Fleet Management Approach for Manufacturers displayed at the Use Case of Battery Electric Vehicles

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***Abstract*— Currently, fleet management approaches only focus on the perspective of the fleet operating company and the operators, but not on the perspective of the manufacturer of the fleet members. The manufacturer aims at optimizing existing fleets and supporting the development process of future fleet generations. Furthermore, data-driven models have increasing importance in fleet applications. Thus, this paper proposes a concept for a holistic fleet management approach for manufacturers supporting the development process of future fleet generations and services. We build our concept on three layers, one for the manufacturer, the fleet operator, and the machines respectively. We also discuss interactions and information flow in between the layers. Thus, enabling manufacturers to integrate operational data of customers into the development process making the products and services more customer-oriented. Before launching data-driven fleet services extensive training data is required. However, when launching new fleets disadvantageously only little data is available. As solution, we discuss the transfer of machine learning models in between different fleets (inter-fleet transfer learning). This enables quickly launching reliable machine models for new fleets with a lack of data.**

Index Terms—Fleet management, battery electric vehicles, operational data, machine learning, transfer learning

I. INTRODUCTION

The transformation of Industry 4.0 and, more generally, of the Internet of Things induced by information technology networks affects machines, vehicles as a type of machines, and the associated vehicle fleets [1]. In vehicles sensors exist at least since 1975 [2], but only got slowly connected starting in 1996 [3]. Still, the sensor data exchange from the vehicle to cloud (V2C) will be boosted by the introduction of 5G networks starting in the 2020s [4]. Based on this data, the operating companies are supported by fleet monitoring and fleet management systems often provided by third-parties which supervise the administration, use, and maintenance of machines [5]. However, these fleet management systems currently are focused on the operating companies, but not on the machine manufacturers.

Machine manufacturers aim to realize product cost savings, while satisfying quality and customer needs. However, customer needs and usage behavior of the machines are not always precisely known or accessible to the manufacturer via customer surveys. This lack of information on the manufacturer side can now be overcome because the aforementioned connectivity of machines becomes a standard enabling data transmission from sensors already existing in the machines of customer's fleets to the machine manufacturers. Consequently, this paper extends the understanding of fleet management focused on operating companies to include the perspective of the machine manufacturers. Thus, this paper proposes a fleet management approach including the perspective of the machine manufacturers. This fleet management approach aims at supporting the machine manufacturer to optimize existing fleets and support the development process of new products and services. Simultaneously, the operational objectives of fleet operating companies shall be considered by this approach. That is why, this approach would be advantageous for the machine manufacturer and their customers. Furthermore, a solution for quickly launching reliable data-driven models for new fleets with a lack of data is proposed by transferring an existing data-driven model of another fleet to the new fleet. We call this transfer of knowledge and models in between different fleets inter-fleet transfer learning.

We present this paper's fleet management approach and its advantages for drivers, fleet operators, and manufacturers at the use case of battery electric vehicles (BEV) fleets because of their rising importance worldwide [6]. BEV mass production as well as the high variety of BEVs coming in the near future require low costs and reduced time during development. The core component of BEVs is not the conventional combustion engine, but the battery which requires new surveillance in a new context. Also in the future, BEVs will be part of shared mobility concepts [7]. Thus, BEV fleet operators are facing operational and maintenance challenges as driver-vehicle assignment is dynamic. For these reasons, BEV fleets are chosen as use case to present this paper's fleet management approach and its advantages for drivers, fleet operators, and manufacturers. Nevertheless, the approach is not only designed for BEV or vehicles, but also for other machine types.

First, we contribute a comprehensive, generalist definition of the term fleets and an analysis of relevant stakeholder roles in the context of fleets. Second, our main contribution is a fleet management approach for manufacturers whose benefits and practical applications are described. Additionally, we will discuss opportunities for transfer learning in the context of fleets and our approach. All contributions are shown at the example of BEV fleets.

