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Enhancement of large engine technology through machine learning

Digitalization & Connectivity

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ABSTRACT

The ongoing digitalization of today's world provides valuable opportunities for improving existing large internal combustion engines (ICE) technology and enabling or supporting the development of new solutions. In particular, machine learning has recently opened up promising new avenues. The analysis and use of large amounts of data that has been generated either experimentally (e.g., by sensors inside ICEs) or virtually (e.g., by simulation tools) effectively provide insights into previously unknown correlations. On the one hand, this allows generation of an added value for research tools such as engine testing and simulation. On the other hand, the additional benefits can eventually be employed in series applications.

This paper presents actual applications of how machine learning approaches enhance the diverse research being conducted on modern large engines. For all applications, realistic and application-related data from experiments or simulations serve for model training and validation and the outcomes are described by means of quantitative results to understand the achieved benefits. The topics covered range from fundamental research on how to enhance simulation methods to fault diagnosis on engine test beds to condition monitoring and predictive maintenance on key engine components such as cylinder liners, fuel injection valves or sliding bearings and finally to engine control applications for combustion anomalies. Each topic is introduced by discussing the underlying task as well as the implemented machine learning approaches, which can include purely data-driven as well as hybrid methods that also take physical relationships into account. Altogether this provides a comprehensive overview of the versatile ways in which machine learning can be beneficially deployed.

1 INTRODUCTION

Large internal combustion engines (ICE) are widely used in power generation and transportation applications [1–3]. In the context of global issues such as climate change, environmental pollution and conservation of resources, ICE manufacturers are currently facing the challenge of achieving substantially reduced emissions of greenhouse gases (GHG) and pollutants while increasing efficiency and durability [4]. The global digital transformation that is ongoing provides valuable opportunities for improving existing ICE technology and enabling or supporting the development of new solutions [5–8]. Artificial intelligence and in particular its subfield machine learning (ML) have recently opened up promising new avenues [9, 10]. With the help of methods from this field, the analysis and use of large amounts of data generated either experimentally (e.g., by sensors inside ICEs) or virtually (e.g., by simulation tools) effectively provide insights into previously unknown correlations [11]. ML has the potential for generating added value in two main areas of large engine technology:

- Development tools such as experimental testing and simulation, which are usually embedded in a comprehensive development methodology
- Series engines, which include specific applications such as condition monitoring (CM), condition-based maintenance (CBM) and control systems

Both areas ultimately contribute to meeting global challenges and will be further outlined below. Subsequently, this publication presents actual applications in which ML approaches enhance the diverse research being conducted on modern large engines. In all applications, realistic and application-related data from experiments or simulations is employed for model training and validation and the outcomes are described by means of quantitative results to understand the achieved benefits. Each topic is introduced by a discussion of the underlying task as well as the implemented ML approaches, which can include purely data-driven as well as hybrid methods that also consider physical relationships. Altogether this provides a comprehensive overview of the versatile ways in which ML can be beneficially deployed.

1.1 Machine learning for development tools

Several comprehensive development methodologies have been proposed for large engine technology that include close interaction between experimental testing and simulation-based development and which feature a stepwise increase in complexity along with technological development [3, 12]. One example that is presented in detail is the LEC Development Methodology (LDM), which has been developed and continuously refined over the years and successfully applied to numerous engine development tasks.

In the LDM (Figure 1), advanced experimental testing and simulation cover the complete range from basic experiments and simulations on fundamental test rigs (e.g., fuel characterization, ignition and combustion investigations, tribology and materials), to single-cylinder engine (SCE) and multicylinder engine (MCE) investigations (e.g., combustion system development and modeling, control systems, HiL testing), to complete systems (e.g., hybridization, exhaust gas aftertreatment, system simulation and life cycle analyses) on test beds as well as in real world labs (field trials) and actual applications. Each stage of advanced testing interacts closely with simulation-based development, which employs the appropriate simulation techniques both to augment experimental results for simulation-enhanced analysis and to enable model development for predicting detailed results purely by simulation. Furthermore, the methodology ensures that the results of measurements and simulations are transferable between different stages, which substantially improves the development process of complex systems.

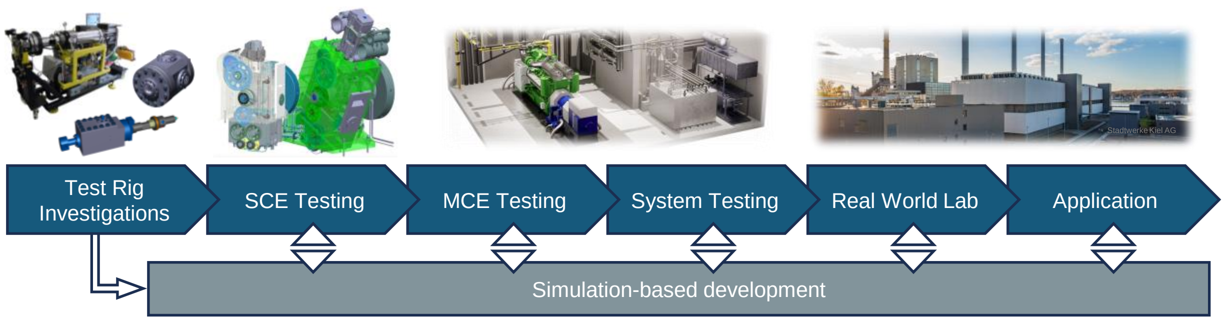

Figure 1. LEC Development Methodology

In development methodologies such as the LDM, there is great potential for application of ML methods in the context of testing as well as simulation. The importance of simulation-based development has continuously increased in recent years in response to increasingly complex systems with a very large number of degrees of freedom. However, complex phenomena cannot always be fully understood and described by first principles. Hybrid approaches based on coupling physics-based and data-driven methods are therefore a promising approach to further improving the quality of the methodology by increasing simulation accuracy or decreasing simulation time. In the field of advanced testing, there is the potential to exploit costly testing time more efficiently (e.g., through a design of experiments approach that reduces the required number of measurements and through advanced methods of measurement error detection to avoid unnecessary repetition of tests) and to obtain a more significant domain knowledge gain from experimental data through advanced data analytics instead of conventional methods.

1.2 Machine learning for series engine applications

In series engine applications, ML is employed in areas such as condition monitoring (CM), condition-based maintenance (CBM) and control systems. To some extent, these three areas feature an interrelationship which is illustrated in Figure 2.

