

Standardized short-cycle measurement approach of load scenarios in powertrains of combine harvesters

Fabian Wohlfahrt, Thomas Göres, Stefan Terörde, Ludger Frerichs

Recording measurement cycles for combine harvesters is essential yet challenging, especially when optimizing and designing modern powertrain structures. The seasonal availability of test environments limits the possibility of extensive measurement campaigns. Additionally, not all relevant load scenarios are present in each testing environment due to variable effects and current agronomical constraints. This approach allows for a broader range of load profiles to be examined within a defined measurement setting. Therefore, a standardized trajectory and a heuristic for the process control of a combine harvester are introduced in this paper. Performing a set of short profiles a cross section of possible load scenarios gets recorded with enhanced reproducibility. Subsequently, the data are compared to reference fleet data to discuss the degree of coverage of the measurement cycle and to evaluate its capability for powertrain assessment in comparison to data from real infield operation.

Keywords

Combine harvester, cycle measurements, efficiency evaluation, powertrain optimization

For the development and optimization of modern powertrain topologies in combine harvesters, an accurate description of load cycles is crucial. The design and application of engine characteristics – such as engine power, set speeds, valve timings, and EGR rates along with key elements of system dynamics like control algorithms for vehicle speed, significantly affect the machine's performance, stability, and efficiency. These factors are central to optimization efforts aimed at enhancing powertrain quality. Recording realistic partial and full-load scenarios provides the necessary framework for such optimizations. To be practical and useful, these scenarios need to be:

- of limited length, so that they can be recorded with manageable efforts during a harvesting campaign,
- representative regarding the covered loads,
- reproducible, so that major machine characteristics can be robustly found in the measurement.

In contrast to many on-road applications, a set of decisive environmental factors cannot be completely determined and influenced (e.g., crop moisture, straw quality, yield and homogeneity...). This creates significant variance factors regarding achievable throughputs and needed power. Solely operating the machine on its real agronomic borders in a given set of conditions covers only a part of significant operation points. Depending on the conditions the machines are either operated on a throughput-limit defined by losses or by a limit set up by the maximal capacities of the powertrain. This depends on local as well as on seasonal effects. A successful machine concept must operate as efficiently as possible on each side of this broad band of conditions. Therefore, it is necessary to collect datasets,

which describe a wide field of conditions. To achieve this needed variety of data a measurement concept gets introduced. This concept provides a systematic variation of process-defining characteristics of the machine. Doing this a higher diversity of loads in a realistic short sequence can be achieved. By using this standardized measurement approach optimization tasks can be equipped with more reproducible testing data allowing a higher standardization of optimization tasks.

Differentiation to existing approaches

In the literature, the efficiency analysis of combine harvesters and the cycle generation for non-road machinery have been explored extensively. However, specific cycle approaches tailored to combine harvester applications are still lacking. For mobile machinery, including specialized applications, standardized cycle approaches have been researched (DEITERS 2008). DEITERS developed the 'Y-Cycle Approach' to analyze the load profiles of wheel loaders. Furthermore, he offered generalized recommendations for creating cycles for agricultural machinery. FLECKORECK (2013) conducted detailed model-based loss analyses using a combine harvester. In this context, he introduced a scheme for dividing different operational states. Still, his data sources were primarily based on real operation scenarios. MÜLLER et al. (2012, 2013) presented an approach to measure the power flows of functional technology on a powertrain of a combine harvester. The focus was set on recordings from real field operations. HÄBERLE (2019) performed real operation measurements with state-based classification. Furthermore, he performed quasi-stationary measurements at various throughput points. In doing so, he characterized the machine loads and load collectives on individual components of the powertrain, specifically the hydrostatic drivetrain. TRÖSKEN et al. (2020) proposed a co-simulation approach to simulate machine loads and fuel consumption in agricultural process chains by combining an agent model for simulating vehicle trajectories with machine models for tractors and combine harvesters. MEINERS (2023) detailed this model-driven approach in his research. Therefore he utilized recorded measurement data from various stationary working points to parameterize models for functional drives, which are later virtually aggregated.

In conclusion, current approaches focusing on load collectives for combine harvesters, rely heavily on large data sets. They typically describe stationary working points more than actual dynamic load profiles. These methods undoubtedly provide a thorough and source-oriented analysis of load phenomena on the powertrain. Doing so they give detailed insights into powertrain efficiency issues. However, they require significant efforts in terms of data collection, post-processing, and time. This is challenging given the brief seasonal availability of suitable harvesting conditions. The approach presented therefore targets a measurement concept designed for rapid data collection within a limited timeframe. Unlike existing research, the focus shifts from how individual loads are measured or modeled to how the machine is operated. This offers a practical method for generating reference profiles that can aid further development efficiently. Figure 1 illustrates the key differences of the proposed approach.

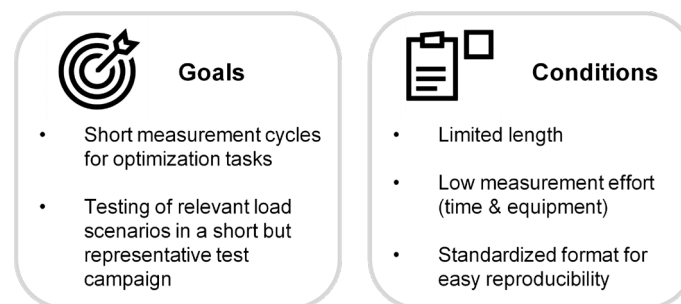


Figure 1: Goals and boundary conditions for the targeted cycle approach

Concept and approach

To develop a standardized measurement approach, it is crucial to identify its key requirements at first. As discussed earlier, the primary objective of the measurement campaign is to record a series of short cycle sequences. Those shall capture the typical behavior of a combine harvester across various potential scenarios. Additionally, achieving a high degree of reproducibility and standardization is essential for ensuring comparability between different measurement campaigns. A third important goal is to enable measurement without the need for extensive additional equipment. This targets to increase the number of machines that can be analyzed. To optimize performance, it is essential to identify the major factors influencing machine behavior. In a second step those factors are categorized as either ‘controllable’ or ‘non-controllable’. Controllable factors include the targeted throughput, the parametrization of actors of the functional technology, the field geometry and the vehicle trajectory. These aspects significantly affect machine behavior by altering power demands during threshing. Also they influence the occurrence and frequency of single operational states. For precision in tests, these controllable aspects should be defined with accuracy and included in a measurement framework.

However, there remains a crucial set of variables during testing that is difficult to control. This includes influences from local, seasonal, and weather-dependent effects that cause variations in plant physiology (e.g., yield consistency, straw height), the threshability of the crop (affected by straw moisture), and field drivability (influenced by terrain slope). Addressing these factors can only be done by selecting specific scenarios for testing. Capturing the full range of possible variations in a single day’s test remains a challenging or even impossible task.