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The remainder of this paper is structured as follows: First, the term fleet is defined and fleets' stakeholder roles are introduced in Section II. Section III presents the state of the art of current fleet monitoring and fleet management systems. In Section IV this paper's fleet management approach for manufacturers is introduced. As one of many possible application scenarios, a use case for BEV fleets focused on battery digital twins is shown in Section V. Finally, possibilities for applying transfer learning in fleets are analyzed in Section VI.

II. Fleets

In the following, definitions of the term fleet are critically examined and the common perception of fleets' stakeholders is analyzed.

A. Definition

Currently, the term fleet has no uniform and widely applicable definition. Thus, first several definitions are critically examined and summarized. Seguing, a definition valid in this paper is presented.

Cambridge advanced learner's dictionary defines fleet as „a number of aircraft, buses, cars, or other vehicles under the control of one company or organization" [8, p. 544]. This definition only refers to means of transportation; other machines are excluded. Jin et al. [9] widen the definition to "a group of machines or assets." Compared to the Cambridge advanced learner's dictionary, using the term group instead of number emphasizes the common characteristics among the fleet members.

But these two definitions exclude fleets with fleet members under the control of different companies or organizations. For example, aircraft of the same type owned by two companies would not be part of the same fleet. For the machine owners or operating companies this would suffice. But from the manufacturer's perspective it would be meaningful to consider these two aircraft as members of one fleet.

Monnin et al. [10] emphasize that a fleet is an abstraction, meaning the fleet members are only grouped virtually. They must neither physically be at the same place, nor owned or operated by the same person or institution. In addition, the fleet size can change over time when new fleet members join and old leave the fleet. Kinnunen et al. [11] add the requirement of similarity among fleet members to the definition of Monnin et al. [10]. Verstraeten and Nowé [12] add that the fleet members perform the same task. Leone et al. [13] emphasize that both homogeneity and heterogeneity exist within a fleet. However, the term products they use is too broad for the technical context of this paper. Michau et al. [14] state that fleet members are operated differently. Though, making this an obligatory criterion means that two equally operated fleet members cannot be part of one fleet. Hence, this seems like an unnecessary restriction.

From these definitions, we derive our definition, that is widely applicable to different scenarios, perspectives and machines, like chemical plants, vehicles, trains, aircraft, windmills, and cogeneration units:

A fleet is a group of machines, that is homogenous with respect to their function, clustered by certain criteria, which may be technical, operational or contextual. Possible criteria are the ownership, the geophysical location or region of operation, the type of user or operator, the model type or generation of the fleet members, as well as the ageing or degradation state of the fleet members. A fleet is only an abstraction and may be divided into sub fleets, mathematically spoken subsets, so that a fleet hierarchy is created. Fleet members can also be part of several fleets in an intersection or union. Usually, some level of heterogeneity among the fleet members exists regarding certain characteristics like the operational conditions.

B. Stakeholder Roles

Until now, few authors have analyzed fleets' stakeholder roles involved in operation and manufacturing of fleets. However, this is essential for a holistic fleet management approach.

Michau et al. [14] consider fleets from the perspective of the manufacturer and operator. However, the operator role needs to be refined further. It may refer to one or several persons operating the machine, like the driver of a vehicle or an operator team of a chemical plant, but could also refer to the institutional fleet operator like a company, which usually will also own the fleet. Hence, when operating a fleet, different stakeholder roles can be involved: These are the owner, the fleet manager, the operators, like machine or plant operators, workers or drivers, and maintenance crews. For fleets these roles are usually neither filled by the same person or team nor are these necessarily part of the same organization.

In the following, possible tasks of each role are described. The owner, usually an institution, is responsible on the strategical level. This includes deciding on the fleet's task, the fleet member selection, and the fleet size. The fleet manager takes responsibility for the operational daily business. She manages accidents, service stops, schedules shift plans, and monitors the overall fleet performance and usage. In the case of BEV fleets, the fleet manager also supervises the charging management, e.g., by selected preferred charging profiles. The operator is working at, with or on the fleet members on the operational level and is responsible for a fleet member's usage. Examples are a vehicle driver and a team operating a steam cracker in the control room supported by a process control system.