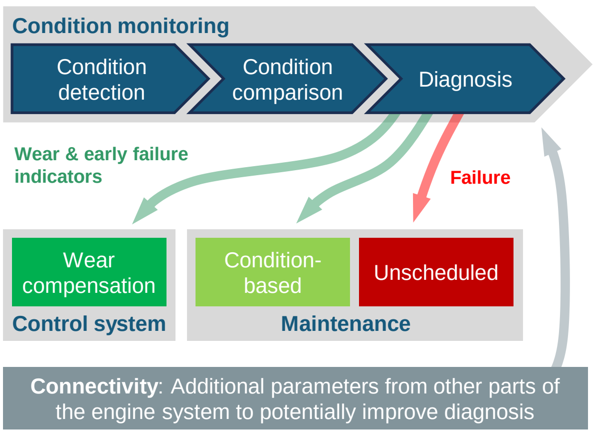

Figure 2. Condition monitoring, wear compensation and maintenance based on [13].

According to Mechefske [14], ***condition monitoring*** (including fault diagnostics) of machinery can be defined as “the field of technical activity in which selected physical parameters, associated with machinery operation, are observed for the purpose of determining machinery integrity.” Weck [13] divides CM into the following three subtasks, which were similarly summarized in [15]:

1 ***Condition detection***: One or more informative parameters are acquired which reflect the current condition of the machinery.

2 ***Condition comparison***: The actual condition is compared with a reference condition of the same parameter.

3 ***Diagnosis***: The results of the condition comparison are evaluated and the type and location of failure are determined.

Within these subtasks, the potential of ML approaches may be exploited in various ways. For condition detection, for example, virtual sensors based on data-driven models can be employed in cases where an informative parameter (or more generally the relevant information) cannot be directly measured by a real sensor and where a physical model is either too complex or not accurate enough, cf. wear assessment of cylinder liners in section 3.5.

For condition comparison, it is often expedient to determine the reference condition based on a data-driven model of the investigated parameter, cf. sliding bearing temperature in section 3.3. Furthermore, ML also offers many different approaches to effectively recognizing abnormalities in data. This offers additional opportunities for condition “comparison,” where there is no longer an explicit reference condition for comparison but rather a ML-based determination that the detected condition is anomalous [10].

With diagnosis, which commonly involves the evaluation of multiple CM parameters to determine the type and location of failure, ML has the potential to augment or even replace common diagnosis systems based on expert knowledge or physical models [16]. In addition to the data available directly from the condition detection, the increasing connectivity of engines and their components offers interfaces with further relevant information for the diagnostic tasks (cf. Figure 2). Depending on the available data and the ML methods considered, the distinction between condition comparison and diagnosis might even become obsolete. Instead, a comprehensive ML framework could be employed for both tasks at once. Based on the diagnosis, further activities can be triggered [13, 17]:

Wear compensation (with control systems, see also further below): An unwanted condition caused by phenomena such as wear and early failure indicators that impairs machine performance may be fully or at least partly compensated for. Control algorithms in particular have the potential to ensure that losses in performance remain minimal for as long as possible.

Maintenance: Wear and early failure indicators may be used for preventive *condition-based maintenance* approaches. While preventive time-based maintenance without condition information may lead to premature replacement, CBM aims to utilize the majority of the available lifetime of the machine while avoiding unexpected failure. The prediction of the remaining useful lifetime (RUL) based on condition information can be employed to optimally schedule maintenance before failure occurs. For both prediction of RUL and optimization of maintenance scheduling, ML approaches show great potential [18, 19]. *Unscheduled maintenance* is required if the result of the diagnosis is a failure. Despite the inconvenient timing, such maintenance can still provide significant added value if it serves to avoid serious secondary damage (including all implications such as safety-related consequences).

The concept illustrated in Figure 2 also provides the opportunity to discuss the integration of a digital twin. According to Vrabic et al. [20], "A digital twin is a digital representation of a physical item or assembly using integrated simulations and service data. The digital representation holds information from multiple sources across the product life cycle. This information is continuously updated and is visualised in a variety of ways to predict current and future conditions, in both design and operational environments, to enhance decision making." Based on Fuller et al. [21], a digital twin is characterized by a bidirectional flow of data between the physical item and its digital representation so that "a change made to the physical object automatically leads to a change in the digital object and vice versa." The existing literature furthermore emphasizes that in many digital twin applications, real-time capability is a key feature that can therefore be considered inherent to the digital twin concept [21–23]. Digital twins with the characteristics outlined above can be effectively utilized in the processes in Figure 2.

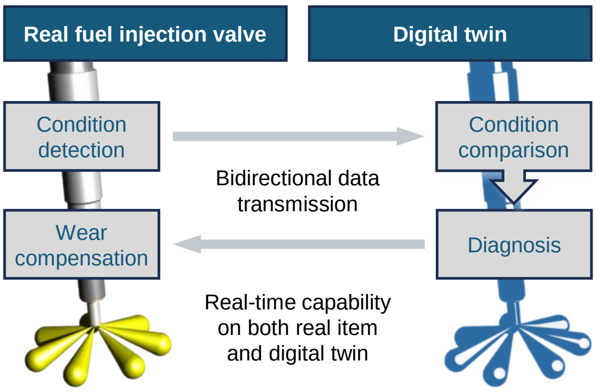

Figure 3. Digital twin concept.

Following the example illustrated in Figure 3, continuous data acquisition for condition detection on a fuel injection valve (physical item) during engine operation can provide data for condition comparison and diagnosis with a corresponding digital twin. Based on the results, the digital twin can in turn provide key data for performing accurate compensation measures on the physical item if required, e.g., due to wear phenomena.

While ***control systems*** have already been referred to specifically in the context of wear compensation, this topic generally encompasses a much broader field of ICE technology. As a result of the ever-increasing complexity of ICEs and the requirements to achieve near-zero GHG and pollutant emissions as well as high engine efficiency and durability, there is great demand for advanced engine controllers [9, 24, 25]. A wide variety of specific control problems affect ICEs, many of which are closely related to combustion (e.g., engine load and speed, combustion phasing, fuel consumption, airpath, knocking combustion, maximum pressure rise rate and engine-out emissions), while others are related to auxiliary systems (e.g., exhaust aftertreatment, coolant and waste heat recovery) [9, 24, 26–28]. The use of ML approaches in control systems opens up various opportunities such as ML-supported tuning of control parameters (which decrease the calibration effort of the control system), data-driven modeling of engine processes as a basis for model predictive control and even model-free machine learning control (MLC) designs [9, 10, 29]. Similar to the condition monitoring process illustrated in Figure 2, ML approaches can also evaluate the current state of the system. An example is the detection of knocking combustion, which is required as an input to corresponding combustion-related control systems (cf. section 3.6) [10, 30, 31].

