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IFAC PapersOnLine 54-10 (2021) 189–195

Potential of Machine Learning Methods for Robust Performance and Efficient Engine Control Development

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Abstract: Increasingly strict legislation for greenhouse gas and real-world pollutant emissions makes it necessary to develop fuel-efficient and robust control solutions for future automotive engines. Today's engine control development relies on traditional map-based and model-based control approaches. Due to growing system complexity and real-world requirements, these expert-intensive and time-consuming approaches are facing a turning point, which will lead to unacceptable development time and costs in the near future. Artificial Intelligence (AI) is a disruptive technology, which has interesting features that can tackle these challenges. AI-based methods have received growing interest due to the increasing availability of data and the success of AI applications for complex problems. This paper presents an overview of the state-of-the-art in Machine Learning (ML)-based methods that are applied for engine control development with focus on the time-consuming calibration process. The overview here shows that the vast majority of studies concentrates on regression modelling to model complex processes, to reduce the number of model parameters and to develop real-time, ECU implementable models. The identified promising directions for future ML-based engine control research include the application of reinforcement learning methods to on-line optimize engine performance and guarantee robust performance and unsupervised learning methods for data quality monitoring.

Keywords: engine control, machine learning, learning control, control calibration

1. INTRODUCTION

Driven by increasingly strict legislation for pollutant and greenhouse gas emissions, and the growing attention for real-world performance, future automotive powertrain complexity will continue to grow. More precisely, the introduction of new advanced fuelling and air management technologies will go hand in hand with an increasing number of control parameters (Atkinson, 2014). Examples of these technologies include fuel rate shaping, variable valve timing systems, electrification and energy recovery systems. Real-world emissions limits set challenging requirements for future engine control systems. These control systems have to guarantee robust performance under various disturbances and system uncertainty, including varying ambient conditions, production tolerances and component ageing.

Traditional map-based control approaches rely on numerous fixed maps. This rigid approach requires switching between maps to cover a wide range of operating conditions. As a result, it will become infeasible, since development time and costs will explode to guarantee robust performance for the increasing number of control parameters. Consequently, model-based control development is attracting much attention and is becoming the standard in automotive industry (Atkinson and Mott, 2005; Azmin et al., 2014; Atkinson, 2014; Fang et al., 2015; Isermann and Sequenz, 2016; Visser et al., 2016; Gutjahr et al., 2017). As illustrated in Figure 1, this approach has led to reduced development and calibration efforts. This is because the engine dynamometer or vehicle testing effort can be reduced, since more control development and calibration tasks are performed at the desk (i.e., virtual testing). Moreover, with the use of physics-based models, the model-based control approaches can deal with different system configurations and extrapolation beyond the tested operating envelope. Concerning robust performance, this approach is sensitive to model uncertainties that can degrade the control performance, and associated feedback controllers can have difficulties to compensate for these uncertainties, besides existing disturbances. Models embedded in the controller can also lack the required accuracy and speed. This especially holds for complex engine processes, such as emission formation.

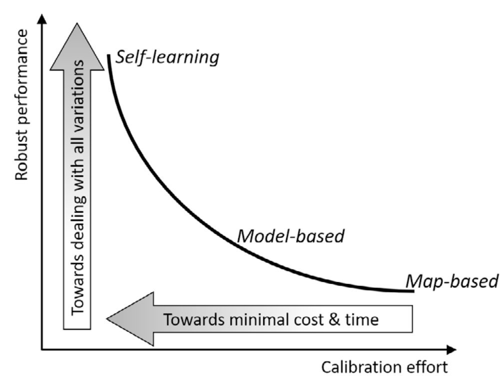

Fig. 1. Trade-off between robust performance and calibration effort and the impact of applied approaches.

