Typical performance cycles of mobile machinery taking into account the operator influence

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Abstract

Mobile machines such as wheel loaders or excavators are used in a variety of applications. Thus the assessment of typical load cases for the design and development process of a machine will never incorporate all possible scenarios. Even bench tests may not be sufficient since environmental conditions and particularly the operator have a major influence on the state of the machine. The paper presented here describes a method to extract typical load cycles from “real-life” measurements of a given task, taking into account different skill and experience of the operator. Firstly cycle-specific features such as criteria for the evaluation of operator skill must be identified. Secondly a general approach for data reduction is used to derive a small subset of significant datasets from an extensive field test database of work cycles. That way, typical task- and feature-dependent cycles can be found. Finally those cycles can be used as input or reference for simulation experiments. This approach is demonstrated for the trenching process with a 20t excavator.

KEYWORDS: excavator, data reduction, operator

1. Introduction

One of the major problems in the development of a mobile machine is the definition of an appropriate load model. The term “load model” is used here in a general context. It not only covers the torques and forces acting on the contact area of the machine’s tool and the environment. For every single component of the mechanical structure, the powertrain, the hydraulic system etc., information about the loads it will be exposed to within the lifecycle of the machine, is required. This is the foundation for an optimal designed machine.

For a modern mobile machine, such as an excavator, another unknown is added to the problem. Due to the variety of available tools that are easily exchangeable through quick coupling units, the machine is used for much more different tasks than just the excavation it was initially designed for. The user application range statistics, **Figure 1**, points out that in 2009 only 5% of all excavators were employed in "heavy duty" operation such as mining, cargo handling or industrial applications. I.e. they are expected to operate under rather constant working conditions over their entire lifetime.

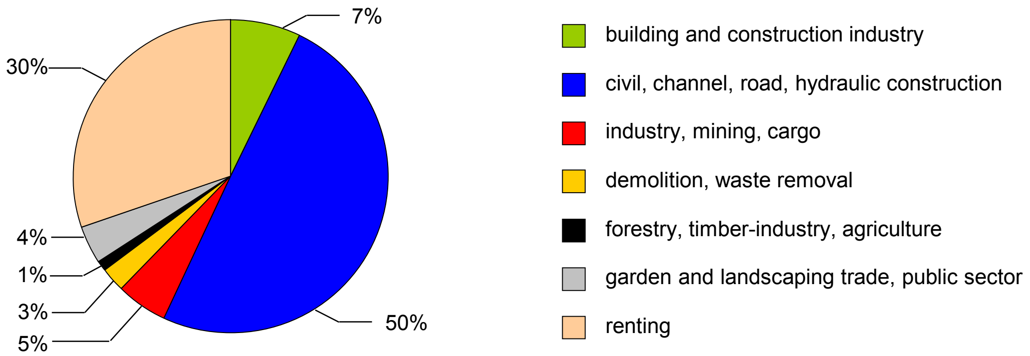

Figure 1: VDMA user application range analysis 2009 (January till June)

The remaining 95% are used in various applications using different tools and performing different work processes. Practically the load assumptions for those machines have to be deduced from a combination of multiple scenarios with high and low performance demands, e.g. excavating and shaping ground, **Figure 6**.

