# Digital Twins and AI in Fluid Power: Improving Systems by Connecting Real and Virtual Worlds

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## Abstract.

Fluid power is a widely used drive technology known for its durability, robustness, and cost efficiency, but it faces challenges related to energy efficiency and environmental impact. To address these challenges, the integration of software functions and digital frameworks is gaining importance for improving component performance, system integration, and product development. The integration of data and software within fluid power systems and components enables companies to increase their innovation potential, thereby establishing digital competence as a key determinant of competitive advantage. Consequently, fluid power is evolving into an interdisciplinary research field that combines mechanics, electronics, computer science, and data analytics. Current research focuses on the usage of digital twins across all phases of the product life cycle. As a result, numerous related concepts have emerged, such as digital frameworks and software functionalities that support component and system development while providing additional insights during operation, for example, through soft sensors that derive new variables from existing sensor data.
Despite these advances, the implementation and maturity of digital twin technologies vary significantly between domains. In the field of fluid power, in particular, the extent to which digital twins have been developed and integrated remains an open question. Therefore, this contribution examines the current state of digital twin development in fluid power through selected examples and identifies the key elements that enable interaction between the physical and virtual domains. The contribution shows that, while research already provides solutions addressing individual aspects of digital twins along the product life cycle, a fully integrated approach that connects these aspects is still lacking. These findings underscore the need for common standards and comprehensive frameworks to fully leverage the potential of digital twins.

**Keywords**. Digital Twin, Asset Administration Shell, Industry 4.0, Artificial Intelligence, Machine Learning, Soft Sensors, Digital Frameworks, Systems Engineering

## 1. INTRODUCTION

Fluid power is a key drive technology applied across almost all industry sectors. Its main advantages include high durability, robustness, and often cost efficiency in acquisition compared to alternative technologies. Combined with flexibility in system design, these properties enable fluid power to meet the specific requirements of a wide variety of applications. Today, fluid power technology forms a central pillar in heavy machinery, manufacturing systems, infrastructure, and energy production. It is also found in smaller applications, such as medical devices and power tools. [1]
Despite these advantages, the widespread use of fluid power presents notable challenges. Since many applications involve significant energy transfer, fluid power systems contribute substantially to industrial energy consumption and, consequently, to $CO_2$ emissions. An estimate indicates that the $CO_2$ emissions from hydraulic machinery account for approximately 5 % of global emissions [2]. For comparison, this corresponds to 2.3 of the global aviation emissions [2], underscoring the considerable potential for improving the efficiency and optimization of fluid power systems. In response, ongoing technological progress increasingly requires the integration of software functions and digital enhancements into products and processes. The effective use of data and information, combined with digital functionalities, is becoming essential for improving component and system performance, as it enables the development of intelligent and optimized systems that contribute to long-term emission reduction. Such advancements can be realized, for example, through the implementation of soft sensors [3, 4] or the digitalization of product development processes [5, 6]. As a result, fluid power is evolving into an increasingly interdisciplinary field, combining expertise from mechanics, electronics, computer science, and data analytics. Current research focuses on approaches such as soft sensors and digital frameworks that aim to enhance the system development process. In this context, the concept of the digital twin plays a central role, representing a fully digital counterpart of a fluid power system or of a component. Against this background, this contribution addresses the following research question: *What is the current development level of digital twins in fluid power?* To answer this question, the concept of digital twins is first defined. Subsequently, selected exemplary research findings related to digital twins in fluid power are presented, followed a brief assessment of the current state of development.

## 2. DEFINITION OF DIGITAL TWINS

The concept of the digital twin has emerged and is interpreted in various ways [7]. To provide a comprehensive understanding of digital twins, the terminology is first clarified and the interpretation used in this contribution is defined. The origin of the term "twin" can be traced back to NASA's Apollo program, where engineers replicated the conditions of space missions on Earth [8]. NASA developed an identical physical replica of the spacecraft used in space to simulate mission scenarios on Earth [8]. To reduce the extensive resource requirements of such physical twins and enable their application in earlier stages of development, the idea of the digital twin was gradually introduced [9].