Self-learning powertrains have the potential to combine minimal calibration effort with guaranteed robust performance (Willems, 2017), see Figure 1. By using available information about the actual and future powertrain behavior, optimal control settings can be determined. Exam-

10.1016/j.ifacol.2021.10.162

ples of control methods that optimize engine performance on-line are model predictive control (Wang et al., 2006; Stewart and Borrelli, 2008) and extremum seeking control (Mohammadi et al., 2014; Ramos et al., 2017; van der Weijst et al., 2019). Alternatively, Artificial Intelligence (AI) has recently attracted much attention because of its high potential in areas with complex systems and large amounts of data, including pattern recognition and vision-based applications. Furthermore, AI could dramatically reduce the control calibration effort and realize learning control for engine applications. Currently, limited research activity is seen in this application area for engine control development. Until now, learning control using AI methods has mainly been applied for energy management strategies in hybrid and electric powertrains. This paper aims to present a brief overview of the state-of-the-art in ML-based engine control development and to identify promising directions for future ML-based engine control research. Based on studied literature and patents, we give an overview of the applied methods and analyze the potential to guarantee robust control performance and efficient calibration process.

2. ENGINE CONTROL CALIBRATION

2.1 Engine control system

At a high level, the engine control system is shown in Figure 2 and contains feedforward and feedback controllers $\mathcal{F}$ and $\mathcal{C}$ respectively, setpoint generator $\mathcal{R}$, observers $\mathcal{O}$, and monitoring and diagnostics system also called On-Board Diagnostics (OBD). The desired control actions u are determined by the controllers based on the control objectives. When available, measured outputs y are utilized for feedback control, or observers are introduced to estimate the non-measurable outputs and θ represents the calibration parameters in the control system. The high-level engine control objective is to realize the driver's torque demand with minimal fuel consumption while meeting emissions and safety constraints under varying operating conditions.

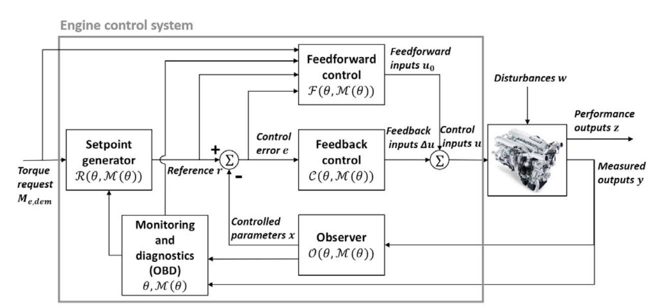

Fig. 2. General engine control system architecture.

2.2 Control calibration problem

The control calibration problem is defined as determining control (and optionally embedded model) parameters θ to achieve optimal functionality of individual control system components $\mathcal{F}, \mathcal{C}, \mathcal{R}, \mathcal{O}$ in different operating conditions and combustion modes. Calibration is performed in both software-in-the-loop (SiL) and hardware-in-the-loop (HiL) environment. It usually requires a lot of resources, such as manpower, software tools and testing facilities. Improving the calibration process implies optimizing the total development time and costs associated with the calibration process.

2.3 Control calibration process

The main stages of the engine control calibration process are shown in Table 1 for the industry standard, model-based approach. The calibration process starts after the control system concept definition and control system design phase. Initially, experiment design is developed offline to determine a set of inputs using design of experiments (DOE) approach to reduce testing time. Once DOE is prepared, measurements are conducted on the engine or vehicle test bench in the data acquisition phase. This data is further used for engine modeling and model parameter tuning in an off-line environment at the desk. Finally, these models are used to tune the control parameters and validate the resulting controllers in two possible ways: 1) off-line development using simulation models (also referred to as model-in-the-loop (MIL)) and 2) on-line development at the engine or vehicle test bench and during on-road testing. Especially, the data acquisition and control tuning phase are time consuming and require a significant expert effort. Multiple iterations of experimentation and data acquisition can be required dependent on data robustness and the quality monitoring process.

3. ARTIFICIAL INTELLIGENCE

According to the EC expert group (EC, 2019), Artificial intelligence (AI) refers to systems that exhibit intelligent behavior by analyzing their environment and taking actions autonomously in order to achieve specific goals. In this paper, we focus on Machine Learning (ML). This is a subset of AI and refers to techniques that enable AI systems to learn patterns and take decisions for improved performance. It includes Deep Learning (DL), which refers to algorithms that can learn from experience, understand the environment in multiple layers, and build more complex artificial neural networks (Goodfellow et al., 2016). DL is typically applied to learning problems, which are too complex to model using ML methods.