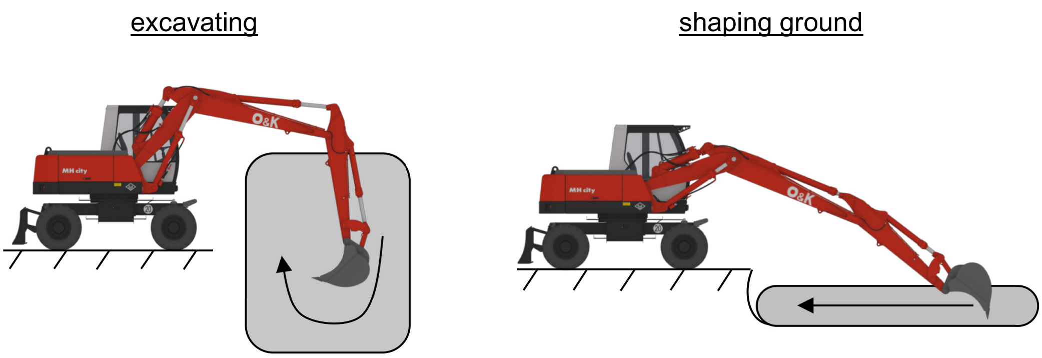

Figure 2: Work cycles with different performance demands for a mobile excavator

Finding an appropriate, general load model for these multi-purpose machines is extremely difficult since the OEM can hardly predict the – customer-dependent – usage of his machine. Moreover the operator comes into play. Even field tests with prototypes may be of limited validity since they are often performed by specially trained expert operators. Having another operator executed the same task can lead to different states of the machine and its components. In addition field test often produce a huge amount of data that cannot be used as load model entirely. Thus a method is required to derive a representative set of work cycles from tests with varying operators.

2. Approach

In the literature there are many approaches that achieve data reduction by averaging a large number of measured cycles. Since the cycle times may vary considerably, a resampling to a common time axis has to be done (/1/). This leads to the problem of a distorted power-time-curve which doesn't correspond to the measured one. That is why a new method shall be introduced here. The measured time series are left unchanged and their properties are described by characteristic quantities, so called „cycle features". Those cycle features are subject to a stochastic deviation brought about by a multitude of external influences. It is claimed that a selection of only a few measured cycles can be used to approximate the overall measurement duration by the help of a statistical model. The reduced data may serve as input for simulation experiments or bench tests. Extrapolation of those results using the identified cycle feature distributions enables the estimation of the machine's operational states for a longer period of operation.

One of the most important influences on mobile machinery is the operator. His behaviour and physical actions specify the power level utilised to fulfil a certain task and the way the power is distributed to the different actors of the drive system (/2/ to /4/). As a consequence there will not be a unique, typical power cycle. Even the most skilled and experienced operators will not be able to perfectly reproduce a previous work cycle. Bearing in mind the manipulation of the environment by the machine's work process, this becomes even more apparent. Regarding todays state of the technology it is not possible to develop a closed formal model for the human operator due to the variety of his mental and physical properties. Additionally, the operator has the ability to more or less quickly adapt to new and unknown situations as well as improving his skills through learning and experience. Hence a phenomenological approach is to be used for the description of the operator influence on power cycles. For that purpose suitable cycle features have to be defined at first. This enables to quantify the operator influence on the energy input of the machine for a selected work process – a so-called process pattern (/5/, /6/). Therefore a statistical model is to be developed which can be used for the design and the evaluation of drive concepts.

One significant feature for the characterization of the operator's skills in machine handling is the simultaneity level. It is defined as the average number of simultaneously controlled actuators, such as hydraulic cylinders or rotational drives, during one work cycle. It can be said that the higher the simultaneity level the more skilled the operator. Another feature for the quantification of the effectiveness of the machine usage for a given process pattern is the cycle time. This is the length of a cycle on the time axis without idle time. Again there can be stated, a lower cycle time implies a higher level of education. The third feature is the average cycle power which is calculated from the arithmetic mean of all instantaneous power values within the cycle.

3. Case study mobile excavator

The development of the statistic model of the cycle features is based on an exemplary field test. Therefore a mobile excavator of approximately 20t operating weight was equipped with numerous sensors and a data logger. It was handed over to a training school for construction equipment operators where the process pattern 'trenching' was executed with different operators, **Figure 3**. Measurement data was recorded for 1^{st} year and 3^{rd} year apprentices as well as two instructors. Finally the experimental data base was screened and the time series were cut into single work cycles. This way a total amount of 285 work cycles could be gained for further investigation.