These roles might not be separated or existing for all types of fleets. For example, on the one hand, a fleet of windmills is operated fully automatically and won't need human operators, but will still be monitored remotely by a System Control And Data Acquisition System (SCADA-System). On the other hand, a fleet constituted of all cars of a certain vehicle model type registered in Germany currently neither has an operational fleet manager nor a joint owner. As each driver or a group of drivers owns one vehicle, no fleet manager as intermediate exists. Contrarily to that, in the case of a non-autonomous ride hailing vehicle fleet, all roles of owner, fleet manager, and driver exist non-separated.

III. State of the Art: Fleet Management of Vehicles

Currently, there exists a wide range of fleet management systems supporting the aforementioned roles of operators and fleet managers. These systems are often offered by manufacturers or third-party companies for different types of machines like floor care equipment [15], intralogistics solutions [16] and especially for vehicle fleets of company cars, leasing cars, and logistics fleets [17, 18]. Simple telematics systems provide fleet monitoring for fleet managers, e.g., regarding fuel and energy consumption, fleet position, and mileage. These monitoring systems only transfer data, aggregate it, and display it to the fleet manager [19–21].

More advanced fleet management systems support fleet managers and operators by integrating operationally useful components like dynamic vehicle routing, maintenance management, and cost management [5, 22, 23]. Especially for BEV fleets, charging management approaches have been proposed [24, 25]. Not only for vehicle fleets, but also for other fleets predictive maintenance approaches have been considered [10, 26, 27]. However, these approaches focus only on a single fleet. Transfers between several different fleets are not considered, so called inter-fleet transfer. To the best of our knowledge, no fleet management approach integrates the manufacturer's perspective to support the development process at the moment.

For the chosen use case of BEVs, manufacturers only have limited data of new vehicles e.g., from test vehicles and endurance testing. Albeit, especially the latter is immensely expensive. Additionally, both only supply a limited data base regarding quantity and variety. They are usually executed by a group of test drivers and do not reflect operational usage of end customers. Thus, a holistic fleet management approach from the manufacturer's perspective will support and reduce costs of the development process.

IV. Fleet Management Approach for Manufacturers

Due to the limitations of state-of-the-art fleet management system for manufacturers, we propose a fleet management approach for manufacturers. First the general layer structure is introduced following a detailed description of the layers and the information flow in between the layers in the next three Sections IV-II.AA to IV-C. In Section IV-D, possibilities for data storage and machine learning model training are discussed.

This paper's approach has a structure of three layers which is depicted in Fig. 1: The machine, fleet operator, and manufacturer layer. Like the automation pyramid [28, 29], the layer structure reduces complexity. The automation pyramid consists of four layers: Enterprise layer, plant layer, process layer, and field layer. Its objective is the production control of plants or machines [28, 29]. Even though this paper's approach has a different objective, it is related to the automation pyramid. This paper's approach puts another layer on top of the automation pyramid: The manufacturer layer. The automation pyramid's enterprise layer is comparable to the fleet operator layer as it refers to the (fleet) operating enterprise. Additionally, plant, process, and field layer are merged into the machine layer because their exact structure is less relevant for the fleet management.

On the bottom machine layer of this approach, each fleet is constituted by grouping machines regarding certain criteria following the chosen definition in Section II-A. Thus, single machines are viewed as fleet members. Each machine is accompanied by an individual digital twin. The digital twin mirrors the life of its corresponding physical twin that can be used for various purposes [30]. The objective of this layer is to support the single machine's operator or operating teams, so it is machine-focused.