3.1 Machine learning methods

In this work, machine learning methods are classified using the framework shown in Figure 3:

Supervised learning (SL) A group of methods that can learn to predict the output of one or more output variables based on labeled (known) input-output behavior (Hastie et al., 2009). The classes of problems in SL are determined based on the nature of the output variable. The SL problem with prediction of quantitative continuous outputs is called regression, whereas the prediction of qualitative outputs is called classification.

Unsupervised learning (UL) Methods that can discover patterns and associations in unlabeled data. The common class of problems in UL is clustering. In clustering, the goal is to partition observations into number of clusters containing collection of objects that are more closely related or similar to objects in the same cluster than in other clusters, see (Hastie et al., 2009; Bishop, 2006).

Reinforcement learning (RL) Methods in which a software agent makes observations and learns to takes actions within an environment based on the reward it receives when it takes a certain action at a certain state. The software agent aims to learn the optimal policy that will maximize the total reward or a function of rewards over time (Sutton and Barto, 2018).

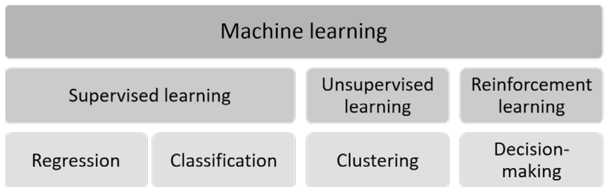

Fig. 3. Different types of learning and class of problems in ML and their capabilities.

3.2 Machine learning potential for engine control

This work aims to identify the potential of ML-based approaches to reduce the development effort and to enhance robust performance for engine controllers. Dramatic reductions in control calibration efforts are foreseen by applying ML methods. These methods combine the following promising characteristics:

- Reduced number of model parameters;
- On-line model parameter identification;
- Automated testing;
- On-line calibration of controllers

SL methods can efficiently parametrize embedded maps and models, hence reducing the number of calibration parameters. With regression methods, significantly reduced number of parameters i.e., hyperparameters, are to be calibrated in contrast to map-based approaches where large number of parameters are manually calibrated by an expert. This characteristic makes SL methods suitable to eliminate existing, numerous compensation maps for varying ambient conditions and transient engine operations. Consequently, also the number of tests that are required to determine these parameters can be minimized. These methods can also be applied to accurately model complex engine processes with a large number of inputs, such as emission formation. Although they have varying computational and memory requirements, a subset of these methods is suitable for real-time ECU implementation. Furthermore, dynamic conditions can be efficiently modeled using DL methods. This offers opportunities for efficient calibration and improved engine performance during transients. RL-based approaches can assist experts by automated testing and control tuning. Ultimately, it opens the route to on-road controller tuning and on-line adaptation by determining the desired control settings using real-time information on the actual and future state of the engine.

ML-based approaches are also of interest to enhance robust performance. Probabilistic SL methods can deal with system uncertainty and non-deterministic disturbances. This creates opportunities to capture varying system uncertainties, such as component ageing. This information can be utilized in off-line control calibration to achieve robust performance. If we go even one step further, by combining these methods with RL algorithms, model and control parameters can be adapted on-line, while explicitly dealing with the modelled uncertainties and disturbances. This approach combines minimal calibration effort with robust performance; the controller can deal with a wide range of variations.

In the next section, we review the actual reported methods and results for engine control.

4. AI-BASED ENGINE CONTROL DEVELOPMENT

Based on a literature and patent search, we aim to give a brief overview of the state-of-the-art in ML-based approaches for engine control development. Table 1 lists the various Machine Learning (ML) methods that are found for engine control applications. Also, the necessary factors to reduce the calibration effort and enhance robust performance are discussed and analyzed. Figures 4-6 summarize the results of this analysis. We focus on supervised learning and reinforcement learning, since only a single study is found for unsupervised learning.

4.1 Supervised learning

Engine models are utilized throughout the different steps in the engine control development process, i.e., control concept definition, control system design, experimental design or controller tuning (see Table 1). These applications require different model accuracy, detail and evaluation speed. In the calibration process, engine models have been utilized: i) as simulation tools; ii) to assist calibration of control parameters (also called model-assisted calibration), and iii) embedded in controllers and reference generators. Especially, SL regression techniques have received much attention over the last two decades for engine modeling. These techniques have shown potential to accurately model complex processes depending on the amount and quality of the data. Figure 4 shows the evaluation of the reference papers based on the necessary factors required for efficient engine modeling and robust performance. These papers are discussed in more detail.