This dualism of ‘controllable’ and ‘non-controllable’ factors needs to be reconsidered in the approach. To reduce ‘avoidable’ variance, it is necessary to initially implement measures that define the ‘controllable’ aspects. In this context, a field geometry is established alongside a fixed headland strategy. This strategy specifies the length of cycles and ensures coverage of all relevant operational states of the machine during measurements. This enhances the transparency and usability of the recorded data. Following this setup, a CAN-based measurement approach is employed. This approach focuses on maximizing the use of existing machine data, particularly fuel consumption and torque, to minimize the need for additional measurement equipment. In addition to establishing a specific field geometry, preparatory measures are set up to identify the base loads of the machine and calibrate its on-board measurement facilities. These measures also allow for adjustments to the machine based on actual testing conditions. Implementing these steps helps mitigate the impact of ‘controllable’ influence factors.

For the ‘non-controllable’ influence factors, it is necessary to establish elements that can manage the remaining variance and create a standardized measurement routine adaptable to various testing scenarios. This approach ensures a consistent range of measured loads and characteristics, independent of specific conditions. A testing procedure is defined that outlines the required experiments and sets operational limits for the machine in each experiment. This procedure provides clear, reproducible guidelines for conducting experiments. Additionally, it aims to simulate different scenarios by varying the throughput levels, higher or lower than those in the actual conditions. This allows for a broader range of load points and a more extensive data set. Doing so it is possible to measure a higher variety of load points and create a broader bandwidth of data. This strategy effectively reduces the impact of ‘non-controllable’ factors.

As a final step, a procedure for post-processing and evaluation is established. This procedure enables the interpretation of collected data within the context of actual machine operation, using telemetric reference-fleet profiles. This crucial step allows for the extrapolation of insights gained from short-cycle tests to real fleet operation data.

Material and methods

An example dataset was collected using the proposed short-cycle approach during a measurement campaign. This campaign was conducted on a Claas Lexion 8800 hybrid combine, which features a 515 kW engine and is equipped with a VARIO 1380 cutterbar (CLAAS VERTRIEBSGESELLSCHAFT MBH 2023). The campaign took place in August 2023. Four cycle measurements were recorded in a wheat field yielding 10 t/ha with a straw height of approximately 60 cm. The crop and straw moisture levels were measured at 14% and 16.5%, respectively, using the combine’s integrated equipment. The combine operated in a chopping configuration. During testing, the vehicle’s speed was regulated by the combine’s speed control system (Claas Cemos Cruise Pilot), which adjusts speed based on engine load, detected loss levels, or a predefined throughput measured in the feeder house.

Steering within the lanes and determining the bed geometry were accomplished using RTK-based steering technology. This ensures precise and reproducible driving behavior. For comparative analysis, a dataset comprising 93 Lexion 8800 machines was utilized. The machines were operating in a chopping configuration in wheat during the 2023 season in Germany. This dataset was used alongside the recorded cycle data from the threshing operations with enabled speed control. This comparison facilitates the interpretation of current throughput levels in the telemetric data.

To evaluate fuel consumption and engine load during the experiment, CAN data from the J1939 engine CAN were utilized. Additional data on throughput, yield, and machine-state classification were collected via the machine’s proprietary CAN bus. Data recording was carried out using Vector CANoe software on a VN 1610 logger. The analysis of the CAN data was performed using a post-processing and state-classification algorithm developed in Matlab. To demonstrate the quality of an ECU-based engine torque estimation, measurement data from a 400 kW class combine powertrain tested on a Schenk W1500 electrodynamic dynamometer was used.

Consideration of the testing field and set-up of the cycle trajectory

To standardize the cycle format, it is essential to select appropriate testing conditions and define a specific field geometry with a planned vehicle trajectory. Initially, selecting a suitable testing field is crucial due to significant variances caused by the field and crop conditions. A general recommenda-

testing. That is done to verify the engine power and fuel consumption data transmitted over the machine's CAN. Especially when comparing different vehicle concepts this is crucial. Measurements of fuel consumption and modeled engine torque have already demonstrated the practicality of using CAN-based torque-data, as confirmed by existing literature (ROHRER et al. 2018, SCHRÖDER and HINRICHS 2022). These findings indicate that the overall system load can be assessed without installing additional torque measurement equipment. Still, checks of the engine system are necessary to ensure the quality of each engine-specific measurement. Figure 3 shows an exemplary testing profile to give an impression about the potentially achievable precision of engine-based torque measurement. It is evident that sufficient accuracy can be reached both during high-load conditions (represented by the threshing events marked as 'T-X') and during lower-load conditions (indicated by the headlands labeled 'HL-X'). Nevertheless, an engine-specific pre-check is recommended due to the dependency on the engine ECU's torque modeling quality.

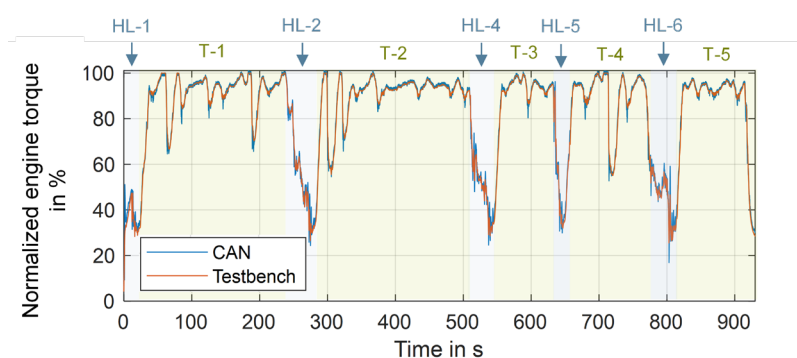


Figure 3: Achievable quality of engine-based torque measurement (comparison with testbench torque) – Field Profile of a 400 kW combine harvester – normalized to maximal available effective engine torque

'T-X': Threshing-sequences – 'HL-X': Headland sequences

Statistical KPIs – Deviation between curves

- Standard deviation: 1.8%
- Cumulated deviance: 0.7%

The first step in the measurement process involves operating the machine at idle to estimate its baseline load. During this phase, the machine runs with the main drive engaged and aggregate speeds set to standard parameters. After the engine, hydraulics, and belt drives are sufficiently warmed up, fuel consumption and engine power are recorded, providing an initial measurement of the machine's base loads. For the example machine, a baseline load of 20% of the installed engine power is observed. As a subsequent step, a first throughput variation is performed. Therefore, a lane (outside the test beds) is harvested varying the vehicle speeds and throughput (Figure 4 and Figure 5). This test captures a profile of the 'threshing resistance' of the field, offering preliminary insights into crop and yield conditions as well as the machine's status (Figure 6). The collected load data is then processed to subtract the measured and torque effects from the hydrostatic drivetrain. By identifying stationary points using a window-filter algorithm, a model is developed to describe the relationship between throughput and process-dependent torque, effectively outlining the threshing resistance.