In summary, the use of ML in both development tools and series engine applications is justified by its potential to generate added value through improved processes and products (characterized by parameters such as efficiency, GHG/pollutant emissions, durability and safety), to provide additional insight into these processes and products and understanding thereof ("domain knowledge gain") and to lower costs (e.g., material and personnel).

2 METHODOLOGY

ML techniques for enhancing large engine technology are commonly used based on specific objectives (e.g., to achieve a specific functionality in a series engine or in a development tool) in combination with the hypothesis that the correlations inherent in an associated database will allow these objectives to be achieved with ML approaches. Frequently, the key to generating such hypotheses is the availability of experts with the corresponding domain knowledge in the field of large ICEs. The LEC data-driven methodology illustrated in Figure 4 is applied to determine whether a hypothesis can be confirmed. As outlined by the three large arrows, the LEC approach is to cover the entire spectrum from data generation to knowledge discovery and knowledge application.

Figure 4. The LEC data-driven methodology.

Data generation and management deals with methods that generate, acquire, transmit and store data. These methods can be applied in both experimental and simulation data generation processes, resulting in a database that provides a solid foundation for further tasks as described below. Due to time and cost constraints, design of experiments (DoE) has proven to be a valuable tool for both testing and simulation and effectively generates databases suitable for employment in a data-driven context. In experimental investigations in particular, the selection of suitable measurement parameters and the employment of advanced sensor and data acquisition systems play key roles in database generation.

At the ***knowledge discovery*** stage, the general objective is to gain new insights, expressed as the discovery and the modeling of yet unknown or unconfirmed correlations. Besides finding patterns and generating corresponding models, there is the potential for creating a significant domain knowledge gain. In the course of this stage, the entire spectrum of different ML and statistical methods is considered (and extended with physical relationships, if required): From explorative correlation analyses to easily interpretable statistical regression models to classical ML methods such as clustering algorithms or support vector machines to highly sophisticated neural networks for deep learning, a problem-related trade-off between the required complexity, interpretability and performance is achieved. This ensures that models in particular are both accurate and as easily understandable as possible. In general, a distinction is made between supervised, unsupervised and reinforcement learning. While supervised learning relies on known target data (e.g., measurement value or knock classification of a combustion cycle), unsupervised learning does not rely on this kind of information [32]. The result is different main application scenarios: supervised learning for regression and classification tasks and unsupervised learning for clustering or anomaly detection. In contrast, reinforcement learning involves an artificial “agent” learning to choose actions based on interaction with its environment [32]. Another important distinction is between offline and online learning. While offline learning is one-off learning, online learning involves continuous learning and thus adaptation to changing conditions. Depending on the particular problem and hypothesis, it is therefore necessary to determine a suitable learning strategy that fosters the application of the knowledge gained.

For LEC’s data-driven methodology, hybrid approaches are also of particular interest. In general, there is a large variety of ways for integrating physical (and engine-related) expert knowledge into purely data-driven methods such as physics-based preprocessing, physics-guided neural network architectures, and hybrid physics-ML models [33, 34]—LEC strives to address all of these in its data-driven methodology.

In the last stage of the LEC data-driven methodology, ***knowledge application*** is achieved either by taking the obtained knowledge gain as an incentive for further research work (e.g., if a data-driven engine model indicates promising engine operating parameter ranges, further experimental tests are conducted to investigate them in detail) or by integrating technology using the applications outlined in section 1 (e.g., digital twins in a CM/CBM framework).

3 APPLICATIONS AND RESULTS

This section presents selected applications of ML and corresponding results from research projects carried out at the LEC. The applications come from both development tools and series engine application areas and include fundamental research on how to enhance simulation methods; fault diagnosis on engine test beds; CM and CBM on key engine components such as cylinder liners, fuel injection valves or sliding bearings and engine control applications for combustion anomalies. Each topic is introduced by a discussion of the underlying task as well as the implemented ML approaches. In all applications, realistic and application-related data from experiments or simulations is employed for model training and validation, and the outcomes are described by means of quantitative results in order to understand the achieved benefits.

3.1 ML-supported simulation of cycle-to-cycle variations in large gas engine combustion

For large gas engines, lean operating conditions are beneficial for achieving high efficiencies while keeping CO_2 and pollutant emissions at low levels. However, an increase in air-fuel ratio leads to less stable operation caused by combustion inhomogeneities between consecutive cycles. Since achieving sufficiently low cycle-to-cycle variations (CCV) is a great challenge for engine manufacturers, comprehensive investigations to better understand the cause of CCV and consequently reduce CCV are ongoing. The research on CCV over the last decades has identified several influencing factors which range from design (e.g., compression ratio, ignition system) to operating parameters (e.g., load, speed) to physiochemical phenomena (e.g., flow field, local mixture composition). Based on the variety of influencing factors, the prediction of CCV to develop efficient control strategies is a great challenge. Computational fluid dynamics (CFD) represent a state-of-the-art development tool for investigating CCV in an engine. The high spatial and temporal resolution of physical effects inside the combustion chamber enables a detailed investigation of CCV which is not possible or only possible on a limited basis with experimental tests. Large eddy simulation (LES) must be used to account for the CCV-related effects in ICEs. Since the numerical treatment of the governing equations in LES is based on a filtering approach rather than an averaging one as used in Reynolds-averaged Navier–Stokes (RANS) turbulence frameworks, the resolution of fluctuating phenomena is possible to a certain extent. However, the computational demands required for LES are significantly higher than for RANS simulations. Therefore, strategies for overcoming computational time issues which arise from a straight simulation of consecutive cycles have been proposed. One possibility is to perturbate flow field variables randomly and use the generated data as initial conditions for individual cycles which then can be computed in parallel, saving computational time required for gas exchange simulations. Although this approach was successfully applied in recent studies [35, 36] it has some drawbacks. First, the parallel simulation of ICE cycles with an LES framework requires enormous computational power and a comprehensive number of licenses is required if commercial software is used. Second, the random perturbation of flow field variables does not guarantee the generation of physically meaningful results.

To overcome the second drawback, the LEC has investigated a ML-supported CFD methodology: a ML-based flow field generation method [37]. The basic idea of this approach is to train a variational autoencoder (VAE) with simulated flow fields prior to ignition timing and artificially generate new velocity fields as well as turbulence intensity fields via the VAE. With this method, the underlying flow structure is conserved to an extent not guaranteed by random perturbation. VAEs are deep-learning generative models which consist of an encoder, a decoder and a latent space. The dimension of the input data is reduced in the encoder to obtain a compact representation in the latent space. VAEs use specific regularization terms to enable a regular latent space and furthermore an interference between decoded points and points in their vicinity [38]. A common field in which this method has already been applied successfully is the generation of artificial images.