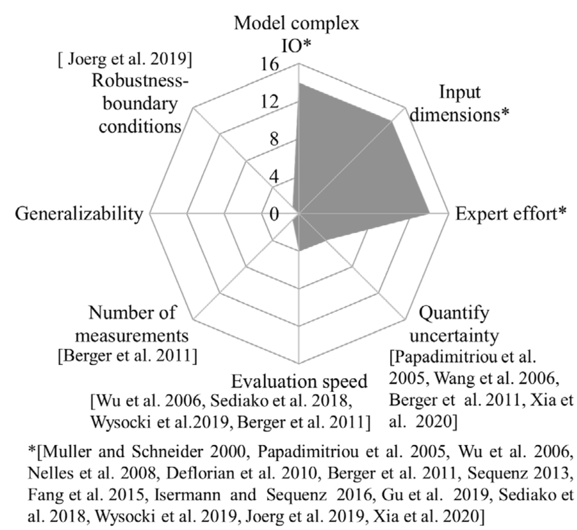

Fig. 4. Analysis of ML-based studies for engine modeling. Numbers on the radar chart are the number of papers.

4.1.1 Engine models as simulation tools

In the control system design phase, engine models are utilized as simulation tools for system analysis. Traditionally, physics-based (PB) engine models were applied. These models require in-depth system knowledge and large development times. The accuracy depends on the chosen model structure and parameters, which are not precisely known for all processes (Isermann and Sequenz, 2016). Moreover, these models require large simulation times, which limit their application for system analysis. A growing body of literature has investigated black-box engine modeling methods as an alternative to PB models. Regression methods, such as artificial neural networks (ANN), radial basis function neural networks (RBFNN), as well as probabilistic methods, such as Gaussian process regression (GPR) and local model networks (LMN) have been studied to accurately model complex, non-linear processes

Table 1. Overview of ML-based literature for engine control development. Stages of the calibration process are highlighted in gray.

			Main stages in model-based engine control development process					
			Control system concept definition	**Control system design**	**Experiment design & Data acquisition**	**Modeling**	**Tuning**	**Validation**
SL	Regression	ANN	Atkinson 2014	Wu et al. 2004 Nareid et al. 2005 Papadimitriou et al. 2005 El Hadef et al. 2013 Sediako et al. 2018 Jo et al. 2019 Wysocki et al. 2019		Wu et al. 2006 Atkinson 2014	Wendeker and Czarnigowski 2000 Wu et al. 2006	
		RBFNN		Papadimitriou et al. 2005		Azmin et al. 2014	Azmin et al. 2014	
		GPR		Berger et al. 2011 Aran and Unel 2018 Gutjahr et al. 2012 Xie et al. 2018	Xie et al. 2018	Xia et al. 2020	Xia et al. 2020	
		LMN		Nelles et al. 2008		Sequenz 2013 Isermann and Sequenz 2016 Gu et al. 2019	Sequenz 2013 Isermann and Sequenz 2016 Gu et al. 2019	
		Hybrid		Joerg et al. 2019				
		RNN (DL)		Müller and Schneider 2000 Kamat et al. 2006		Müller and Schneider 2000 Fang et al. 2015	Müller and Schneider 2000 Fang et al. 2015	
		MLP (DL)		Deflorian et al. 2010	Deflorian et al. 2010			
	Classification							
UL	Clustering			Pan et al. 2019				
RL	Decision making	MDP		Malikopoulos et al. 2007			Malikopoulos et al. 2007 Wagner 2019	
		Model-free		Xu et al. 2021				
		Deep RL	Neema et al. 2020					

with high number of inputs. These methods are suited for modeling steady-state engine operation. Moreover, limited system knowledge and expert effort is required due to the black-box nature of these regression models. GPR is more appropriate than neural networks (NN) for small number of training datasets. NN surpass GPR in regard to computational effort with large training datasets. LMN are more suitable where a strong human interaction in the process is needed and the training dataset is large (Berger et al., 2011). For dynamic engine modeling, fewer studies have been conducted. These studies employ deep learning methods, such as recurrent neural network (RNN) and multi-layer perceptron (MLP), which are suited to process sequential data and model complex, non-linear processes.

