribution of power and energy.

3.2 Evaluation

The feasibility of the proposed method was evaluated based on an investigation of a large number of synthetic load cycles extracted and compared to a reference cycle. This reference cycle is based on measured battery current and battery voltage from a heavy-duty prototype HEV city-bus in Gothenburg, Sweden. Using the measured voltage and current together with the logged SOC-level estimated by the battery management unit, the *Q*-matrix was calculated according to the method described in previous sections, based on this single reference load cycle. In addition, the logged battery data was used to extract parameters for the simple battery model needed for SOC-estimation.

Using the proposed SOC-strategy and general settings for SOC-average and SOC-limits as well as battery data from a relevant Li-ion battery (see Table 1) a number of synthetic cycles were generated and evaluated according to the error functions described in previous sections.

Table 1 Battery properties and SOC-strategy settings

Parameter	Abbr.	Value	Unit
<u>SOC-strategy</u>			
Reference SOC	*SOCtarget*	50	%
Upper SOC limit	*SOCmax*	60	%
Lower SOC limit	*SOCmin*	30	%
Initial SOC	*SOCinitial*	50	%
SOC-str	*SOCslope*	10	-
Sampling time	t_{step}	0.1	s
Optim.-factor, SOC	K_{SOC}	1/10	-
Optim.-factor, RMS-power	K_P	1/500	-
Optim.-factor, Energy window	K_W	1/40	-
<u>Battery</u>			
Total energy	$W_{Battery}$	3000	Wh
Total capacity	$C_{Battery}$	5	Ah
Total internal resistance	$ESR_{Battery}$	0.45	Ω
Open circuit voltage at 50% SOC	U_{OCV}	630	V

Firstly, the minimum cycle length was evaluated using error functions 4 and 5. The outcome of this part indicated that, for this particular reference cycle and set of conditions, the cycle must be at least 30% of the original length to capture the fundamental properties (see Figure 4). Other reference cycles, or the usage of a combination of cycles to calculate the *Q*-matrix, would most likely yield other results. In addition, the choice of the discrete power vector *S* is of fundamental importance in the evaluation; if a low number of power levels (states) are included in *S*, all states with high probability in the reference cycle are likely to occur in the synthetic cycles after a comparably low number of steps. The example in this paper used an *S*-vector of [-100:1:100]% of rated peak power, resulting in a 101x101 sized *Q*-matrix. This fact will in turn require the cycle length to be in the same range as the number of elements in *Q* (≈10000) to allow the cycle to span over the complete range of states.

In Figure 4 the cumulative error between the power distribution and energy distribution is presented as function of the fraction of the reference cycle length.

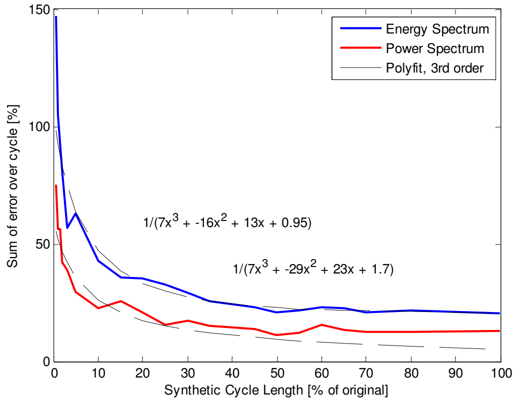

Figure 4 Cumulative error between power- and energy distribution and the reference cycle for different synthetic cycle length.

The correspondence between the power- and energy distribution for the synthetic cycle and the reference cycles as a function of cycle length is also clearly evident in Figure 5 to Figure 8 where the distributions are shown for 5% and 80% respectively.

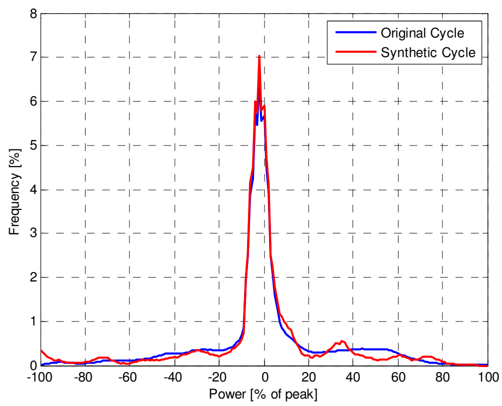

Figure 5 Power distribution at 5% cycle length

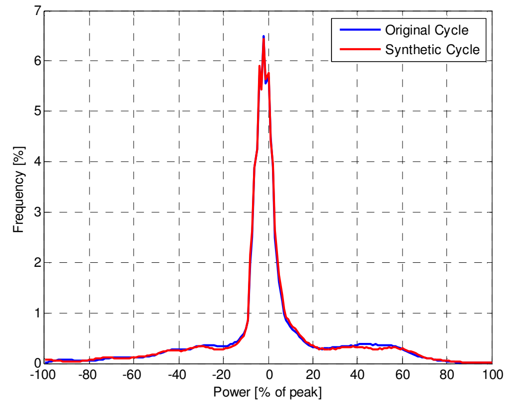

Figure 6 Power distribution at 80% of cycle length

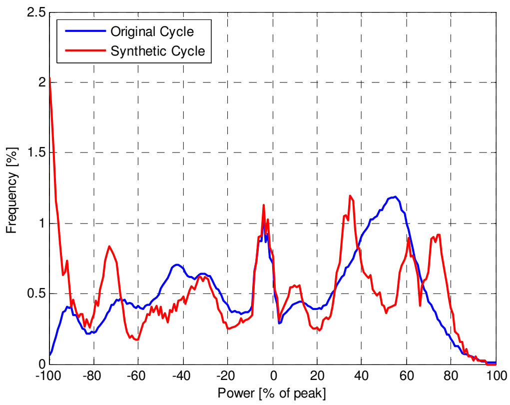

Figure 7 Energy distribution at 5% cycle length

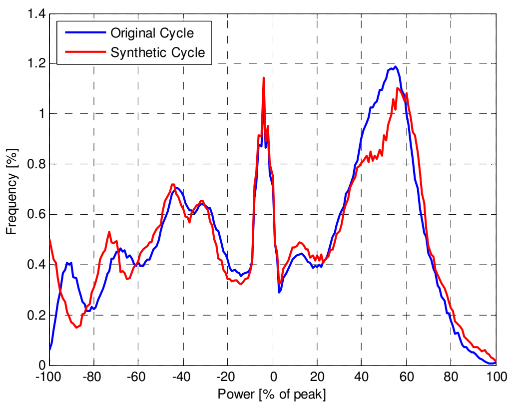

Figure 8 Energy distribution at 80% cycle length

In addition to optimising the cycle generation process for good correspondence to the reference cycle in terms of power distribution and energy distribution, the SOC-changes must be taken into considerations. Nevertheless, the presented method has shown promising results and may be used for simplifying the set-up of battery tests, the evaluation of load cycles and to combine several reference cycles into one test cycle.

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