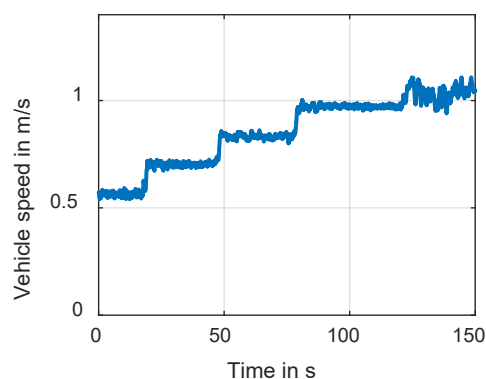


Figure 4: Vehicle speed of variation profile

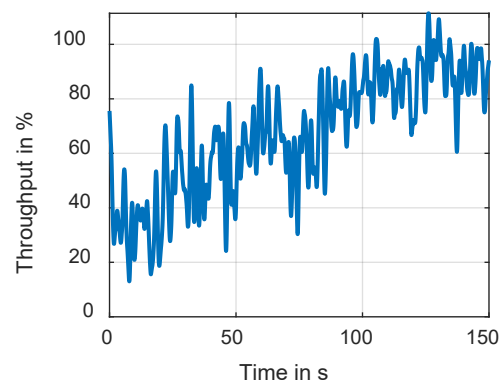


Figure 5: Throughput variation (relative sensor)

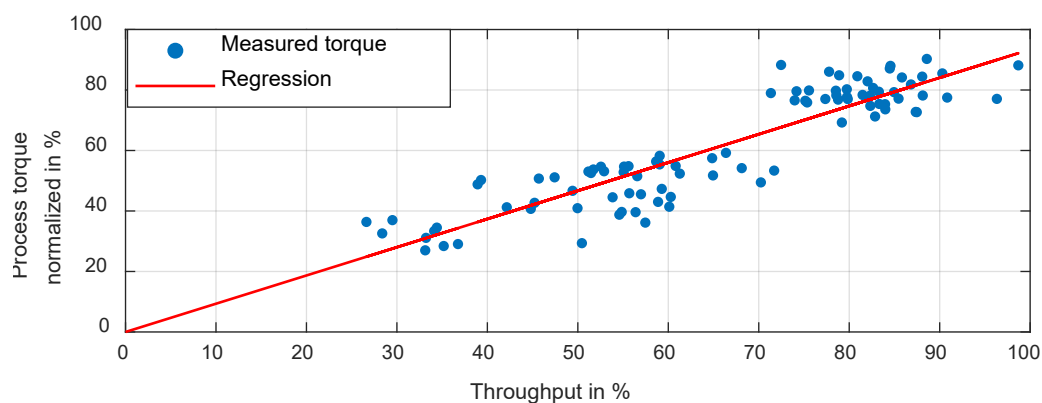


Figure 6: Estimated line of 'threshing resistance' – depiction of throughput induced engine torque (normalized to maximal process torque) vs measured throughput (relative value)

Depending on the measurement objectives, machine parameters such as aggregate speeds and concave settings can be calibrated to suit current field conditions or set to standard values. These preparatory steps allow for a substantial description of the loads. By measuring base loads during idle, a significant source of load is captured. Initial throughput variation tests enable the evaluation of vehicle characteristics across the entire throughput range. This allows for a deeper assessment of dynamic, throughput-induced effects under various scenarios.

Testing procedure

After preparing the machine, the actual testing can begin. The target of the testing program is to cover a broad band of realistic measurement profiles with different loads, that can occur in different real operation scenarios (e.g., full load in tough straw, part load if loss limits are reached). Still, not all these scenarios and conditions can be present on a specific testing day. Therefore, it is necessary to measure variations from the actual working point. These variations help demonstrate how the machine performs under different field conditions. To achieve this diversity, a set of four cycle profiles is conducted. Three of these profiles are defined as part load scenarios, constrained by process quality or throughput limitations. The fourth is a full load scenario, constrained by the powertrain's capacity. The decisive control factor to achieve this variation is the targeted throughput. As throughput increases, a trend towards higher process losses is typically observed (KLÜSENDORF-FEIFFER 2009, RADEMACHER 2015). The relationship between the absolute level of loss and throughput can vary de-

pending on the specific conditions, which determines the most suitable operational point under the actual conditions. Figure 7 shows the schematic distribution of the operational points for the four-cycle profiles. For clear distinction in the following paragraph characters from A-D for are assigned to the single load cycles.

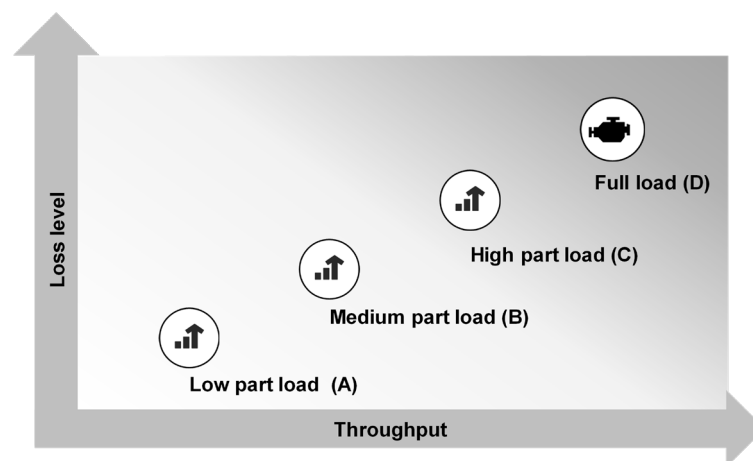


Figure 7: Testing plan and schematic throughput/loss-characteristics of the four cycle profiles

It is a goal to achieve accurate measurements that represent both current and potential field conditions without the need for extensive testing. Therefore, a careful selection of throughput levels is crucial. One challenge is that the specific behavior of the process is not known prior to the experiment. Nonetheless, the set-throughput must be determined before testing each cycle. Additionally, due to the volatile nature of field characteristics (KLÜSSENDORF-FEIFFER 2009) it is necessary to execute the cycles in close temporal succession to ensure comparability. To address this, a test heuristic is proposed that initially adjusts the machine to the actual field conditions and then systematically varies the set throughput from this baseline to assess different scenarios. Figure 8 illustrates this approach in a flow chart.

In the first experiment, the machine gets operated loss-based ('loss-limited cycle'), a common strategy to adapt to actual conditions and achieve the desired agronomic outcomes. An accepted loss level must be established; for the experiments, a threshold of 1% losses was used to calibrate the machine speed and loss sensors. However, this value is adjustable to any predefined target loss level. Recording this data set, a cycle measurement based on the actual conditions on the field is performed. Typically, in wheat, operational points can range from medium part load (labeled as 'B' in Figure 7) to full load ('D'), depending on the installed engine capacity and the machine's separation capability. A concrete classification is possible in comparison to the achievable full load point. This is performed in consecutive steps. After characterizing the actual conditions, the second cycle focuses on the engine at full load ('engine-limited cycle'). Here, the machine operates at the maximum limit defined by the available engine power, disregarding the impact of losses. This operation corresponds to point 'D' from Figure 7. The measurement allows to draw conclusions about machine behavior in conditions without loss limitation.