On the middle fleet operator layer, each fleet is supervised by the roles of technical monitoring and fleet manager. The technical monitoring focuses on the fleet member's health and load from a technical point of view. The fleet manager takes responsibility for the operational daily business like described in Section II-B. Depending on the technical expertise and need of the fleet manager, the roles of technical monitoring and fleet manager can be executed jointly or separately, either by a person or a team. At all events, for larger fleets that are not operated by a single person or institution technical monitoring and fleet manager can be roles allocated at the manufacturer, e.g., in the after sales or service department. The objective of this layer is to support fleet-related activities of the fleet operator, so it is focused on fleet operators.

On the top manufacturer layer, all technical monitoring and fleet managers from the fleet operator layer are connected to the manufacturer's development environment. The objective

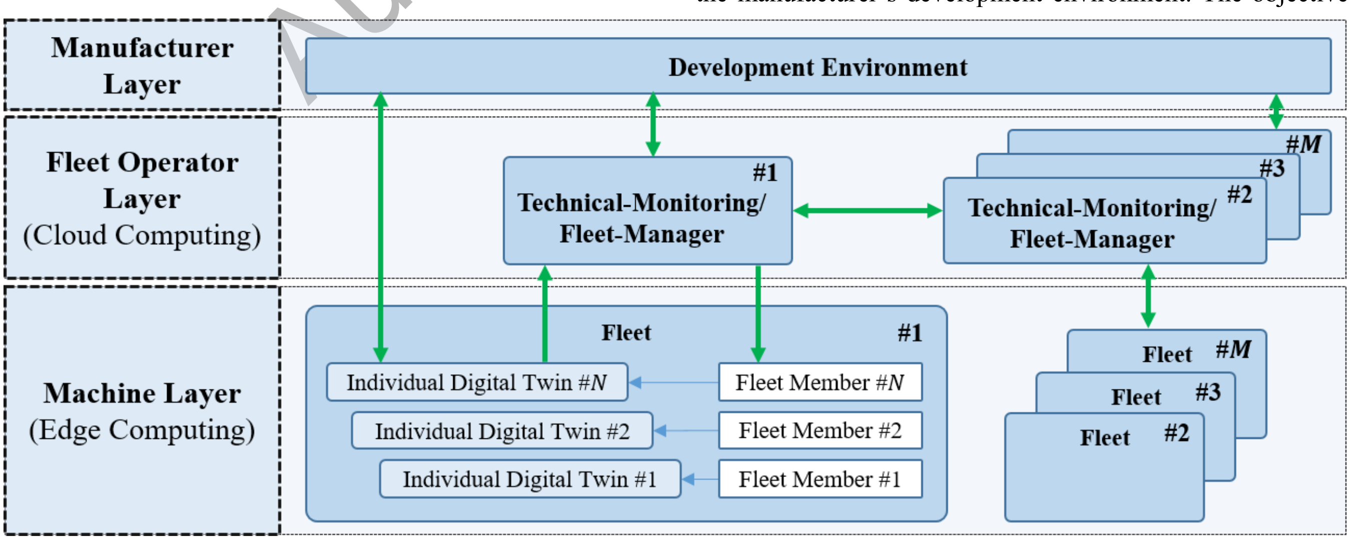

Figure 1. Fleet management approach for manufacturers (Coarse depiction)

of this layer is to support the manufacturer of the fleet members independently of the composition of the fleets, so it is manufacturer-focused.

In contrast to the middle layer, which is centralized in the cloud, the machine layer follows the paradigm of edge computing as it enables moving computation and data storage away from a central cloud [31]. This division is motivated by cost, security, connectivity, and bandwidth limitations. Data and computations like model execution that are necessary for the reliable and secure operation of the fleet members stay on the machine. However, additional digital services provided to the fleet's stakeholders and model training are executed in the cloud. The manufacturer layer may be realized independently as the manufacturer desires.

When extending this approach from a single to multiple manufacturers of the same machine type, interchangeable layers with standardized interfaces for information flow in between the layer become an option. Information flow in between the layers will be limited by data access directives of the involved manufacturers. Consequently, fleet data is only shared with the manufacturer of the fleet members, not with other manufacturers. Also, of all layers only the fleet operator layer can realistically be exchanged to limit external access of third-party manufacturers to critical functions.