Figure 3: Trenching with 20t mobile excavator

For a first analysis of the cycle features, all previous knowledge about the test persons, such as age or years of experience, was suppressed to test the objectivity of the approach. **Figure 4** a)-c) shows the distributions of three cycle features respectively for all 285 work cycles. The visible variance of the cycle time as well as of the simultaneity level and the average cycle power impressively emphasizes the need to describe work cycles through their features and statistic distribution models. Moreover the interpretation of the data leads to the assumption that data points may be arranged in groups which are to be identified.

The k-means algorithm /7/, a partitioning cluster analysis method, can be used to classify similar work cycles. A distance metric is introduced that quantifies the affinity of two cycles using the three cycle features simultaneity level, cycle time and average cycle power. Therefore the Euclidian distance was chosen from a number of various metrics found in the references. Since the cycle features are quantities with physical units, they have to be normalized to dimensionless quantities before doing any calculations. Subsequently, an iterative process is launched to assign the work cycles to a given number of cluster centres in a way that the sum of the distances between feature vector and corresponding cluster centre becomes minimal.

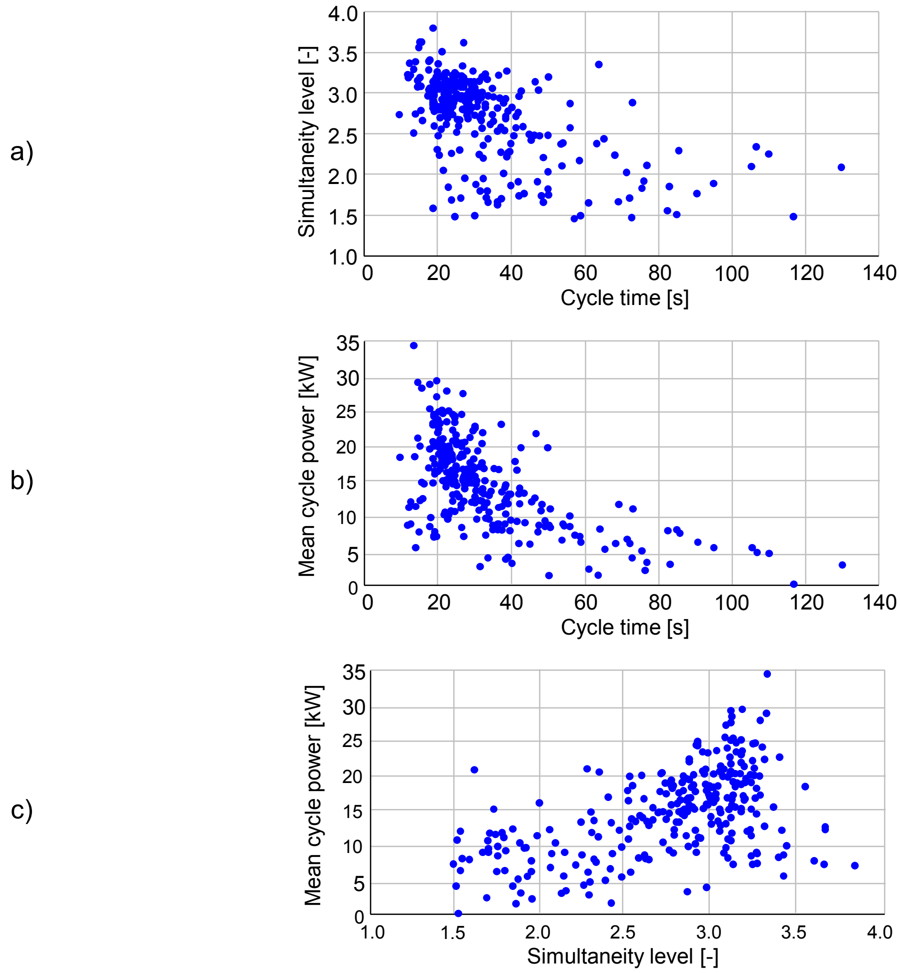

Figure 4: Cycle features for 285 work cycles

After a screening of the available data base, the cloud of data points was partitioned into two clusters. The result is displayed in **Figure 5**. The data points of the first cluster show a large variance of cycle times and a low simultaneity level. These cycles can be interpreted as those of inexperienced operators. In contrast, the data points of the second cluster are less scattered, have lower cycle times and a higher simultaneity level which indicates more experienced operators. In order to test whether the result of the cluster analysis corresponds to the level of education, the relative frequencies of allocating a cycle to the experienced or inexperienced group were established for each test person. The result is shown in **Figure 6.**