To train the VAE, the LEC [37] used the velocity fields and the turbulent intensity fields of ten presimulated engine cycles of a large gas engine in a cylindrical region around the spark plug at ignition timing (snapshots), see Figure 5. These simulations are based on a production engine setup and were validated with SCE measurements. The artificially generated flow fields (which include velocity and turbulent kinetic energy, TKE) were then combined with the flow field snapshot of the first cycle (which includes all other relevant parameters). A total of 20 artificial flow fields was generated, yielding the initial conditions for further combustion simulations. Figure 6 shows the in-cylinder pressure and the heat release rate of the artificially generated cycles in red color and the ten presimulated cycles in grey. The result highlights that flow field-induced CCV can be created while maintaining the underlying flow characteristics.

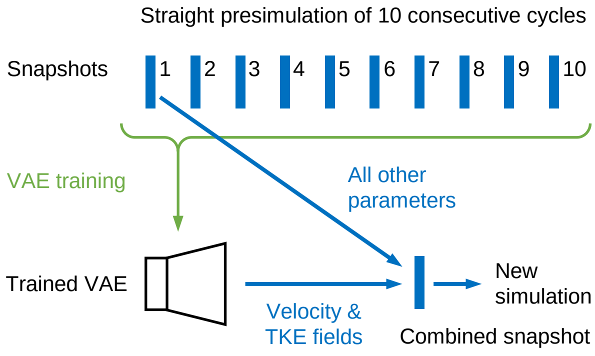

Figure 5. Methodology for artificial flow field generation with VAE.

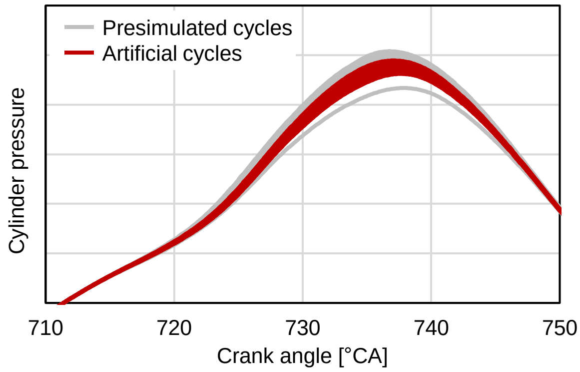

Figure 6. Comparison of presimulated cycles and cycles based on artificially generated flow fields.

While the method is capable of producing physically meaningful results and reducing the required simulation time by approximately 50% compared to the straight simulation of the same number of cycles (due to the omission of the gas exchange process), CCV is weakened due to a certain generalization effect of the VAE which can be quantified by the coefficient of variation of the maximum cylinder pressure of 1.06% for the initial ten cycles and 0.65% for the artificially generated cycles. This weakening is currently subject to further investigations.

3.2 ML-supported measurement fault diagnosis on engine test beds

Experimental investigations on engine test beds are an integral part of the LEC Development Methodology, cf. section 1.1. Since the hypotheses derived from them greatly depend on the data obtained, measurement faults can have serious consequences. Finding such faults offline is possible with postprocessing, but it is also time-consuming and costly because unnecessary test repetitions may be required. Therefore, it is of great importance to detect and diagnose faults early at the test bed. ML methods can play a decisive role in this process.

The method for fault diagnosis on engine test beds developed by the LEC (Figure 7 a)) includes three main process steps: residual generation, fault detection and fault isolation. In the initial step, a set of residuals is generated using model-based methods, limit checks and plausibility rules (formulas) such as inequalities for various pressure and temperature values. In the next step, these residuals are checked by applying fault conditions to determine if there is a fault in the system or not (fault detection). In the final step, a geometrical classification method is used to calculate fault probabilities for all measured variables in order to determine which sensors are faulty (fault isolation) [39].

Since the modeling of internal combustion engines in their entirety is extremely complex, the use of physics-based methods for fault diagnosis on engine test benches is limited [40]. As a consequence, simple limit checks and plausibility checks are widely used in practice. With such methods, it is usually only possible to detect large measurement errors or total sensor failures. Since research engines are normally equipped with extensive measurement technology that produces large amounts of data and the measured variables are highly correlated, the LEC is researching how to enhance fault diagnosis by extracting suitable information for that purpose using ML methods.

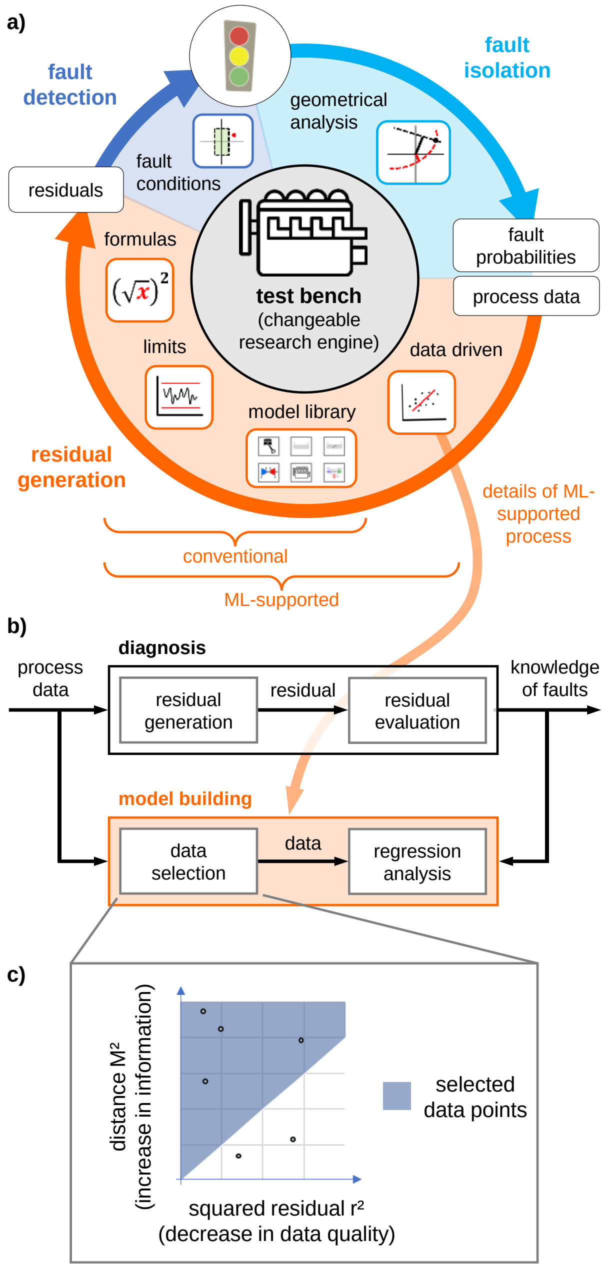

Figure 7. Overall fault diagnosis methodology a) including ML-supported process for residual generation b) and data selection technique c).