Figure 4 shows the focus areas for engine modelling research. It is evident that there are open topics that need more attention. Concerning minimizing the number of measurements, limited research has been conducted. However, Berger et al. (2011) compared the model accuracy of GPR and polynomial stepwise regression by varying the size of the training dataset. The results showed that for NO_x emissions, GPR is more accurate even with the reduced size of dataset. On the question of robustness at boundary conditions, regression methods lack extrapolation capability unlike physics-based models and have not been dealt with in depth. Recently, Joerg et al. (2019) have investigated hybrid modeling, in which robustness of physics-based models in boundary cases is combined with high accuracy regression models, such as NN and GPR. As far as the generalizability of these regression methods to data from different engines is concerned, it has not yet been established.

4.1.2 Controller tuning

In model-based control development, engine models are utilized in an off-line optimization framework for controller tuning (or calibration), see Table 1. Traditionally, multiple polynomial models were employed to model local steady-state engine operating conditions (Berger et al., 2011). These models are more suitable for low dimensional input space. To model the complete operation region, a large number of experiments and expert effort is required due to high model complexity. To overcome this complexity, a growing body of literature has investigated global engine models as an alternative to these local models. Especially, SL regression methods, such as ANN, RBFNN, GPR and LMN have been studied for global engine modeling. These methods are suited for modeling steady-state engine operation. For example, the calibration and optimization tool ETAS ASCMO applies GPR for global engine modeling (Gutjahr et al., 2017).

Focus areas for controller development are summarized in Figure 5. Most of these studies overlook the effect of system uncertainties, such as model and input uncertainties, manufacturing tolerances and ageing, on the calibration parameters. A standard practise to compensate for these uncertainties is to generate fixed correction maps, which require high expert effort. Probabilistic methods, such as GPR and RBFNN, can quantify model uncertainty, which can be used to calibrate for robust control performance. However, these methods have not been widely applied; currently, use of deterministic models is still common practice for off-line calibration. In a recent study, Xia et al. (2020) derived a GPR to model the RCCI combustion process. They used this model for robust, off-line optimization of fuel economy in the presence of disturbances and uncertainties and of safety and emission constraints. The results showed that the algorithm could determine optimal feedforward control settings under the studied input uncertainties and model uncertainties. However, no results were provided that quantify calibration effort reduction by this approach compared to the standard practise. Few studies have employed SL methods for applications other than engine modeling. Wendeker and Czarnigowski (2000) modeled the speed of adaptation factor using ANN for an indirect, adaptive control approach for air/fuel ratio control in SI engine. This approach was implemented in an off-line environment.

4.1.3 Embedded models in controllers
RNN has been used to develop a dynamic engine torque model and neuro-controller embedded in feedback controller for torque control in SI engines (Müller and Schneider, 2000). The results show that the neuro-controller is able to track the torque demand for small and large load steps. However, no comparison is made between the proposed approach and the benchmark engine controller for criteria, such as computational requirements and effect on calibration effort. Due to lack of evidence, the potential advantage of this RNN-based neuro-controller approach is not yet clear. To substitute the conventional map-based feedforward controller with a SL method, Aran and Unel (2018) proposed an approach, which in turn would reduce the number of calibration parameters. The authors used a GPR model to parametrize the inverse air-path model in the feedforward controller of a diesel engine control system. This study implemented the GPR model in an off-line environment. GPR is chosen, as it can achieve good accuracy with small amount of datasets. The PID controller is replaced with a sliding mode controller. The results show improved reference tracking performance and reduced feedback control actuation, which is attributed to the accurate feedforward controller. The authors claim that less training data is required for the proposed approach compared to a map-based feedforward controller. This study does not include the effects of system uncertainties and different ambient conditions in the controller design, and therefore, robustness to these disturbances cannot be guaranteed. Moreover, the reduction in number of calibration parameters and requirements for on-line ECU implementation are not quantified in this study.