Fig. 2 depicts the detailed fleet management approach for manufacturers with the subcomponents of each layer as well as the information flow in between the layer. These are described in the Sections IV-A to IV-C and shown at the example of BEV fleets.

A. Machine Layer

On the machine layer, each fleet member's digital twin is composed of individual information regarding the components of interest. Depending on the complexity of the ageing causes of the component either component statistics are recorded or intelligent on-board models are used. Component statistics encode how the components have been stressed during usage. For BEVs this could include simple metrics as mileage or the number of charging cycles. Component statistics may suffice for operating materials, tire wear and components of the drive train.

More complex ageing mechanisms can be captured by intelligent on-board models. For BEV fleets such complex ageing mechanisms exist in the battery [32]. Intelligent on-board models may be physical, hybrid or machine learning models. However, physical models require complex model development for each new model. Thus, hybrid and machine learning models are beneficial. Though, they are dependent on data gathering from fleet usage. This data may serve for validation of physical models.

The definition and adjustment of the component statistics and intelligent on-board models is done by the manufacturer from the highest layer. This enables interoperability and comparability of the digital vehicle twins. Furthermore, the task of designing digital twins would be too complex and out of scope for fleet operators.

B. Fleet Operator Layer

On the middle fleet operator layer, the roles of technical monitoring and fleet managers are supported by the technologies of intelligent data aggregation, fleet analysis toolbox, predictive maintenance and data driven optimization methods. Access to these functions depends on the technical expertise and need of the fleet manager.

Like in state-of-the-art fleet management systems, the fleet manager is supported with a fleet analysis toolbox that provides operationally relevant information like current states of the fleet's vehicles and their components. In the case of BEVs this would be e.g., the State of Charge (SOC) and State of Health (SOH). For fleet analysis, the manufacturer can