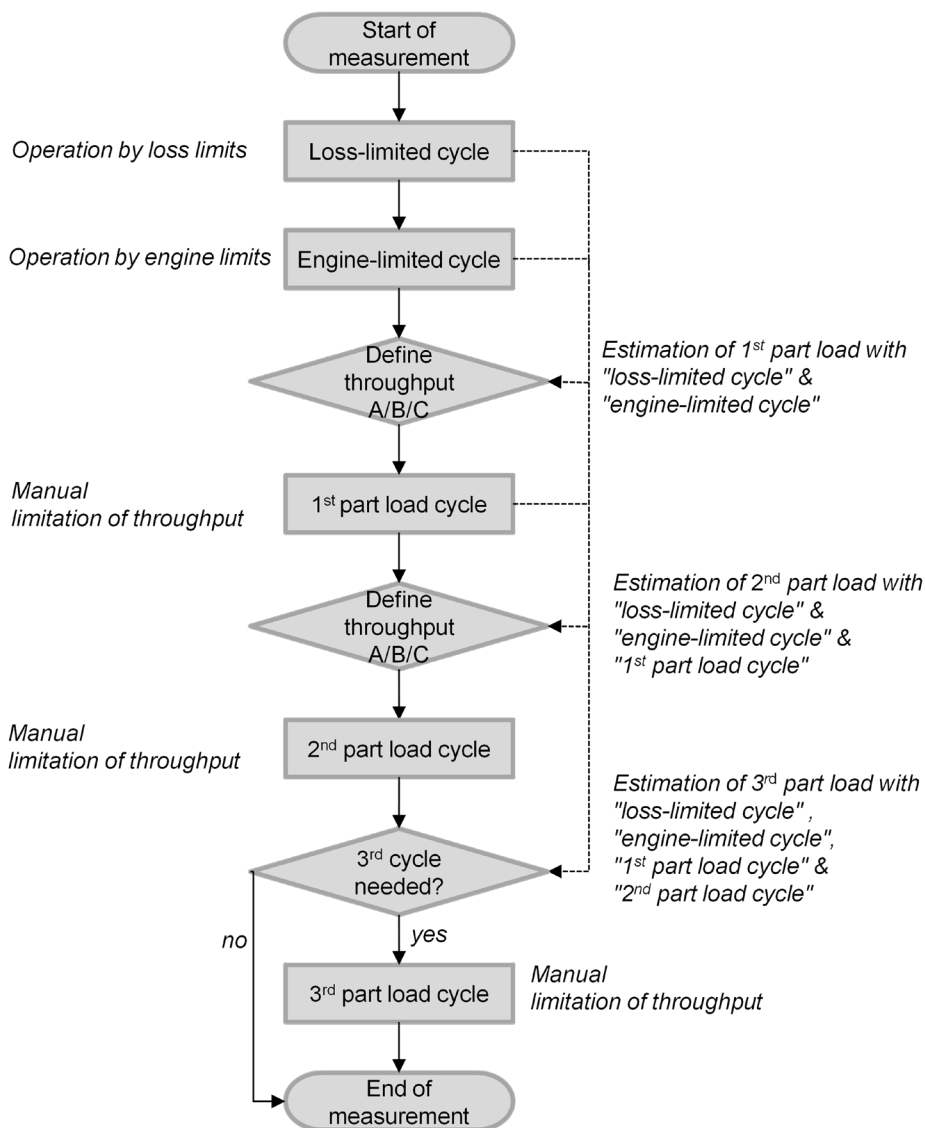


Figure 8: Flow chart for execution of the measurement campaign to adjust set-throughput and operation points

After performing the first two cycles it is necessary to determine, which operation points are still uncovered (compare to Figure 7). This requires evaluating and categorizing the outcomes of the initial cycle. As already mentioned, the assignment of the 'loss-limited cycle' depends on the concrete crop conditions. It therefore needs to be determined in relation to 'engine-limited cycle'. The decision therefore is taken heuristically. To achieve this, a partly subjective evaluation of the drivability and machine utilization is executed. As a general indicator, the ratio between mean engine power during the cycles in reference to a 'no-load' point (determined in preparation) can be used (compare to Equation 1). This ratio provides a measurable approach to determine the most fitting classification from Figure 7. Values of < 30% are an indicator for a classification as 'A', for values of 30–60% 'B', 60–90% 'C' and > 90% 'D'. In addition to these quantitative estimations, the subjective evaluations of experienced drivers regarding the operation points are also considered. This qualitative input is crucial as the simple KPI-based measure does not capture the variability in field conditions or its impact on driving behavior.

$$X_{Loss-Cycle} = \frac{P_{Loss} - P_{noLoad}}{P_{Engine} - P_{noLoad}} \quad (\text{Eq. 1})$$

with P_{Loss} as mean power during loss-limited cycle, P_{noLoad} as mean power of machine (w/o throughput), and P_{Engine} as mean power during engine-limited cycle.

Based on this cycle-point classification, the following throughput levels are defined to target the open operation points (Figure 7) and tested. After performing the third cycle run ('1st part load cycle') the result as well as the subjective impression of the driving behavior are reviewed. Based on this assessment the fourth run is executed ('2nd part load cycle'). If the 'loss-limited cycle' and the 'engine-limited cycle' are nearly identical, or if a failure occurred during earlier runs a '3rd part load cycle' can be performed. This allows for greater coverage of potential load points and repetitions. For that case, a fifth 'spare'-bed-pair is prepared. Consequently, a sequential approach is established to record variations in field cycles, enabling a broad evaluation of different load points. By applying a straightforward heuristic to estimate load points, a practical guideline is derived that allows for the assessment of four distinct load scenarios under one field condition. This approach utilizes the results from individual experiments to cover a wide range of scenarios. The heuristic acknowledges the significant variability in field scenarios and cycle runs. Instead of seeking precise accuracy with exact throughput and loss values, a framework is established that expands the range of recorded points. This provides objective assessments of various load scenarios.