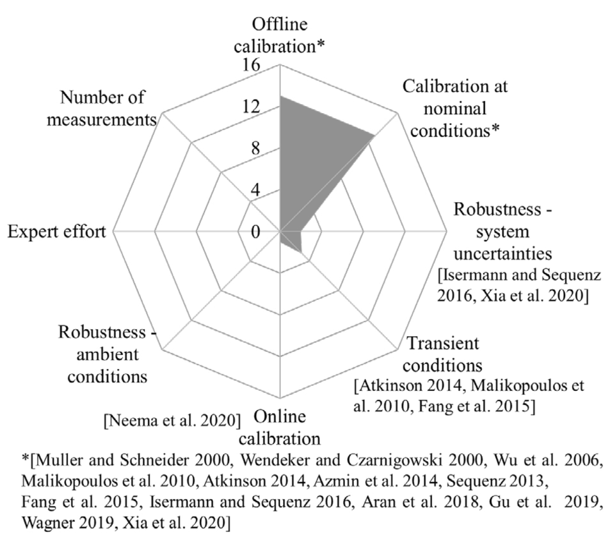

Fig. 5. Analysis of ML-based studies for controller development. Numbers on the radar chart are the number of papers.

4.1.4 Embedded models for observers
Observers (also called virtual sensors) are generally used as a substitute to physical sensors for control, and as a software redundancy for OBD. Map-based, physics-based and semi-empirical models are the industry standard, but have their limitations. Map-based observers are suitable only for estimation in steady-state conditions. Physics-based and semi-empirical observers cannot achieve high accuracy across the wide operating conditions and generally required high development times for complex processes, such as NO_x formation.

To overcome these limitations, different regression methods have been studied in the literature. Figure 6 shows analysis of these studies for necessary factors to reduce calibration effort and enhance robust performance. ANN and GPR have been used for steady-state prediction as these methods can model complex non-linear process accurately over wide operating conditions. Also, ANN can achieve faster evaluation speeds compared to physics-based observers. GPR is suitable for small training datasets, however, it suffers from high computational effort. For dynamic modeling, deep learning methods such as RNN and MLP have been used. One of the main limitations with neural networks, especially RNN and MLP is that a large amount of data is required for training. This could lead to large number of experiments if real data is used for training. An observation similar to regression-based engine models is made here regarding the focus areas of the literature. Most of the literature makes no attempt to quantify the benefit of regression models with respect to the evaluation speed, required number of experiments, requirements for on-line ECU implementation, deal with uncertainty and generalizability towards different engine measurements.

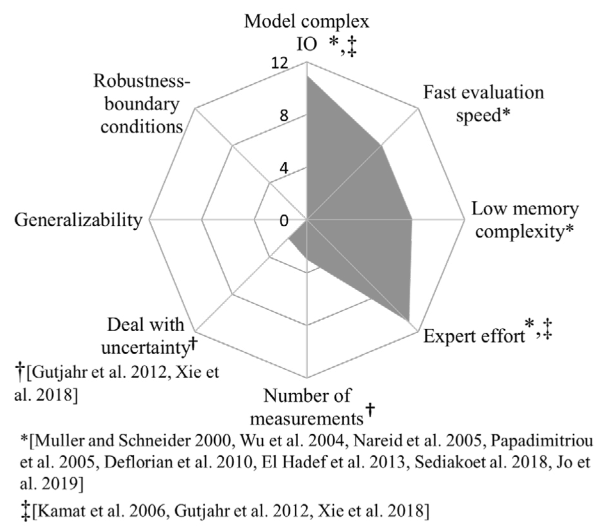

Fig. 6. Analysis of ML-based studies in development of observers. Numbers on the radar chart are the number of papers.

4.2 Reinforcement learning

For RL, limited application in engine control development has been found. Studies found are very recent with focus on automated calibration and, are still in research phase.

Off-line control calibration Malikopoulos et al. (2010) aim to overcome the sub-optimal transient performance observed with map-based controllers, which are calibrated at steady-state points. They propose an off-line feedback controller calibration approach using RL. The control objective is to minimize fuel consumption in SI engines with spark timing as a control input. In this work, the engine is treated as a controlled stochastic system, which is modelled as a Markov decision process (MDP). The engine calibration problem is formulated as a sequential decision-making problem with uncertainty. The main idea is to perceive the driver's driving style and learn to optimize fuel consumption in transients. For the above-mentioned control objective, an improvement in average BSFC by

1.4% compared to a baseline map-based approach is observed for a step input in throttle position. Such a data-extensive learning approach raises questions about computational effort, quantity of data and effect of data quality on controller performance. However, these topics are not addressed in the paper.