As shown in Figure 7 b), multiple linear regression models that represent the correlations of the measured variables in the fault-free case are built and trained. A crucial point for research engines is that a separate training data set normally does not exist, so model training and fault diagnosis have to be performed simultaneously [41]. As all data is not known a priori, the models have to adapt to new data situations directly on site, which requires an online learning strategy. This strategy must take into account computational costs and memory requirements as well as the risk of using faulty data points to build the models.

Data selection techniques are used to filter incoming data to find appropriate data for model training. For this purpose, data points are compared in the space spanned by distance and a residual [42]. Points with a large residual and a comparatively small distance are excluded from model training since large residuals may indicate an error in the data and small distances in a training data space may be interpreted as low additional information content that does not need to be included in the model. Using a statistical method that combines these two measures, the data points can be classified as belonging to one of two categories and used either for model building or not (Figure 7 c)). The trained models are then used for residual generation in which the model results are compared to the measured values. In the subsequent residual evaluation step, these residuals are analyzed to diagnose faulty sensors. The residuals are divided into two classes using the expected value, which is zero, and an interval representing the allowable deviation from this perfect value. Residuals falling within this control range are considered fault-free, while the others are considered faulty, indicating an error in the data.

Figure 8 shows the diagnostic results of a consistent series of SCE tests. Based on a measurement database that consists of 116 measurements in steady-state operation and was judged by experts to be error-free, abrupt measurement errors were simulated for 27 measured variables (including various mass flows, temperatures, pressures, speed, torque and exhaust composition) at four different measurement error levels (5%, 10%, 50% and 100%) for each variable, resulting in a total of 108 fault scenarios. The threshold values for fault detection were set with a certain safety margin so that no faults were detected in the base case. The diagnostic performance was evaluated using the detection rate (number of correctly detected faults divided by number of actual faults) and the isolation rate (number of correctly isolated faults divided by number of actual faults).

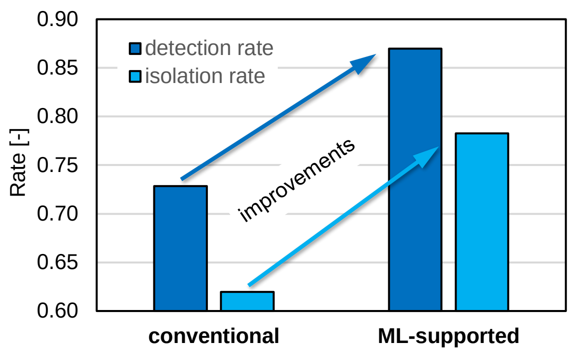

Figure 8. Improvement of detection and isolation rates with machine learning.

As illustrated, the use of ML methods to generate data-driven models for residual generation significantly improves both the detection rate and the isolation rate and can thus help in substantially reducing the time and cost required for unnecessary test repetitions.

3.3 ML for condition monitoring of sliding bearings in ICEs

Sliding bearings such as crankshaft main bearings are key components of ICEs recently subject to new challenges: Newly developed low viscosity oils that have the potential to reduce overall friction as well as advanced operating strategies that involve frequent starts and stops of ICEs (e.g., to react swiftly to power grid demands) are characterized by an increase in metal-to-metal contacts between the sliding bearing and the pin and therefore bearing wear [43, 44]. To avoid engine failure caused by excessive bearing wear or abrupt bearing failure, CM of sliding bearings has thus become an important element in monitoring ICEs in series applications.

Several informative parameters or methods may help to detect the condition of a sliding bearing, for example vibration or acoustic emissions, oil contaminates, oil film thickness and metal-to-metal contacts [43]. These methods differ not only in the effort in applying related measuring instruments and the complexity involved in extracting relevant information from raw measurement data but also whether information can be obtained about an individual bearing or just the entire bearing and lubrication system. Another bearing condition detection method that is fairly simple to apply, does not require any basic data processing routines and provides bearing-individual information is bearing temperature measurement. By following the LEC data-driven methodology, it was demonstrated that bearing temperature measurements are well-suited to bearing CM and helpful in obtaining detailed knowledge (domain knowledge gain) about the influence of engine operating parameters and lubricant oil parameters on bearing temperature [15, 43].

First, experimental investigations employing an MAN D2676 LF51 in-line six-cylinder diesel engine with a displacement of approximately 12.4 dm³ were carried out at the LEC in order to create a meaningful database [43]. The temperature of the crankshaft main bearings was measured using type K thermocouples fitted into bores in each individual bearing support. Different engine operating parameters (e.g., speed, torque, oil temperature and pressure at the engine inlet) and lubricant viscosities were investigated in steady-state operation to generate a database consisting of 105 engine operating points.

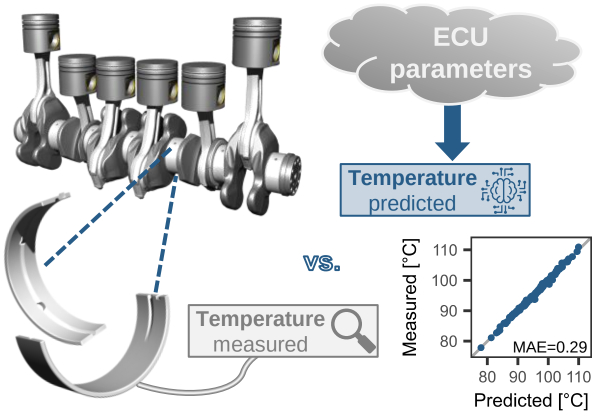

Figure 9. Machine learning for model-based condition comparison of crankshaft main bearings in ICEs.