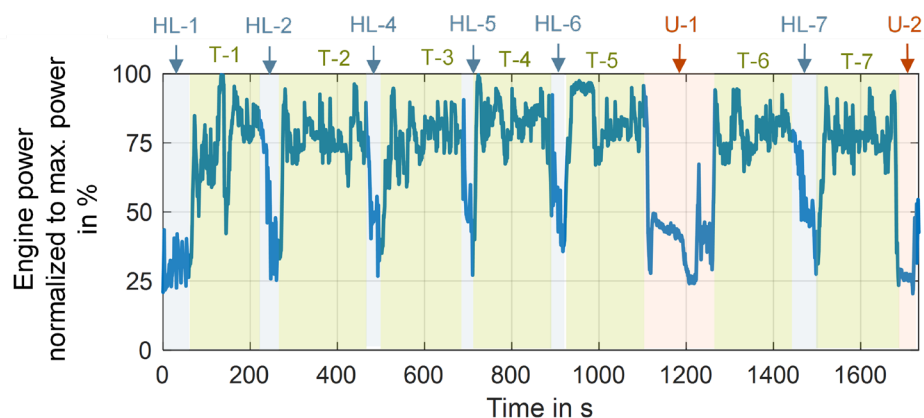


Figure 9: Exemplary visualization of the engine utilization in the Loss-Limited Cycle with depiction of different operational states ('T-X': Threshing, 'HL-X': Headland, 'U-X': Unloading)

Results

To demonstrate the cycle concept, four distinct load profiles were recorded. The unloading process was conducted whilst standing, owing to logistical constraints present during testing. Figure 9 exemplifies the engine utilization measured in the loss-limited cycle to illustrate the procedure. Within the load profile, the seven threshing states (labeled 'T-X'), headland sections ('HL-X'), and two unloading events ('U-X') are distinguishable by varying load levels. This profile effectively demonstrates load dynamics and a realistic sequence of operational states.

Figure 10 displays the experimental design of the recorded dataset (Figure 7). In this specific instance, the 'loss-limited cycle' was categorized as a 'medium part load' scenario, surrounded by

part load cycles. These four datasets provide a comprehensive foundation for evaluating various load scenarios of the machine application. Each profile spans approximately 30 minutes, facilitating a compact testing program that can be completed in less than one testing day. Additionally, the profiles are of a suitable length for repeated testing, whether in simulations or on testbenches.

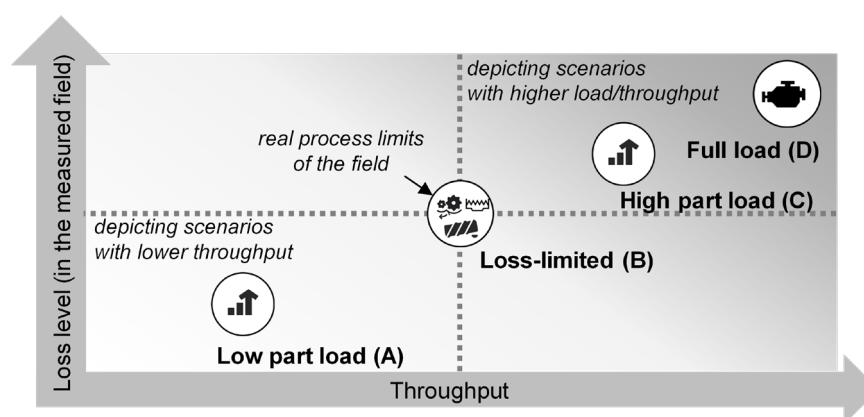


Figure 10: Schematic design of experiment plan – targeted load points for single measurement cycles

To accurately assess the recorded profiles, it is necessary to transform the measurement data to facilitate targeted comparisons with realistic fleet operations. Initially, state-based filtering is applied to classify the data according to the operational state. This enhances the comparability of data. Loads within these profiles are allocated to their respective operational states. This reduces the influence of variables such as headland behavior and field geometry on the main operational state evaluation. Additionally, specific operational states, like headland operation and unloading, can be evaluated separately. The composition and weighting of these states can be adjusted in subsequent evaluations of cycle profiles. This is of certain significance, as realistic field profiles often do not take place in such small parcels. This leads to a potential overestimation of headland operation in unfiltered measurements. Utilizing a state machine approach, data classification employs both the J1939 engine CAN and the proprietary CAN bus of the machine. This classified data enables a cycle-based evaluation of the measurements. Each profile is initially assessed for throughput, as well as power and fuel consumption, across different operational states. Table 1 presents central KPIs for the exemplary cycle runs. For normalization of the engine power the maximal available engine power is chosen. The fuel rate and the throughput are normalized to the maximal values of the full load cycle.

Table 1: Overview of main KPIs of the exemplary measured cycles of the tested Lexion 8800

Central KPIs – mean values	Loss-limited	Full load	Low part load	High part load
Operational state: threshing				
Engine power in % (normalized to max. power)	81	93	66	89
Throughput in % (normalized to values from ‘full load’-cycle)	86	100	75	84
Fuel rate in % (normalized to values from ‘full load’-cycle)	87	100	73	95
Operational state: headland				
Engine power in % (normalized to max. power)	46	46	43	49
Fuel rate in % (normalized to values from ‘full load’-cycle)	53	53	51	56
Operational state: unloading (standing)				
Engine power in % (normalized to max. power)	33	39	36	42
Fuel rate in % (normalized to values from ‘full load’-cycle)	41	46	44	50

As a second step, the single measurements are compared to real fleet data. The composition of the threshing states is highly relevant in this context. Figures 11-14 show the frequency distribution of the recorded engine loads during the four cycles. The figures demonstrate a wide range of engine loads.

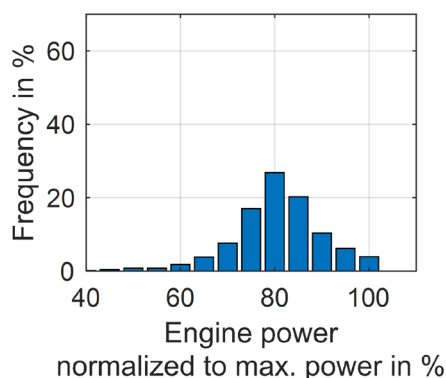


Figure 11: Engine utilization during ‘medium part load’/‘loss-limited cycle’ whilst threshing