The expression "digital twin" was first introduced by Grieves in 2003, who characterized it as an ideal concept for product life cycle management, connecting physical components with their virtual counterparts through continuous information exchange [10]. In 2010, NASA described the digital twin as a multiphysics simulation model representing a technical system [11]. Since then, numerous definitions of the concept have been proposed, each one highlighting specific aspects according to the perspective of the respective field or user, such as simulation, life cycle management, or data-driven services.

A general definition that serves as the foundation for this contribution is provided by [7], which describes digital twins as virtual representations of physical entities that are interconnected through real-time data exchange for various applications such as monitoring, design, optimization, maintenance, and remote access. The digital twin serves as a link between the physical and virtual domains. In this context, a digital twin can be understood as the virtual counterpart of a physical object. At the system level, this could include, for example, an excavator in mobile hydraulic applications, a press in stationary hydraulic systems, or a handling machine in pneumatic applications. At the component level, it may represent individual components such as a valve or a pump. Between the physical and virtual worlds, various tasks are carried out that correspond to different phases within the product life cycle (see **Figure 1**).

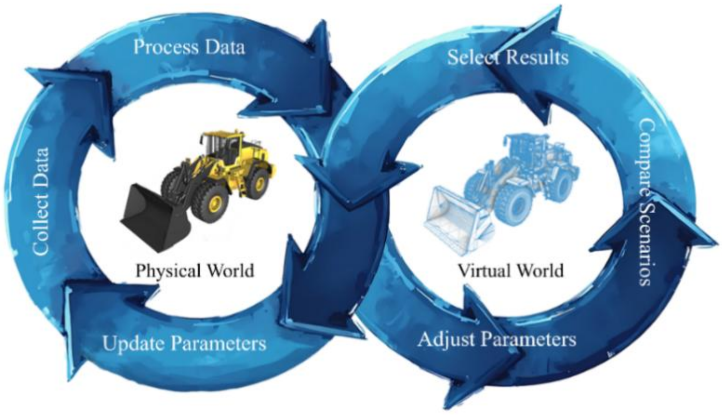


Figure 1: Connecting the virtual and physical worlds using digital twins.

With respect to the product life cycle, several stages can be identified that link the virtual representation to the physical asset. The digital twin facilitates the following steps:

- *Collect data*: Acquisition of data from various sources, such as field devices or sensors, followed by appropriate structuring and organization of the data.
- *Process data*: Transmission of the collected data between devices, specifically from the physical system to the digital twin, and preparation of the data for subsequent analysis. For instance, transferring parameters from the real application into simulation environments.
- *Adjust parameters*: Adaptation of parameters for specific applications, such as the calibration or parameterization of simulation models within the digital environment.
- *Compare scenarios*: Examination of different operating conditions using the digital twin, including parameter studies or evaluation of new configurations, e.g., assessing the performance of a new component.
- *Select results*: Identification and selection of suitable solutions based on scenario analysis, for example, determining an optimal set of parameters for controller settings or system components.

- *Update parameters*: Integration of the optimized parameters into the physical system, thereby closing the feedback loop between the digital and physical domains.

## 3. UNDERSTANDING THE RELEVANT COMPONENTS OF DIGITAL TWINS

Digital twins should be developed in parallel with product development and interact with the fluid power system during operation. To clearly define digital twins, their key aspects must be specified. This starts with defining data, information, and knowledge, as these constitute what digital twins exchange with real systems. A simplified product life cycle process for fluid power systems then illustrates where digital twins are created and applied. In the following, simulation models are addressed, as they often form the basis for digital twin modeling. Finally, the Asset Administration Shell (AAS) is introduced as an example of an interoperable interface for data exchange.