More recently, Wagner (2019) proposed an approach, in which RL was used to learn off-line the optimal control parameters to limit maximum turbine speed by manipulating fuel mass in CI engines. The authors argue that such an approach can overcome the drawbacks due to model uncertainty associated with model-assisted control tuning. The algorithm is implemented and validated in an off-line environment. Results show that the control objective could be achieved. Unfortunately, no information is reported on the RL algorithm, applied cost function, impact on calibration effort, and the effect of data quality on control performance.

On-line control calibration In a recent patent, Neema et al. (2020) propose a deep RL-based approach on on-line control calibration of an air-path control systems. An agent learns an optimal reference generator for both steady-state and dynamic conditions in real-time, such that performance targets of fuel consumption, torque demand and emissions are achieved in long-term. Multiple practical challenges arise regarding choice of RL algorithm, amount and quality of data. These challenges are not addressed by the authors. With this approach, a data-driven adaptive calibration approach can be foreseen that adapts the reference generator based on sensor information during real-time operation.

In general, it is seen that the discussed RL-studies do not quantify the impact of AI-based controller approaches on calibration effort. Moreover, impact on robust performance with AI-based approaches is not well established. A neglected area in the field of engine calibration is control calibration for transient conditions, which currently relies on engineering experience and requires high calibration effort for map-based approaches. Moreover, most studies focus on off-line calibration, where it is common practice to fix the calibration parameters, which offers limited robustness under various disturbances and uncertainties. With regard to learning control, RL is an emerging approach. It is gaining attention for its potential to learn and adapt control parameters based on sensor data to realize automated calibration and robust performance.

5. CONCLUSIONS AND OUTLOOK

Based on a literature and patent search, a brief overview of the state-of-the-art in Machine Learning (ML)-based engine control development with focus on the calibration process is determined. From this study, the following trends are observed: *(i)* Supervised learning (SL) regression methods have received much attention over the last two decades. These methods are mainly applied for engine modeling to assist off-line calibration and for realizing real-time, embedded models for observers. More recently, studies are found that focus on embedded models in controllers and on uncertainty modeling using probabilistic regression methods. In most studies, SL methods have been employed in an off-line environment; *(ii)* Unsupervised learning (UL) did not attract much attention; so far, clustering seems not of interest in engine control development; *(iii)* Reinforcement learning (RL) is an emerging field that is applied for automated engine controller calibration. Limited studies have been found and mainly focus on off-line applications.

ML-based methods promise a large potential to dramatically reduce the calibration effort associated with engine control development. Besides reducing the number of calibration parameters by efficiently parametrizing embedded maps and models in the controllers, a huge impact is foreseen by automated controller calibration and automated testing. Especially, on-line, RL-based control adaptation is identified as a promising direction for future research. This will not only minimize the need for an elaborate, expert-intensive calibration process, but will also guarantee robust performance under a wide range of real-world operating conditions.

Multiple challenges arise to implement RL-based engine control development methods. Firstly, off-line training on a simulated environment has limitations due to use of deterministic models or of collected test bench data, which both do not cover the full range of real-world scenarios. Moreover, learning by exploration on the real engine is limited, because safe operation has to be ensured throughout learning. Partial observability and stochasticity of engine behaviour needs to be handled in order to guarantee robustness against system uncertainties and noisy sensor signals. High computational effort is another challenge with on-line implementation of RL-based control methods. See Ding and Dong (2020); Dulac-Arnold et al. (2020, 2021) for more detail on challenges of real-world RL. Also, these methods have to guarantee safe operation and to deal with real-world emission constraints. A second promising area for future research is data quality monitoring. UL-based methods can overcome the limitations of the existing manual validation process in the data acquisition phase. This process is time-consuming and prone to human error.

ACKNOWLEDGEMENTS

The authors thank DENSO for providing financial support for this study and the Powertrain R&D team at DENSO Aachen Engineering Centre (AEC) for the constructive discussions.

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