Based on this database, LEC was able to develop a ML-based approach for bearing CM using bearing temperature measurements [15]. As illustrated in Figure 9, the approach employs a data-driven model of bearing temperature that is derived from readily available engine operating parameters from the electronic control unit (ECU). The parameters considered include engine speed and torque, oil temperature and pressure, intake air temperature and pressure and excess air ratio. To derive a reliable bearing temperature model, several ML methods for supervised regression tasks were evaluated (linear regression with and without lasso regularization, gradient boosting regression and support vector regression). A repeated nested k-fold cross-validation was applied to avoid overfitting and enable model comparison. The best model was a support vector regression with a radial basis kernel. Tested again on unseen data, this model was able to predict the bearing temperature with a mean absolute error of less than 0.3°C. Considering the temperature range from approximately 76°C to 112°C, the results appear to be highly accurate. Therefore, the bearing temperature model is found to be suitable as a reference during condition comparison since even small discrepancies between the model result and the measured values can provide valuable information about anomalies in bearing condition. Further investigations are currently being carried out at the LEC to expand the presented approach to CM of crankshaft main bearings during transient engine operation.

3.4 ML-based combustion parameter prediction using intelligent diesel fuel injection valves

In large engines that rely on conventional diesel and diesel-ignited dual fuel combustion concepts, diesel fuel injection valves play a key role in engine performance. Through advanced instrumentation of such valves, there is the potential to obtain detailed information about the injection process for purposes such as closed-loop control of the injection process (e.g., to overcome manufacturing tolerances and wear phenomena), CM of the injection valve as well as recording of relevant parameters over time as a basis for CBM approaches [45]. Beyond these aims, which mostly focus on the injection valve itself, there is great potential for using such valves in combination with other digital systems in ICEs [45]. A specific topic jointly investigated by OMT SpA and the LEC is the potential for predicting combustion parameters that are usually obtained with costly and delicate cylinder pressure indication systems. In series engine applications, this could provide an alternative way to generate the data required for combustion control purposes or serve as the basis for backup capability and mutual CM of the fuel injection valves and the indication system [45].

To generate cycle-resolved value-added data (VAD) about the injection process, OMT SpA has developed an “intelligent” common rail diesel fuel injection valve which includes a piezoelectric pressure transducer in the orifice plate between the control valve and control volume. Its signal is processed in real time along with other measurements using a neural network-based framework [6]. The VAD includes informative parameters such as start of injection, end of injection and ballistic/non-ballistic operation. Experimental investigations employing this injector were carried out at the LEC using a medium-speed four-stroke SCE with a displacement of approximately 15.7 dm³ to study how accurately key combustion parameters such as indicated mean effective pressure (IMEP), maximum cylinder pressure (p_{MAX}) and 50% fuel mass fraction burned point (MFB50) can be predicted from standard engine parameters and injector VAD (Figure 10). The former included readily available parameters from a production engine ECU such as engine speed and charge air and exhaust gas temperatures and pressures. To assess the information gain from the injector VAD, two scenarios were considered: models with and models without injector VAD as features [45]. 715 time-averaged measurements (from 247 different engine operating points with up to three repetitions each) were considered for modeling using several ML methods (linear regression with and without lasso regularization, kernel ridge regression, and gradient boosting regression). A repeated nested k-fold cross-validation was applied for proper model tuning and comparison. In both scenarios and for all targets, either kernel ridge regression or gradient boosting regression yielded the best results. Based on an evaluation with unseen test data that was not used for model training and comparison, it was possible to evaluate the overall predictive performance of the ML approach as well as compare both scenarios.

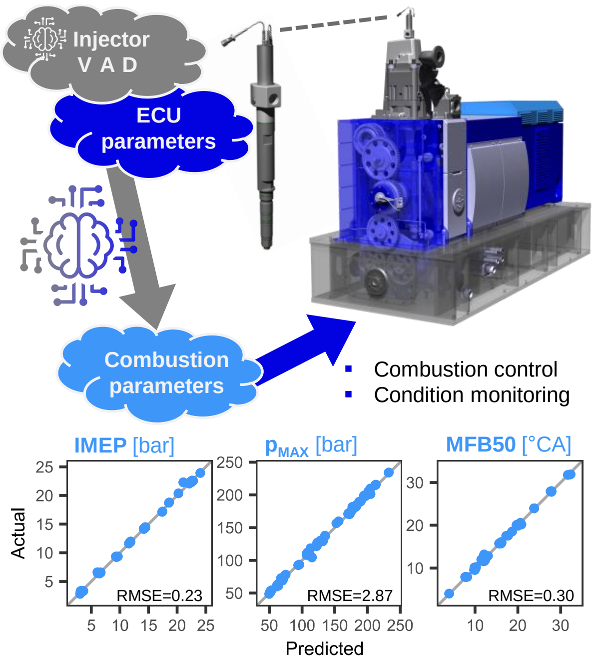

Figure 10. Combustion parameter prediction with an intelligent injection valve for combustion control and CM purposes.

In general, the overall prediction accuracy was high (cf. Figure 10) and it was found that in terms of the root mean squared error, there is a slight advantage in accuracy when the injector VAD is included (IMEP: 0.24 vs. 0.23 bar; p_{MAX}: 4.83 vs. 2.87 bar; MFB50: 0.40 vs. 0.30°CA) [45]. With help of the generated models, the following application cases for production engines based on injector VAD can be conceived [45]: (1) For an engine without an indication system, it can be concluded that the accuracy achieved in the modeling results would be largely sufficient for combustion control purposes; (2) For an engine that features intelligent injection valves and an indication system, backup functionality of the combustion control system and mutual CM between the indication and injection system are conceivable, in particular to detect if the systems are affected by wear. To further investigate these wear-related considerations, a follow-up experimental investigation involving artificially worn injection equipment has been conducted. Its objective is to gain additional knowledge of injector wear and determine how it affects the data-driven prediction of combustion parameters. Ultimately, this may also contribute to the development of a digital twin concept for a large engine fuel injector, which allows for condition-based maintenance and control system-based compensation of injector wear (cf. Figure 3).

3.5 ML for optical wear assessment of cylinder liners in large ICEs

Proper functional interaction between pistons and liners is essential in any reciprocating engine. Due to the movement of the pistons relative to the liners, the inner surface of the latter is subject to constant wear. To avoid out-of-spec function, cylinder liner wear monitoring is therefore advisable. During engine operation, liner wear can be assessed indirectly, for example by detecting wear debris in the lubricant oil system or by monitoring vibration signals [46]. However, position-resolved and precise wear quantification is hardly feasible with such indirect methods. In contrast, direct wear measurement is currently not possible during engine operation. For large gas engines in particular, the current state-of-the-art methods require disassembly and cutting of the examined liner followed by high-resolution microscopic surface depth measurement. These precise surface depth measurements are then commonly used for wear quantification based on material ratio curves (MRC) [47]. In summary, such a procedure for direct cylinder liner wear measurement is destructive, time-consuming and costly. Instead of using a stationary confocal microscope for the depth measurements, the LEC targets to apply a small handheld digital microscope that records ordinary color (RGB) images of the surface. Even though the color images do not contain direct depth information, deep learning-based computer vision methods such as convolutional neural networks (CNN) and cycle-consistent generative adversarial networks (CycleGANs) can compensate for this and obtain reliable surface depth information in the form of depth image, MRC or texture parameter predictions [48–50].