*Data, information, knowledge – Clarification of terms often used synonymously*

A continuous exchange of data between the digital twin and its corresponding physical object is essential. Therefore, it is important to establish a clear understanding of the concepts of data and information. However, in practice, the terms data, information, and knowledge are often not clearly differentiated and are frequently used interchangeably. Furthermore, a wide range of definitions can be found in the literature. To ensure conceptual clarity, this contribution adopts the framework proposed by North [12], as shown in **Figure 2**, which provides an overview of these terms along with examples from fluid power.

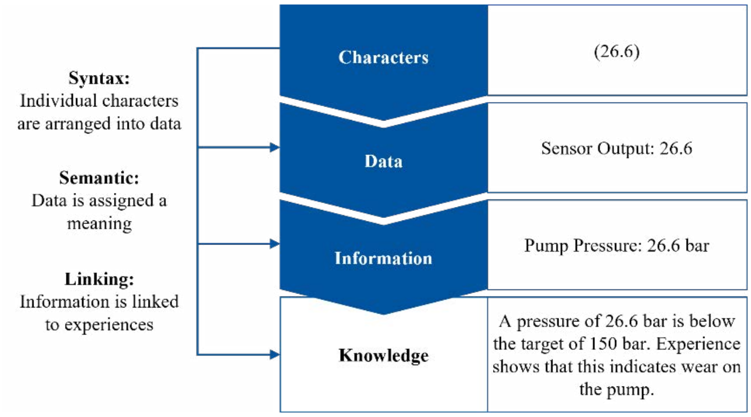


Figure 2: Different between characters, data, information, knowledge according to [12] extended with an example from fluid power.

According to North [12], data is generated through the application of syntactic rules to characters. It therefore represents arbitrary, non-interpreted sequences of symbols, such as a random string of numbers. In the context of fluid power, data can be understood as raw measurements obtained from a real application, for example a sensor output of 26.6. By assigning semantics, data is transformed into information. Information thus refers to data that is embedded within a meaningful context. For instance, interpreted data such as pressure signals from a specific pump (e.g., 26.6 bar). Knowledge, in turn, arises from linking information with experience. For example, knowing that a certain system pressure is critical for the operation of a hydraulic system, or that a specific pressure value indicates possible pump wear.

To enable a successful exchange between the real system and its digital twin, a shared understanding is essential. The real system and the digital twin must both be able to interpret data in the same way.

*Product life cycle – Developing and using digital twins*

The product life cycle of fluid power systems, as illustrated in simplified form in **Figure 3**, can be divided into several phases. The division of the phases of the development process is adapted from [13]. The starting point is the requirement phase, where the requirements for the development task are defined and identified. After that, in the initial concept phase, the system layout is designed based on experience and system requirements, resulting in a schematic concept of the system layout. During the subsequent detail development phase, a simulation model is created by integrating component models within a suitable simulation environment. This approach aims to size the components appropriately and determine optimal parameter sets. After simulative optimization, the real system is commissioned. Although parameter transfer to the physical system is still predominantly performed manually, the simulation model continues to support the system during operation. Throughout the product life cycle, it is used for tasks such as efficiency enhancement, process monitoring, and the testing of planned reconfigurations. After the machine's operational phase, various considerations regarding its further use arise during the end-of-life phase. An explanation of various strategies for the further use of a product in context of circular economy can be found in [14].

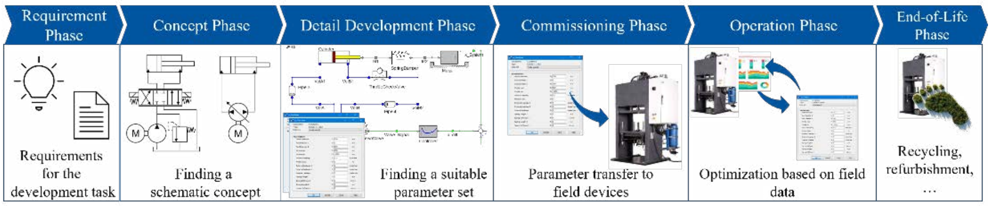


Figure 3: Simplified product life cycle phases.