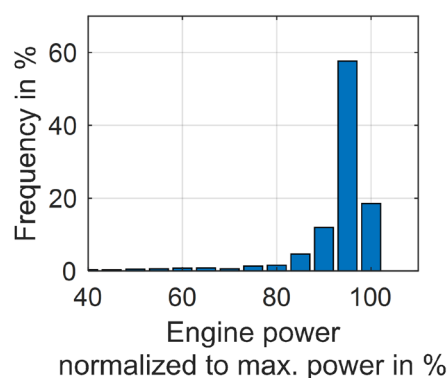


Figure 12: Engine utilization during ‘full load’ cycle whilst threshing

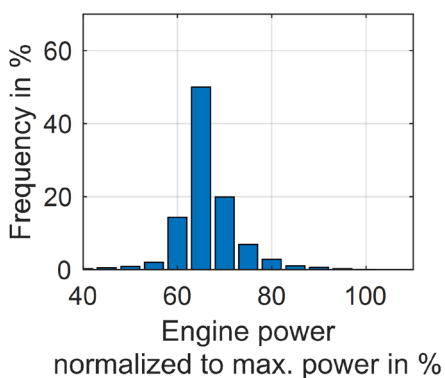


Figure 13: Engine utilization during ‘low part load’ whilst threshing

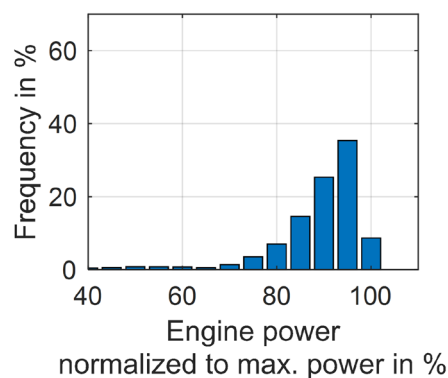


Figure 14: Engine utilization during ‘high part load’ whilst threshing

Figure 15 shows the load distribution of the introduced fleet of 93 Lexion 8800. It is evident that although the cycle data covers a wide range of engine loads, no single cycle can fully capture the entire load profile of the current fleet.

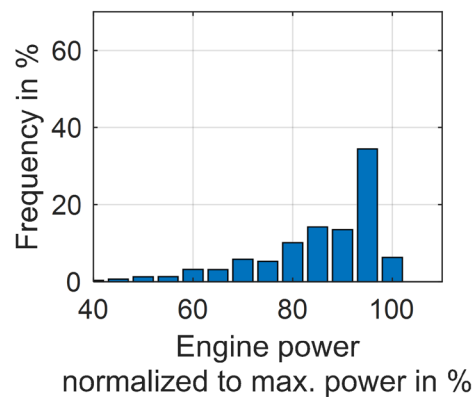


Figure 15: Distribution of engine utilization from telemetric fleet data (wheat – chopping from 2023 – 93 machines – vehicle speed control activated – 1670 hours of database)

Cycle weighting approach

To effectively evaluate machine performance, a weighting approach is essential. This method aims to develop a practical procedure for weighting different load scenarios to a synthetic cycle. Such an approach facilitates the assessment of potential design trade-offs, for example, in engine consumption characteristics or the selection of hydrostatic units, using clearly defined key performance indicators. The objective is to devise a weighting key for calculating a mean cycle representation from individual measurements. It shall reflect the engine load characteristics, throughput, and fuel consumption of the actual fleet. To achieve this, an algorithm is developed to reconstruct the engine-load distribution observed in telemetric fleet data with the measured short cycles. Alternatively to potential numerical optimization methods such as a least-squares algorithm, a straightforward empirical rebinning algorithm is introduced as a viable alternative for establishing cycle distributions (Figure 16). As a first step, this rebinning method calculates mean power values for each cycle run ('calculation of rebinning axis'). Subsequently, these values are used to rebin the existing telemetric fleet profile ('rebinning of reference data'). For each bin in the fleet data profile, the method identifies which cycle's mean value is closest to the bin's central value and assigns it accordingly. As a result, a weighting key is created, which gives a probability to every short cycle. This allows the weighted interpretation of the single measurements. This weighting key can be used to sum up single frequency profiles and mean values to overall cycle values ('synthesis of weighted profiles').

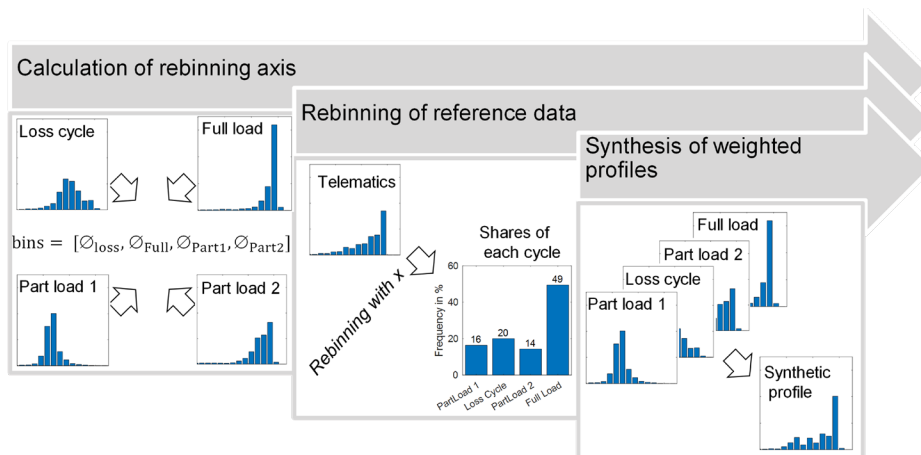


Figure 16: Concept for profile-weighting

For better illustration, this approach is demonstrated on the exemplary dataset. Figure 17 shows the mean values for the engine utilization of the single cycles introduced above. It can be seen, that the values are aligned in ascending order with a certain distance to each other.

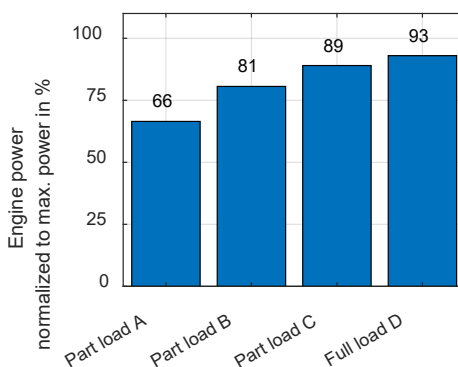


Figure 17: Mean utilization of single cycles

This allows a distinct assignment of certain bins from the telemetric data to a certain cycle. Therefore, it is checked, which of the four new bins is nearest to the original bin of the telemetric dataset (Figure 18).

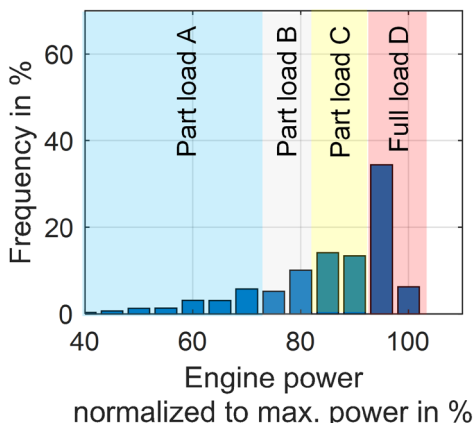


Figure 18: New binning of the telemetric profile

The single frequency values of the telemetric profile are then added up to a weighting key (Figure 19). To deploy this method, a sophisticated design of experiments and load points is needed assuring that the measurements cover different load scenarios. In cases where experiments have equal mean loads, manually adjusting the weights may be necessary. In this exemplary case a significant part of operation in ‘full load’ scenarios occurs. Still, part load scenarios represent a significant share of the process time. To plausibilize the method, the weighting key is compared to the limiting values of the speed control of the fleet data. The limiting value refers to information from the vehicle speed control, that indicates, why the machine is running at its current speed. This depends on the engine load, losses as well as on maximal throughputs and speeds, which are manually adjusted by the driver (Figure 20). This analysis helps explain why a machine operates at a particular throughput level. The heuristic analysis reveals a distribution that is comparable in terms of the amount of full load and part load scenarios encountered.