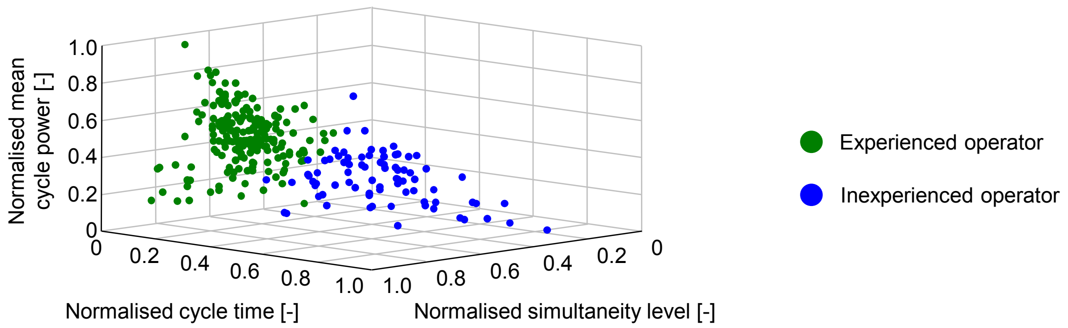

Figure 5: Result of the 3-dimensional cluster analysis

As was expected from their education level, the cycles of operators 1 to 3 respectively 11 and 12 were primarily assigned to the experienced group. Subjects 4, 5 and 10 were apprentices of the first teaching year and allocated to the inexperienced group by means of the cluster analysis. A significant difference between group assignment and level of training was detected for subjects 6 to 9. Operators 6 to 8 correspond to the experienced group, whereas for apprentice 9 no clear assignment could be made.

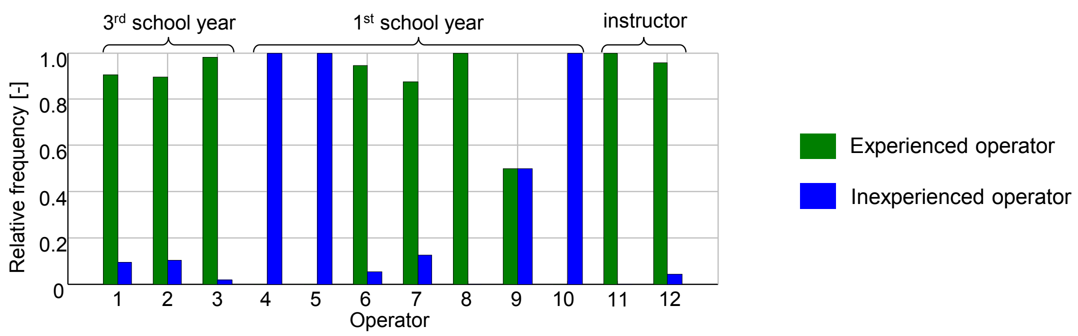

Figure 6: Cycle allocation to clusters

Generally speaking, the classification of operator skills using the characteristic features described in this section is more objective then the grouping by education level.

4. Processing

Based on the classification result, a statistical model can be determined for each group. It allows for drawing conclusions from a sample to a whole population. Therefore a Shapiro-Wilk-Test for examining the assumption of normal distribution was applied. The result shows that on a significance level of 5% the hypothesis of a normal distribution has to be rejected. Considering the marginal distributions of the features a high skewness was discovered. By applying the transformation (1) which was proposed by /8/ the assumption of normality can be satisfied. A suitable λ was found such that the transformed data corresponds to a normal distribution described by (2) (/9/).