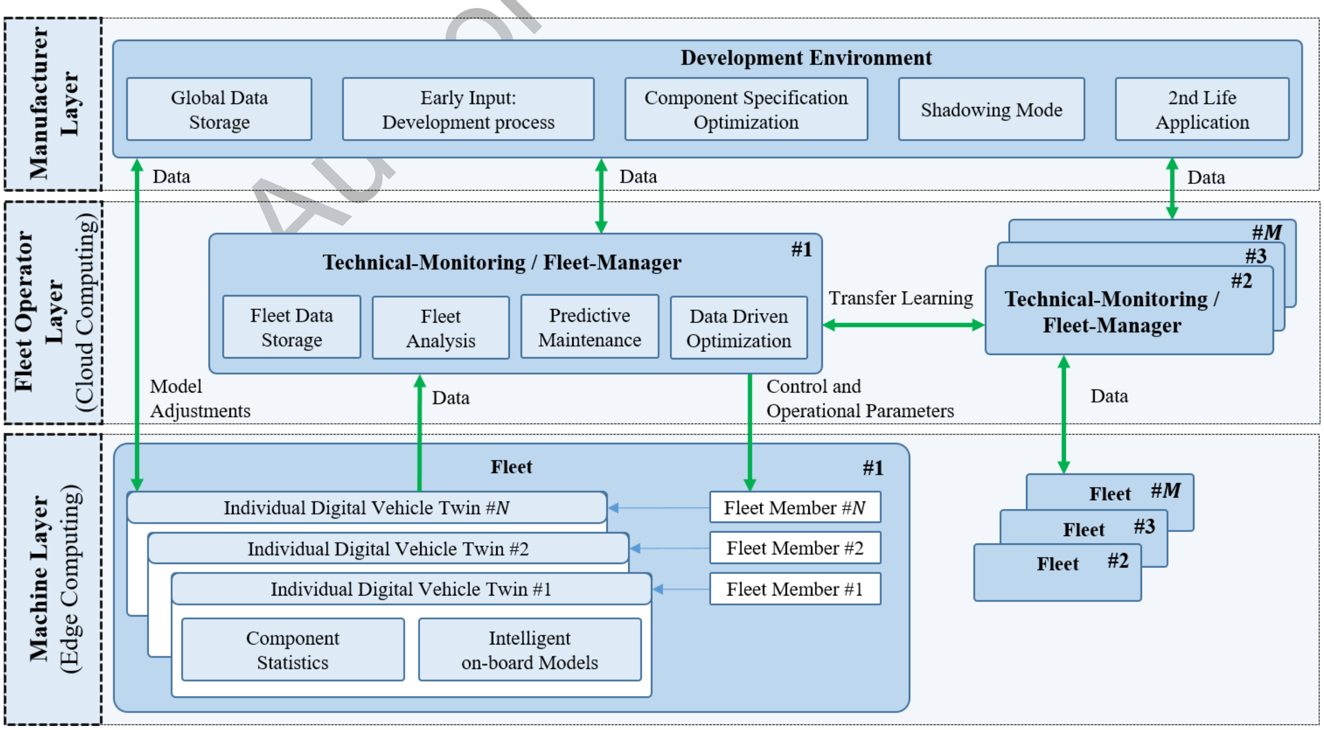

Figure 2. Fleet management approach for manufacturers (Detailed depiction)

provide services to the fleet operator over the entire product life cycle like residual value estimation. Also interfaces to third-party providers are possible on the fleet operator layer.

Furthermore, the data from the component statistics and the intelligent on-board models gets aggregated component-wise, for each fleet member, and the entire fleet in the fleet data storage for displaying in the fleet analysis toolbox. This data is relevant for the fleet manager, but also for the technical monitoring of the fleet. This way relatively fast ageing components within the fleet can be identified, analyzed, and potentially maintained.

The fleet manager has the capability to customize the control and operational parameters of the fleet members related to the operational strategy. Hence, the fleet manager can implement measures to extend the lifetime, minimize operational costs, and maximize the fleets performance or utilization. Before updating customized control and operational parameters to the fleet, the technical monitoring and the fleet manager are supported by data driven optimization models. These enable simulations to identify the desired impact of the chosen control and operational parameters beforehand. For BEV fleets customized control and operational parameters could specify the configuration of the low power mode at low SOCs. The same applies to the charging management with preferred charging rates and configurations related to ageing accelerating operational states and events.

On the middle fleet operator layer, information exchange in between the different technical monitoring and fleet managers across fleets is possible. Section VI elaborates further on the motivation and implementation of this.

C. Manufacturer Layer

On the top manufacturer layer, fleet data stored for each fleet on the fleet operator layer is aggregated fleet-comprehensively in a global data storage.

This global data storage may serve as early input to the development process of new products and services because it contains information of the real usage behavior of several fleets. Currently, such information may only be acquired qualitatively by customer survey indicating customers' needs, but not the customers' real usage of the machines. Especially, data of overloading and common load scenarios is interesting for the development to specify new machine models. Consequently, the product requirements document (PRD) of future components will be based on actual customer demand. This also applies to the interaction of the components as complete product. Based on the cross-fleet historic data storage, the manufacturer can develop customer-demand orientated services for hardware and software components.

Additionally, development engineers can interact with the fleets directly to roll out fleet-wide software updates. An example are model adjustments of the underlying structures of the fleet members' digital twins. This improves the information basis for fleet managers provided by the digital twins. Development engineers can also prototype functions on a sub fleet to get fast customer feedback [33]. Additionally, shadowing testing [34] which is known in the software domain can be applied on the fleet when connected to the development department. This is especially relevant for software functions and digital services provided to customers, drivers, fleet managers, and fleet operators.