The data required for training and testing the ML-based approach was acquired from an experimental database created using more than 100 liners from Type 6 gas engines from INNIO Jenbacher GmbH & Co OG. For the measurements, two segments were cut out of each liner that covered the area near top dead center parallel to the piston pin axis and the area near bottom dead center perpendicular to the piston pin axis; these two areas are expected to include the most and the least surface wear. In both areas, up to 15 distinct measurement positions were optically measured with the high-accuracy stationary reference device as well as the simpler handheld one.

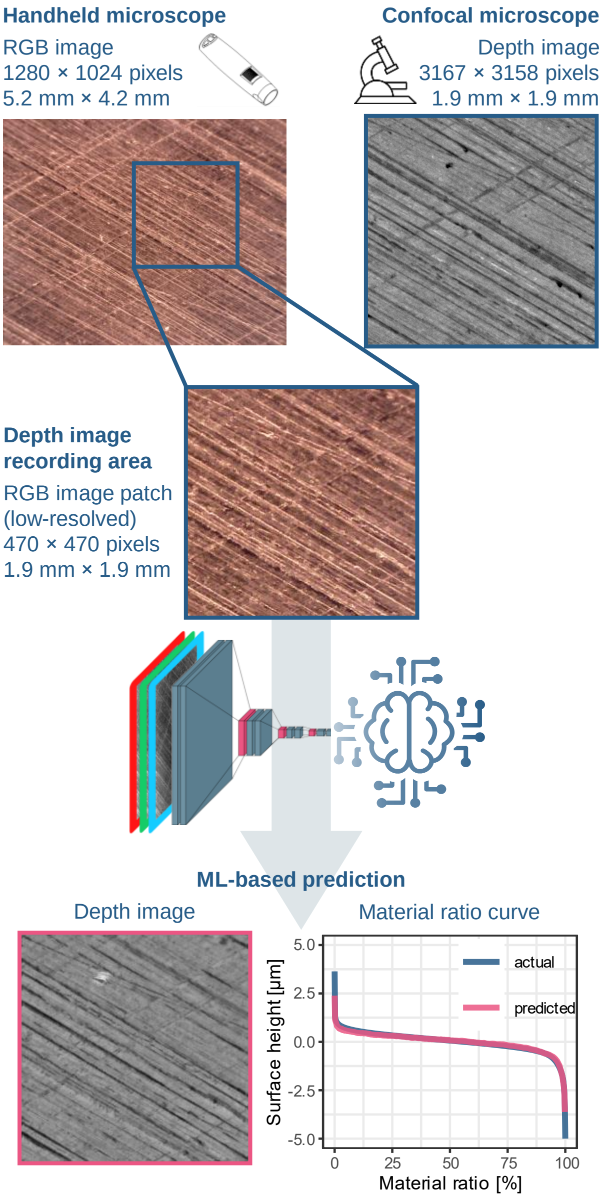

Figure 11. Prediction of surface depth image and MRC with help of a deep learning framework.

As shown in Figure 11, the high-resolved depth images from the confocal microscope are fully contained within the corresponding handheld device images. In the preprocessing step, the corresponding image sections were algorithmically registered. A total of 3075 image pairs were generated in this way. With liner operating hours ranging from 2550 h to 30000 h, the database includes a representative distribution of surface wear.

As illustrated in Figure 11, the low-resolved handheld images serve as input for a deep learning framework. Depending on the actual target (depth image, MRC, texture parameters), a customized framework is applied (e.g., CNN- or CycleGAN-based). In addition, an uncertainty quantification of the input images was introduced recently to detect quality deficiencies and strengthen the reliability of the approach [50]. Overfitting was prevented with help of an elaborate cross-validation strategy. For unseen data that has not been used during training, the best frameworks currently achieve a mean absolute error of 0.465 µm for the depth image and 0.102 µm for the MRC prediction. Since the liner surface depth spans roughly 10 µm, these results provide reasonable predictions and highlight the potential of the presented approach. Nevertheless, several options may be explored to improve the approach such as obtaining additional data for training or investigating alternative handheld devices. In this way, it may ultimately be possible to develop a method for nondestructive, rapid and inexpensive on-site wear assessment during engine standstill.

3.6 ML-based knock detection for large gas engines

To increase the efficiency and thus reduce CO_2 emissions, large gas engines must be operated at high-load operating points with high compression ratios. Since these conditions promote knocking combustion, the reliable detection of knocking cycles in production engines is a key input for combustion control systems so that the engines can be operated near the knock limit and thus achieve high efficiencies. Regardless of whether cylinder pressure or vibration signals are used, the underlying idea behind conventional knock detection methods is to compare data from an individual cycle to a threshold value. If it is exceeded, the cycle is labeled as knocking. Although methods using maximum amplitude pressure oscillation or signal energy pressure oscillation criteria were able to achieve reasonable results especially at heavy knock cycles [51], these methods have one major disadvantage in common: Careful calibration to engine operation conditions is required, leading to detection methods that are highly tailored to one engine, one event or one operating point. Therefore, the goal was to use ML techniques to develop approaches for knock detection that are as generally applicable as possible and avoid engine-dependent model adjustments. Two approaches were established at the LEC using supervised ML approaches [30, 31].

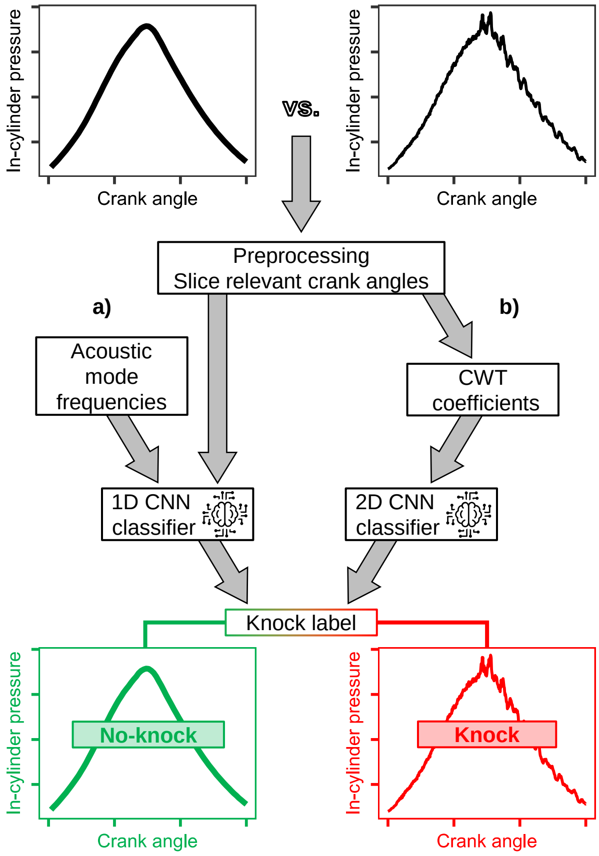

Figure 12. ML-based knock detection methods: a) theory-guided 1D CNN, b) continuous wavelet transformation and 2D CNN.