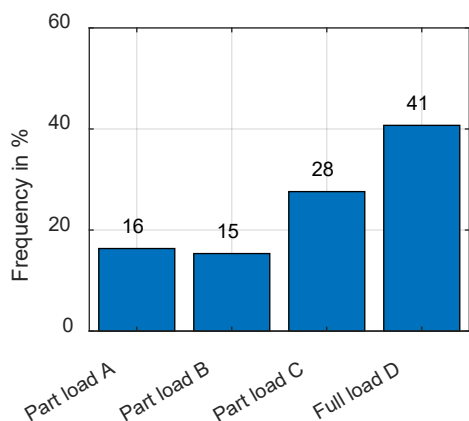


Figure 19: Resulting weighting key

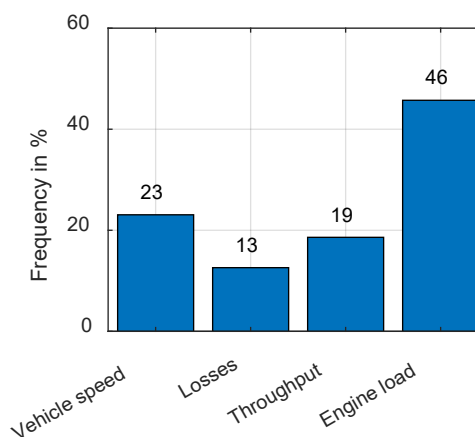


Figure 20: Limits for vehicle speed control

After validating the weighting key against these values, a cycle synthesis is carried out. Figure 21 and Figure 22 show the weighted frequency profile derived from the measurements in comparison to the telemetric load profile. In this case, a good compliance of the engine utilization profile can be

reached. Still, it is important to verify this result for individual testing programs as this method relies on a distinct distribution of the single load profiles.

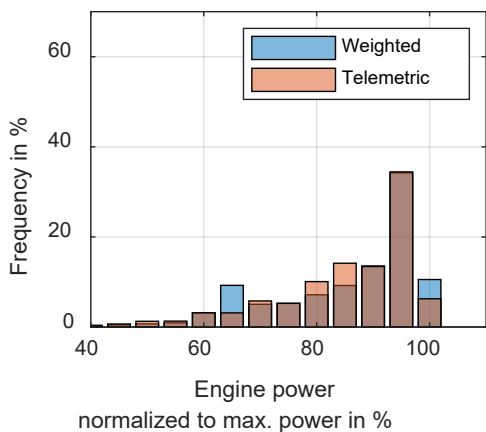


Figure 21: Comparison of weighted profile with telemetric profile of reference fleet

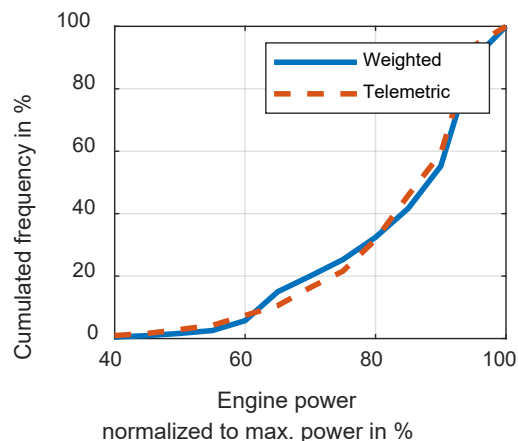


Figure 22: Comparison of weighted profile with telemetric profile of reference fleet - cumulated

After accounting for the threshing process, other operational states are also considered. This paper primarily focuses on field operations, which include ‘threshing,’ ‘headland,’ and ‘unloading,’ together representing a typical field drive cycle. However, additional states such as idle operation and road travel also require consideration. To provide an accurate reference, telemetric data is utilized.

Figure 23 displays the distribution of operational states in the fleet data alongside the cycle profiles for comparison. It is visible that still 19% of the operational states are not represented by threshing processes. Furthermore, a certain deviation between the fleet data and the cycle data can be stated. Headland operation tends to be overrepresented in the cycles, as real field conditions typically feature longer lanes relative to the frequency of headland turns. Still, a compact length of the cycles is decisive to make them recordable in practical use as well as in utilization for testing. The unloading sequences range in a more comparative time share, as their occurrence depends rather on the throughput than on the field geometry. Here, the yield of the field is the more decisive factor. To

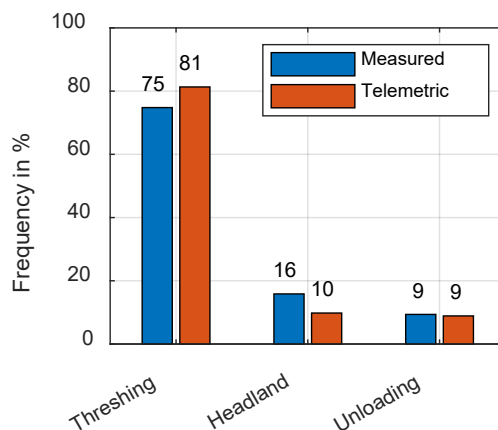


Figure 23: Comparison of operational states - measured cycles vs telemetric fleet data

achieve better comparability a second weighting process of the single operational states based on the operational times from the telemetric data is performed. This process enables the creation of a field cycle that reflects key performance indicators for power demand, throughput, and fuel consumption.

Table 2 shows a comparison of the weighted measurements from Table 1 with the telemetric field data. It uses mean values from four cycles for the operational states of ‘headland’ and ‘unloading’. The cycle values correspond closely with those from the telemetric fleet, confirming the effectiveness of the weighting algorithm in representing engine utilization during the threshing process. This also applies for the fuel rate. The throughput tends to be underrated by the measurement. Variations are expected due to the real fleet operating in fields with differing yields, densities, and threshing resistances. Furthermore, the steady calibration of the yield measurement cannot be secured in real field operation leading to a degree of uncertainty. The headland measurements are within a comparative range to the telemetric data allowing the evaluation of this operational state. A certain level of relative deviance can be observed. This is connected to individual driving behavior, which underlies certain statistical variances (as it can be already seen in Table 1). It is also important to consider the lower measurement frequency of the telemetric data when evaluating the sampled measurement points, as it may contribute to deviations. The recorded unloading processes show a higher power consumption than the fleet data. This is related to a variation of unloading drives with different power consumptions (the test machine has the most powerful one installed) as well as a higher degree of waiting time with unfolded grain tank unloading tube in the telemetric data, which is also counted as part of the unloading time by the state model. Overall, the weighted cycle data suggest a realistic portrayal of the machine’s characteristics, with estimated deviations in engine utilization and fuel consumption around 1–2%.