2nd life applications of fleet members or their components usually need to be scheduled to meet supply and demand timely. This applies for example to BEV batteries transferred to a 2nd life applications for stationary energy storage. Also, components with high value for recycling may be observed closely at their end of life (EOL) to improve scheduling the recycling plant. Both use cases are interesting for the business model of Batteries as a Service (BaaS) [35].

D. Data Storage and Machine Learning Model Training

The question of the location of data storage and machine learning model training depends on multiple factors like the origin and quantity of the training data and the computational power needed for training. For example, for minimizing the data transfer the intelligent on-board models could be trained on the edge device where the data is located. Contrarily, fleet-comprehensive models that require training data of all fleet members of a fleet can be trained either centralized in the cloud or federated. The latter is advantageous, when the data interface between the fleet members and the cloud causes privacy issues or suffer from unreliable and slow network connections. Privacy issues may occur when data regarding the detailed usage of the fleet members is transmitted. For vehicle fleets, this includes information like the location, driven routes, and periods of use. To overcome these issues federated learning may be applied in a fleet context. Federated learning is a machine learning setting where many clients (e.g. the fleet members) collaboratively train a single model under the control of a central server, while the training data stays decentralized with the clients. Each client independently computes a parameter update to the current model using its local data and only communicates the parameter updates to the central sever, where all updates are aggregated to a new global model [36, 37].

In contrast to federated learning, distributed learning assumes the availability of all training samples in a centralized location. From there data can be shuffled and distributed over computation nodes [38]. In this case, privacy issues could be tackled by anonymizing the transmitted data.

V. Use Case of Battery Electric Vehicle Fleets

In 2020 the price of the battery of an BEV accounted for more than 30 % of the vehicle's production cost and is therefore the most valuable component inside an BEV [39]. One major cost driver during the development process is battery testing. To guarantee the longevity of battery cells, endurance testing consumes time and resources, but is mostly restricted to limited testing facilities.

The same limitations are applicable to the management of customers' BEV fleets. To monitor battery aging due to vehicle usage, frequent workshop measurements of the battery's SOH would be necessary. This battery knowledge would enable optimization strategies, predictive maintenance, and support of future development to improve battery systems. Unfortunately, this procedure is unfeasible for workshop facilities and customers.

In order to make battery testing scalable, to lower the cost, and to reduce real battery testing efficiently, simulations with digital battery twins show great potential [32, 40, 41]. Heinrich et. al [42] investigated battery models based on real in-vehicle driving data only. Their battery model was used to estimate the battery SOH by performing standard laboratory battery tests virtually with almost experimental accuracy.

Such models can be trained inside the vehicle during operation (edge computing). Hence, the whole battery functionality can be compressed to a minimum amount of model parameters. This compression enables an efficient and scalable data transmission between single vehicles and the fleet management.

The fleet operator can thereby analyze each member of the fleet individually (cloud computing). Comprising the knowledge of all operated fleets, optimization strategies, predictive maintenance, and adjustments for the battery operational parameters can be derived. This procedure benefits the customer's performance and can be further used to improve development of products and services.

Understanding the real utilization of vehicle components by a variety of different customers, the development of new model generations can be optimized in terms of requirement specifications, prevention of over-engineering, and new exploitation concepts.

VI. Transfer Learning for Fleets

Fleets are heterogeneous which means that certain characteristics are over or under-represented in different fleets. Heterogeneity may be caused by different components built in the fleet members, different model generations or different operational load of the fleet members. This heterogeneity motivates transfer learning in between different fleets, so called inter-fleet learning.

Transfer learning aims to improve learning a new task by transferring knowledge from a related task that has already been learned [43]. The related task is called source task, while the new task is also referred to as target task. The used data is from the source domain respectively the target domain which in this case are different fleets, the source and target fleet respectively. In other words, in this paper transfer learning is regarded as inter-fleet learning, not as intra-fleet learning like in [12, 44].