$$\tilde{X} = \begin{cases} \dfrac{X^{\lambda} - 1}{\lambda}, \text{if } \lambda \neq 0 \\ \log(X), \text{if } \lambda = 0 \end{cases} \tag{1}$$

$$f(\tilde{X}) = \frac{1}{2 \cdot \pi \cdot \sqrt{|\Sigma|}} \cdot \exp\left[-\frac{1}{2} \left(\tilde{X} - \mu \right)^{T} \cdot \Sigma^{-1} \cdot \left(\tilde{X} - \vec{\mu} \right) \right] \tag{2}$$

After this, a mean vector μ and a covariance matrix Σ were estimated for each group. Transforming the probability density function to the original feature space and comparing it with the absolute frequencies of the samples, a high order of convergence can be found. **Figure 7** also shows the necessity to distinguish between different types of operators, as the distributions significantly differ from each other.

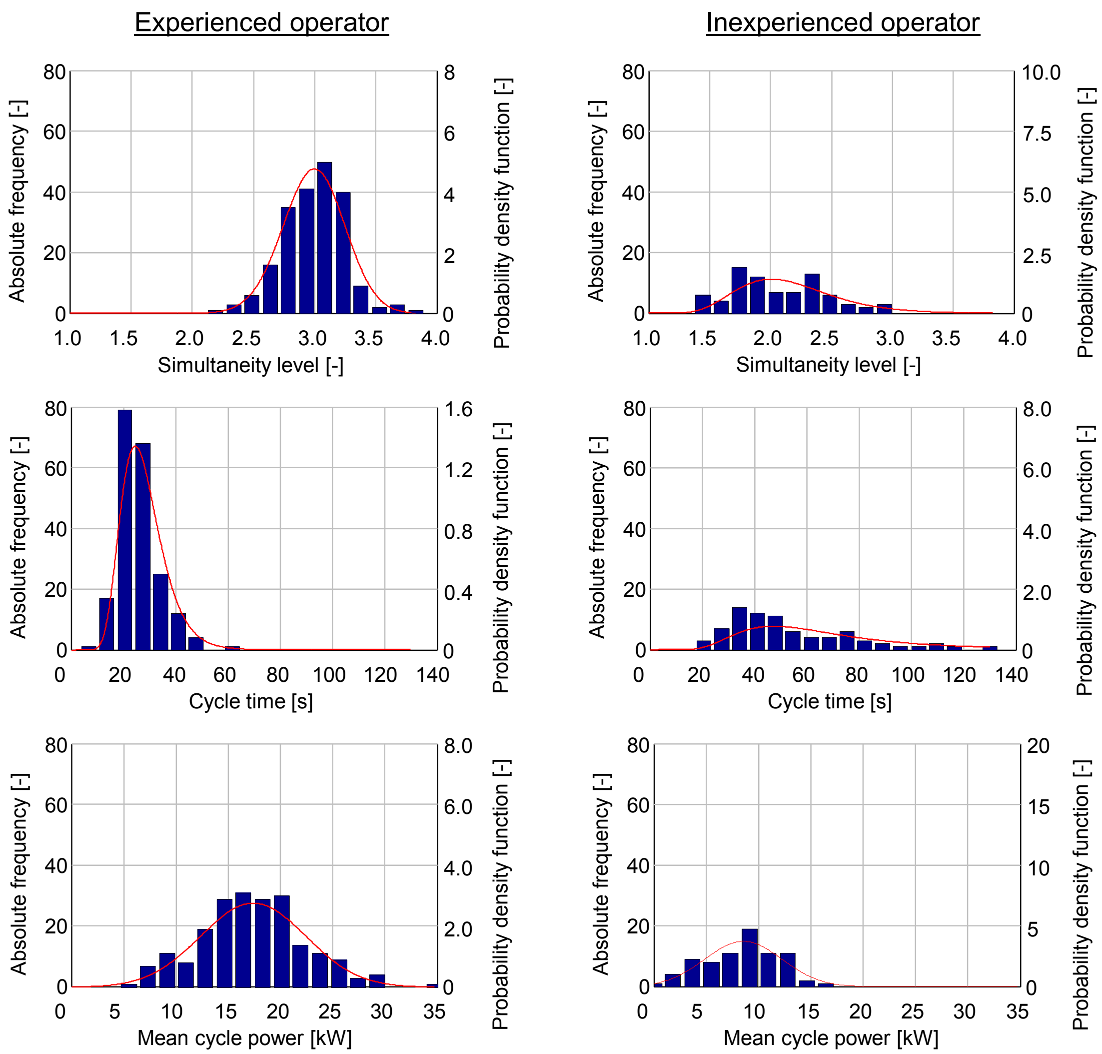

Figure 7: Absolute frequency (blue) and probability density function (red) of the cycle features

These representations can be used to derive design criteria, taking into account statistical uncertainties. For example, the expectation of the probability density function is a proper measure