*Simulation models – Foundation for modeling digital twins*

Simulation models form the foundation for modeling digital twins. Depending on the required level of accuracy, different types of simulation approaches are employed, as described in [1]. The simulation of fluid power components and systems is an essential tool in product development and optimization. It not only shortens development time but also provides access to parameters that are difficult or even impossible to measure experimentally. Once a model has been created and validated, extensive parameter studies can be performed efficiently and with minimal additional effort. Depending on the level of modeling detail, simulations can range from zero-dimensional to three-dimensional analyses. Furthermore, they can be classified as either static or dynamic, depending on whether time-dependent variations in state variables are considered or only stationary processes are examined. In concentrated (lumped)-parameter simulation, systems are modeled using discrete elements, and this approach is often used for fluid power system simulation (see **Figure 4**). In contrast, distributed-parameter simulations enable spatial and temporal resolution of state variables and are often used to analyze specific geometries of fluid power components, such as a valve geometry.

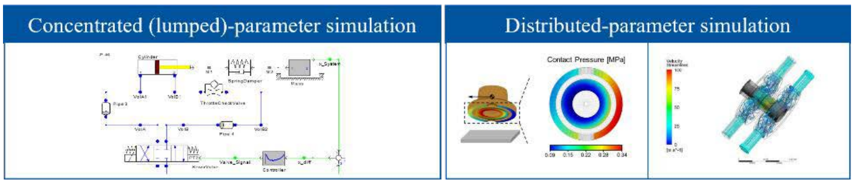


Figure 4: Exemplary representation of concentrated-parameter and distributed-parameter simulation according to [1].

*AAS – Interoperable data and model interface*

A possibility to transfer data and models through the digital twin is provided by the Asset Administration Shell (AAS). The AAS was developed in cooperation with the "Plattform Industrie 4.0" initiative [15] and the foundational framework of the AAS was published in DIN SPEC 91345 [16]. The AAS concept is becoming increasingly important in fluid power [17]. It serves as a digital representation of an asset, such as a hydraulic valve, enabling Industry 4.0-compliant interaction. It contains comprehensive descriptions of the asset and its associated services within a defined context throughout the entire product life cycle [16].

The AAS comprises submodels that describe an asset by means of SubmodelElements, for example properties or files [18]. Submodels can be standardized into templates to capture the relevant SubmodelElements needed for particular use cases (e.g., the submodel template "IDTA 02023 Carbon Footprint" to provide carbon-footprint-related data of an asset [19]) [18]. Both submodels and SubmodelElements can be annotated with semanticIds, which act as unique identifiers linking to semantic descriptions stored in standardized dictionaries (e.g., ECLASS [20] or IEC CDD [21]) [18]. These semantic references specify the exact meaning of the content contained within the annotated elements. The schematic concept of the AAS is shown in **Figure 5**.

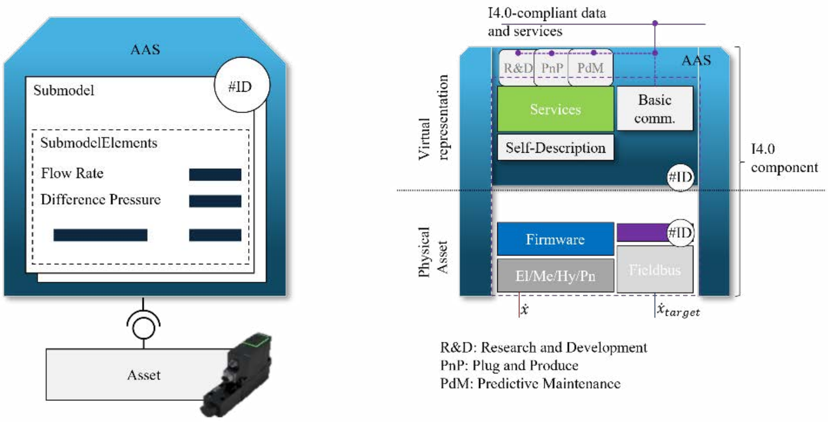


Figure 5: Schematic concept of AAS (left) and exemplary implementation of AAS in the application case of automated commissioning (right).