When launching a new fleet, reliable machine learning models for the new fleet are needed very quickly to support established services. Otherwise the models are only optional. Nevertheless, the available amount of data for model training is limited in the initial phase. Extensive data gathering as solution is often expensive and difficult. Another solution is to transfer an established model of another fleet to the new fleet (inter-fleet transfer learning), as soon as a small amount of data of the new fleet has been gathered. Due to security and privacy, in most cases the manufacturer and not fleet operators will provide inter-fleet transfer learning.

The lack of data of the target fleet which makes transfer learning beneficial may not only occur because of the young age of the target fleet. Transfer learning will also be promising, if the target fleet is small or has a special usage behavior. Five cases of inter-fleet transfer learning are presented for a source and target fleet at exemplary vehicle fleets in Table I[1] (In the first case, the target fleet is young either because a model update or refurbishment has been rolled out (1a), a completely new model type has been released (1b) or the target fleet's members are either not frequently or not intensively used (1c). In the second case, the target fleet and source fleet are of the same model type and generation but have different configurations of certain components from the beginning of their life (BOL) (2a) or after replacement of certain components due to maintenance at a service stop (2b). This may require different, but similar models. In the third case (3), the target fleet and source fleet are of the same model type and generation but have a significantly different load due to usage.

Not only transfer learning between machine learning models can be applied but also causal connections and analytical results can be transferred. For example, if an operational area has been identified as critical regarding battery ageing in one BEV fleet, this knowledge may be transferred to another BEV fleet.

Sticking to the use case of BEV fleets, the application of transfer learning for battery SOH estimation and forecasting can be beneficial, as there are common characteristics of different battery systems, but specific usage and ageing inducing causes are different for each battery type assembled in the fleet members.

TABLE I
POSSIBLE CASES OF INTER-FLEET TRANSFER LEARNING AT EXEMPLARY VEHICLE FLEETS

Case of inter-fleet transfer learning	Source fleet	Target fleet
1) Target fleet young		
1a) Model update or refurbishment	VW Golf 7	VW Golf 8
1b) New model	VW ID.3	VW ID.4
1c) Target fleet not used frequently or intensively	Used by sales representatives	Used for weekend trips only or mainly
2) Same model, but different configuration		
2a) from begin of life (BOL)	VW ID.3 Pro (58 kWh net battery, 107 kW motor power)	VW ID.3 Pro S (77 kWh net battery, 150 kW motor power.)
2b) after service stop	VW ID.3 Pro (no battery modules exchanged)	VW ID.3 Pro (n battery modules exchanged)
3) Same model, but special load of source or target fleet		
VW Crafter	average load	Trip length < 200 m, pauses > 1 h

[1] Exemplary ID.3 model specification from [45].

VII. Conclusion

Existing fleet management approaches focus on the perspective of the fleet operating company. These fleet management approaches do not consider the perspective of the machine manufacturer or include several fleets. This paper proposed a concept idea of a holistic fleet management approach for manufacturers with inter-fleet transfer learning. The approach is based on the opportunities of the connectivity between single machines, whole fleets, across different fleets, and the manufacturer. The approach and its information flow have been showed at the example of BEV fleets. Using this approach, manufacturers can access real operational data of their customer's fleets and integrate it into their development processes. Also, possible cases of transfer learning across different fleets implementable with this approach have been presented. This approach can be applied to fleets of different machine types, like for example vehicles, trains, aircraft, and windmills. However, it requires large fleets and might not be worth the investment, if fleet members have low capital costs, due to two reasons: Firstly, a sufficiently large and variable data basis is necessary for a manufacturer to benefit from this fleet management approach. Secondly, investments for infrastructure and operational realization of this fleet management approach will be significant so that economics of scale cannot be realized easily for small fleets. Future work should consider the implementation and validation of this theoretical concept. This applies especially to the suggested interfaces in between the layers. Related to this, the possibilities of interchangeable and connectable layers from different manufacturers can be discussed further.

Disclaimer

The results, opinions, and conclusions expressed in this publication are not necessarily those of Volkswagen Aktiengesellschaft.

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