for the cycle duration (**Figure 8**). The group of experienced operators shows a value of 24.5 seconds, while the inexperienced operators have a value of 47.3 seconds. When determining the average cycle performance, the expectation value is unsuitable since 50% of cycles require more power. A high quantile e.g. the 90%-quantile can be more adequate. As a result, the mean cycle power is approximately 23.8 kW for experienced operators and 13.3 kW for the inexperienced.

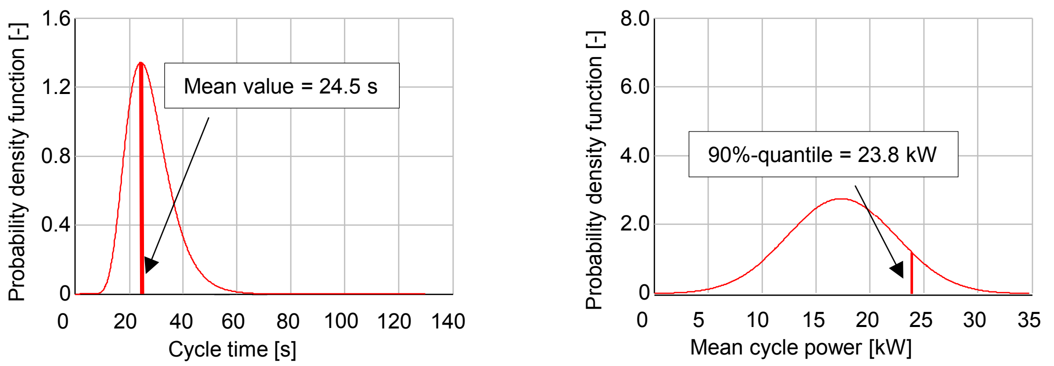

Figure 8: Determination of design criteria taking into account statistical uncertainties

In addition to the definition of design parameters, the statistical model can be used for extrapolation to longer operation times. First a limited number of cycles have to be selected, which are meant to be representative. These cycles form the basis of further investigations so a homogeneous distribution in the feature space should be aspired. A hierarchical cluster tree can be used for the selection. **Figure 9** shows ten representative cycles for the two operator groups respectively.