Table 2: Comparison of the exemplary calculated cycle based on the measurements of a Lexion 8800 in comparison to telemetric fleet data (normalization according to Table 1)

Central KPIs – Mean values	Weighted cycle	Fleet data
Operational state: threshing		
Engine power (normalized) in %	82	85
Throughput (normalized) in %	84	94
Fuel rate (normalized) in %	88	88
Operational state: headland		
Engine power (normalized) in %	46	48
Fuel Rate (normalized) in %	53	50
Operational state: unloading		
Engine power (normalized) in %	38	30
Fuel rate (normalized) in %	45	37
Complete cycle		
Engine power (normalized) in %	74	76
Fuel rate (normalized) in %	81	80

Conclusions

A measurement approach was developed to standardize the assessment of a broad spectrum of load scenarios on a combine harvester. By defining unified trajectories and field-geometries a compact and reproducible framework is created. This framework minimizes sources of uncertainty during measurements through a set of preparatory tasks. The proposed experimental design enables the capture of a wide range of relevant operational points in a single day, independent of varying field conditions. The application of the introduced weighting heuristic facilitates a linkage to data collected from actual operations. Classification by operational states mitigates the influence of field geometry on the measurements. Thus, this approach standardizes data recording in a practical manner, supporting structured data collection for ongoing development tasks. The data profile demonstrates good conformity with telemetric data.

Still, the presented approach can – evidently – not address the entirety of all variability effects and still requires careful selection of machine parameters and field scenarios for testing. One significant limitation is the inhomogeneity in fields, which can vary considerably even over short distances, affecting the absolute comparability of results. This is particularly relevant when comparing two machines in-field. Consequently, the cycle approach is not intended to replace endurance runs or multi-crop validation, nor is it suitable as a legislatively binding method for universally measuring machine efficiency. This is especially true as yield-specific results are highly sensitive to the chosen boundary conditions in the fields. The associated weighting key and the resulting weighted profiles should be viewed as tools for objectification – such as defining ‘game rules’ for potential optimization strategies – rather than precise representations of reality.

However, for internal evaluations, these profiles can serve as an objectified benchmark. They enable testing of defined profiles covering a specified range of load points. The approach presented should be seen as a method for recording realistic reference data with less effort and in a standardized way. When applied to related testing and analysis tasks, this method allows for the optimization of component selection and design – such as diesel engines, alternative drives, and cooling systems – as well as central control systems, including vehicle speed controls. Integrating this measurement approach within a suitable simulation model is a logical subsequent step. To evaluate and optimize the powertrain efficiency this approach can play an important role in future development processes. However, it does not comprehensively cover all operational states. In addition to the recorded field cycle data, measurements of idle and road travel states are necessary to fully encompass the range of operational points. In conclusion, this paper presents a practical approach for gathering field data to evaluate the realistic cycles of modern combine harvesters. Assuming accurate data capture, this approach allows for the recording of central machine characteristics with high fidelity to real fleet data, thereby providing an objective foundation for developing more efficient harvesting solutions.

References

- Claas Vertriebsgesellschaft mbH (2023): Mähdrescher – Claas Lexion – Produktbroschüre. https://cdn.claas.com/app/2022/lexion/download/lexion_8900-7400_de-de.pdf, accessed on 19 Dec 2023
- Deiters, H. (2008): Standardisierung von Lastzyklen zur Beurteilung der Effizienz mobiler Arbeitsmaschinen. Dissertation, Technische Universität Braunschweig
- Fleczorek, T. (2013): Effizienzbewertung von Antrieben mobiler Antriebsmaschinen am Beispiel eines Mähdreschers. Dissertation, Technische Universität Braunschweig

- Häberle, S. (2019): Anforderungs- und einsetzungsgerechte Auslegung von Fahrtrieben mobiler Erntemaschinen. Dissertation, Universität Hohenheim
- Klüßendorf-Feiffer, A. (2009): Druscheignung als zentrale Führungsgröße im Erntemanagement. Dissertation, Humboldt-Universität zu Berlin, <https://doi.org/10.18452/15975>
- Meiners, A. (2023): Potentialbewertung effizienzsteigernder Technologien bei Landmaschinen in Verfahrensketten mit Körnerfruchternte. Dissertation, Universität Hohenheim
- Müller, C.; Anderl, T.; Böttinger, S. (2012): Lastkollektive und Leistungsverteilung am Mähdrescher. *agricultural engineering.eu* 67(4), S. 270–273, <https://doi.org/10.15150/LT.2012.308>
- Müller, C.; Häberle, S.; Böttinger Stefan (2013): Lastkollektive von Mähdrescherantrieben für spezifische Teilaufgaben beim Mähdrusch. In: VDI-MEG Kolloquium Landtechnik 2013, VDI-MEG, 12.–13.09.2013, Hohenheim, S. 33–40
- Rademacher, T. (2015): Gegen Motor oder gegen Verluste fahren? *profi* 7, S. 64–67
- Rohrer, R.A.; Luck, J.D.; Pitla, S.K.; Hoy, R. (2018): Evaluation of the Accuracy of Machine Reported CAN Data for Engine Torque and Speed. *Transactions of the ASABE* 61(5), pp. 1547–1557, <https://doi.org/10.13031/trans.12754>
- Schröder, A.; Hinrichs, M. (2022): Abschlussbericht: Entwicklung und Feldtest eines Abgasstufe 5 Multi-Fuel-Traktors ‘MuSt 5-Trak’ – Adaption von Motorsteuergeräten und dessen Implementierung in ein Versuchsfahrzeug – FKZ 22408217. https://www.tfz.bayern.de/mam/cms08/biokraftstoffe/dateien/multi-fuel-traktor_abschlussbericht.pdf, accessed on 4 Oct 2023
- Trösken, L.; Meiners, A.; Frerichs, L.; Böttinger, S. (2020): Modellbasierte Berechnung von Kraftstoffverbräuchen landwirtschaftlicher Verfahrensketten. *agricultural engineering.eu* 75(4), <https://doi.org/10.1515/LT.2020.3253>

Authors

Fabian Wohlfahrt, M.Sc. is a Development Engineer and **Dr.-Ing. Thomas Göres** is Vice President SF Advanced Development and **Dipl.-Ing. Stefan Terörde** is Head of Advanced Development Functional Technology at Claas Selbstfahrende Erntemaschinen GmbH, Mühlenwinkel 1, 33428 Harsewinkel. E-mail: Fabian.Wohlfahrt@claas.com

Prof. Dr. Ludger Frerichs is Head of the Institute of Mobile Machines and Commercial Vehicles, Technische Universität Braunschweig, Langer Kamp 19A, 38106 Braunschweig