While both methods take the cylinder pressure signal as input, they differ in the preprocessing of the signal and the applied ML architecture. A brief description of both methods gives insight into their functionality and application to measured cylinder pressure.

Theory-guided 1D CNN (Figure 12 a)): The main idea of this approach is to relate knocking combustion to a certain resonance frequency in the cylinder pressure signal. The resonance frequencies for certain modes can be calculated using the well-known Bessel equation. Based on these frequencies, a 1D CNN is built in which the size of the kernel (or filter) is adapted to the frequency values. This procedure helps the CNN to detect the relevant frequencies of knocking combustion efficiently. Since this approach builds the CNN with a focus on the resonance frequency of an engine, which depends on the speed of sound in the cylinder, it can be seen as a hybrid approach (physics-guided network architecture). As the resonance frequency is the key influencing parameter, tuning of model constants can be reduced to engine size rather than specific engine operation points. Further details of the approach are found in [30].

Continuous wavelet transformation and 2D CNN (Figure 12 b)): This method primarily aims to preprocess the cylinder pressure signal before the data is fed into a ML algorithm. A continuous wavelet transformation (CWT) is applied in which the pressure signal is transferred into the time-frequency space by using a wavelet function, in this case the eighth Gaussian derivative. This step yields a 2D representation in form of a scalogram of the cylinder pressure. In the next step, the scalogram is processed by a 2D CNN which learns to detect knocking combustion by finding relevant features in the picture. By transforming the cylinder pressure signal into a picture of the time-frequency space, this method exploits the well-proved ability of CNNs to characterize pictures by their content. A detailed description of the approach and its validation is found in [31].

The applicability of both models was demonstrated with a representative dataset that includes 2880 individual cycles of three large gas engines. The engine bores range from 145 mm to 190 mm. In order to generate a labeled dataset, five engine experts categorized each cycle as either knock or no-knock. For model training and testing, the data was split according to a stratified sampling of knocking cycles as well as engine operating points. Table 1 shows the comparison between the model predictions (ML1 [30] and ML2 [31]) and the individual expert label (E1–E5) as well as the majority vote label (EM). A high Matthews correlation coefficient value denotes a strong correlation between the expert label and the respective ML prediction. The results indicate that although the individual expert labels disagree to a certain extent, both models are able to predict the knock tendency very well and thus show a high potential of being generally applicable since the underlying data covered three different types of large gas engines.

Table 1. Matthews correlation coefficients of the expert labels and the two investigated ML-based knock detection methods.

	E1	E2	E3	E4	E5	EM	ML1	ML2
E1	1.00	0.72	0.66	0.71	0.66	0.81	0.73	0.76
E2	0.72	1.00	0.71	0.76	0.71	0.87	0.79	0.77
E3	0.66	0.71	1.00	0.72	0.65	0.81	0.76	0.78
E4	0.71	0.76	0.72	1.00	0.69	0.86	0.83	0.83
E5	0.66	0.71	0.65	0.69	1.00	0.78	0.72	0.72
EM	0.81	0.87	0.81	0.86	0.78	1.00	0.85	0.87
ML1	0.73	0.79	0.76	0.83	0.72	0.85	1.00	0.88
ML2	0.76	0.77	0.78	0.83	0.72	0.87	0.88	1.00

4 SUMMARY AND OUTLOOK

The digital transformation and in particular ML provide valuable opportunities for improving existing large ICE technology and enabling or supporting the development of new solutions. The analysis and use of large amounts of data generated either by experiments or simulations effectively provide insights into previously unknown correlations, which allows creation of added value for development tools as well as series engine applications. As part of development methodologies such as LDM, there exists a large potential for application of ML methods in the context of testing as well as simulation. In series engine applications, ML is employed in areas such as CM, CBM and control systems. Overall, added value is generated by improved processes and products (characterized by parameters such as efficiency, GHG/pollutant emissions, durability and safety), additional insight into these processes and products and understanding thereof ("domain knowledge gain") and lower costs (e.g., material and personnel).

ML techniques are commonly used to enhance large engine technology based on specific objectives in combination with the hypothesis that the correlations inherent in an associated database will allow these objectives to be achieved with ML approaches. To investigate if a hypothesis can be confirmed, the LEC data-driven methodology is applied, which covers the entire spectrum from data generation to knowledge discovery and knowledge application. This paper presented actual applications of how ML approaches enhance the diverse research being conducted by the LEC and its partners on modern large engines. In all applications, realistic and application-related data from experiments or simulations was employed for model training and validation and quantitative results were used to describe the outcomes and to understand the achieved benefits. Based on the added value that has already been generated and the overall high potential, it is expected that the use of ML approaches to enhance large engine technology will continue to expand in the future.

5 DEFINITIONS, ACRONYMS, ABBREVIATIONS

CBM: Condition-based maintenance
CCV: Cycle-to-cycle variations
CFD: Computational fluid dynamics
CM: Condition monitoring
CNN: Convolutional neural network
CO_2: Carbon dioxide
CWT: Continuous wavelet transformation
DoE: Design of experiments
ECU: Electronic control unit
GAN: Generative adversarial network
GHG: Greenhouse gas
HiL: Hardware-in-the-loop
ICE: Internal combustion engine
IMEP: Indicated mean effective pressure
LES: Large eddy simulation
LDM: LEC Development Methodology
LEC: Large Engines Competence Center
MCE: Multicylinder engine
MFB50: Mass fraction burned 50% point
ML: Machine learning
MLC: Machine learning control
MRC: Material ratio curve
p_{MAX}: Maximum cylinder pressure
RANS: Reynolds-averaged-Navier-Stokes
RGB: Red green blue color model
RUL: Remaining useful lifetime
SCE: Single-cylinder research engine
TKE: Turbulent kinetic energy
VAD: Value-added data
VAE: Variational autoencoder

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