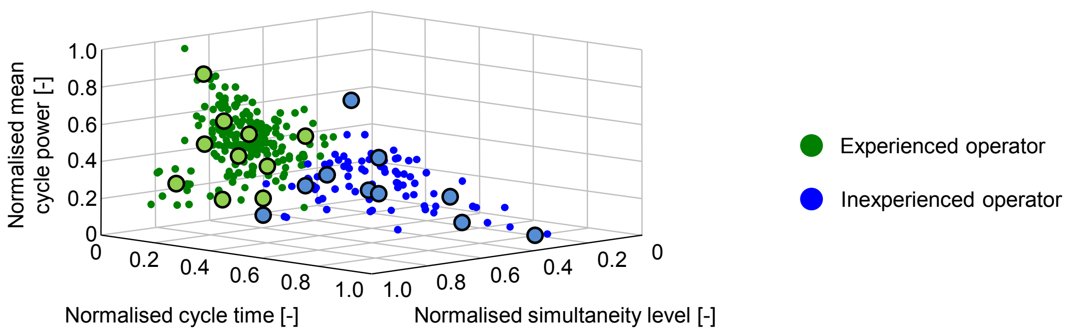

Figure 9: Representative cycles (circled points) in the feature space

As the time-dependent load and velocity data is available, for these 10 chosen cycles the evaluation of energy consumption and pollutant emission of the propulsion system as well as the operation point distribution at any system component (e.g. diesel engine) in the system can be done using simulation or bench tests. Subsequently the results (e.g. operation point distribution per cycle) are weighted with the values of the probability density function, corresponding to the cycles, and a superposition is applied. The quality of the extrapolation can be shown on the operation point distribution of the arm cylinder. **Figure 10** a) shows the spectrum taking into account all of the 208 cycles of the experienced operator group. In contrast, the results of 10 representative cycles are shown in Figure 10 b). In Figure 10 c) the spectrum considering a single working cycle, being the closest point to the maximum of the probability density function, is shown.

a)

b)

c)

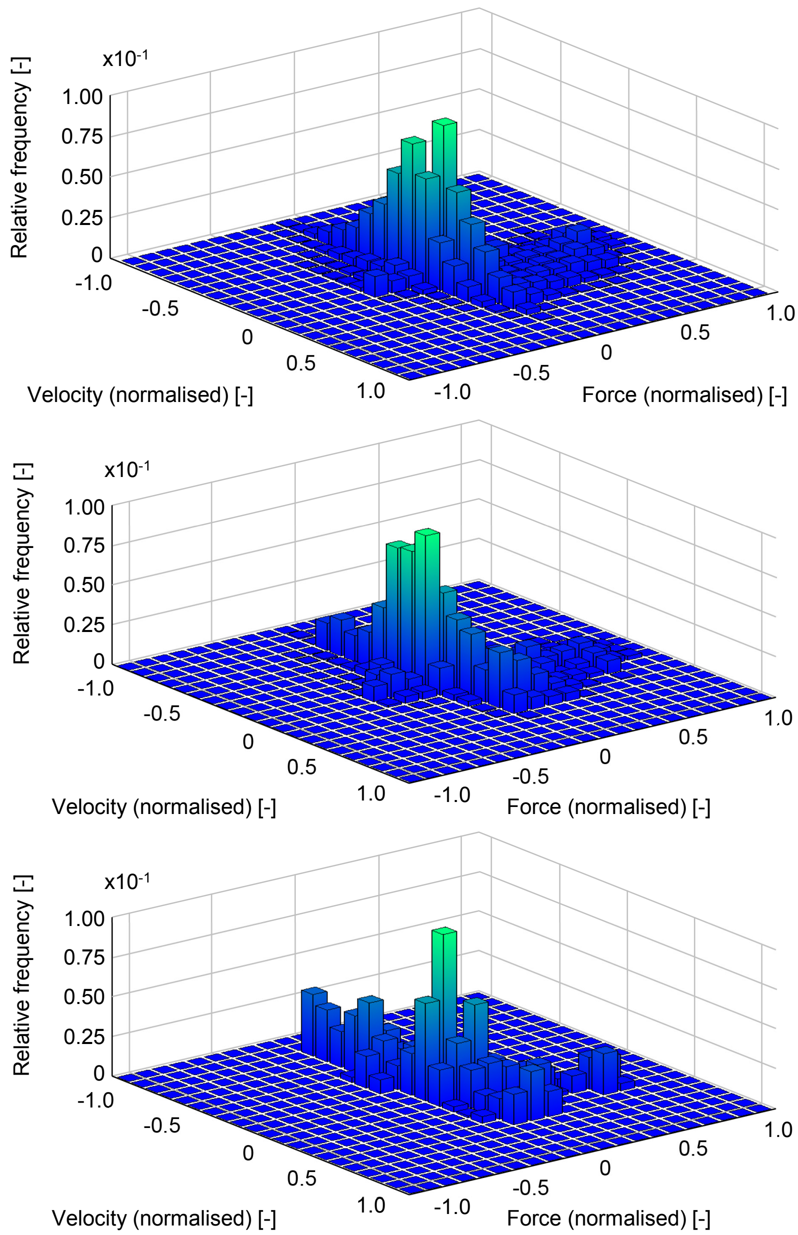

Figure 10: Operation point distribution of the arm cylinder for experienced operators

5. Summary

The method described in this paper provides a way to determine representative performance cycles from extensive measurements. The operator influence is incorporated by a statistical model of characteristic features. That way, the operating behaviour of a machine, for a process pattern and operator type, can be described through only a few representative working cycles which are manageable inputs for simulation or bench tests (**Figure 11**, /10/).

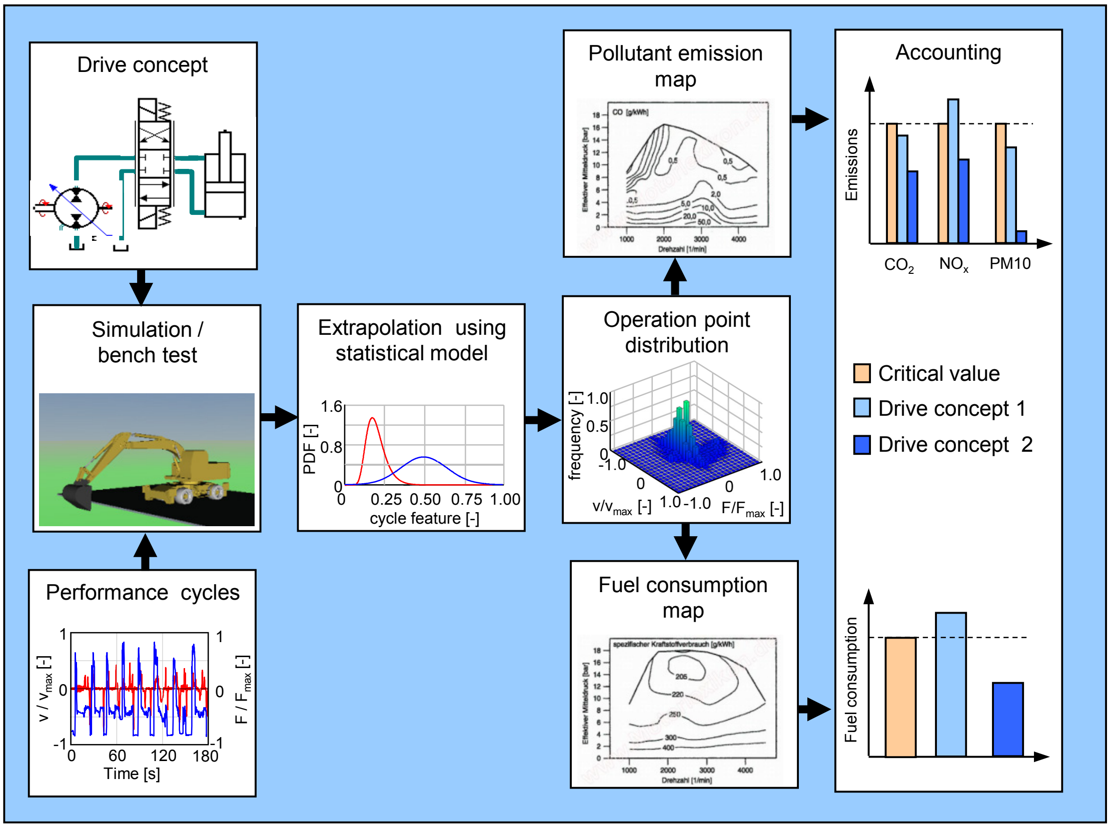

Figure 11: Workflow for propulsion system benchmark

Making use of a statistical model, the results can be extrapolated to longer operation periods. Hence an effort reduction is achieved, since in this example the operation point distribution of 208 cycles is mapped onto 10 representative cycles.

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