By providing an interoperable interface for product data and models, the AAS facilitates seamless collaboration among stakeholders, including component suppliers, system manufacturers, and operators, across the fluid power system development process [5]. By employing the AAS, data can thus be exchanged and utilized consistently across different systems and stakeholders.

## 4. CONNECTING THE VIRTUAL AND PHYSICAL WORLDS VIA DIGITAL TWINS

The following section presents relevant research findings relating to the process steps shown in **Figure 1.**

### *4.1. Collect data*

Collecting and structuring data from various sources, such as field devices and sensors, is a crucial step in the development of digital twins. In addition to conventional hardware sensors, software-based solutions such as soft sensors play an increasingly important role. Soft sensors calculate or estimate process variables using mathematical models or data-driven algorithms instead of direct physical measurements. They are often used to determine variables that are difficult to measure from variables that are easy to measure. Moreover, in the field of hydraulic systems, current developments show a clear trend toward components with integrated intelligence and extended functionality. As a result, soft sensors are gaining importance as they offer a cost-effective way to obtain relevant process information while reducing the need for additional hardware.

One example of soft sensor application is the calculation of volume flow from pressure signals. Measuring the volume flow in fluid power systems continues to pose a major challenge. On the one hand, volume flow sensors are almost invasive sensors and therefore they have an influence on the flow. On the other hand, volume flow sensors are often very expensive, which is why fluid power systems are often designed without them. A virtual flow sensor enables the flow rate to be determined, which in turn makes it relatively easy to draw conclusions about the system, such as calculating hydraulic energy or, for example, detecting leaks at an early stage. Conventional sensors are often unable to detect highly unstable flow conditions due to their slow response times or their dependence on assumptions that only apply to steady, laminar flows, as described by Hagen-Poiseuille's law. By extending the applicability of measurements to turbulent and unstable flow regimes, soft sensors enable condition monitoring in fluid power systems. In addition, a soft sensor can also functionally improve the informative value of conventional sensors.

The development of a virtual volume flow sensor is shown in [3, 22], where the sensor was developed based on Hagen-Poiseuille's law to calculate the transient flow conditions of the volume flow. Theoretical models for transient, laminar, turbulent, and compressible flows were developed and validated by one-dimensional and three-dimensional simulations as well as experimental tests. The results showed that the soft sensor can measure transient volume flow and is well suited for practical industrial applications (see **Figure 6**).

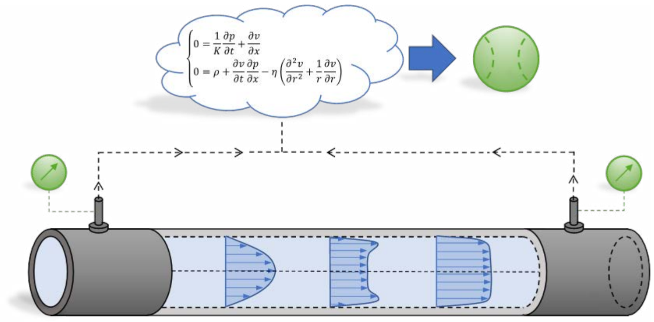

Figure 6: Schematic design of virtual volume flow sensor. The volume flow is calculated based on measured pressure signals.

Another example of the use of soft sensors is the flow calculation, based on the force of the electromagnetic valve actuator. The development of such a sensor is shown in [4] and the concept is illustrated in **Figure 7**. The approach aimed to develop a methodology for volume flow estimation on direct-actuated valves with solenoids for constant pressure systems. This approach provides a cost-effective, software-based sensor solution. By detailed modeling of the valve, inherent disturbances can be considered and thus the volume flow through the valve can be inferred from the electrical variables of the actuator as well as the armature position.

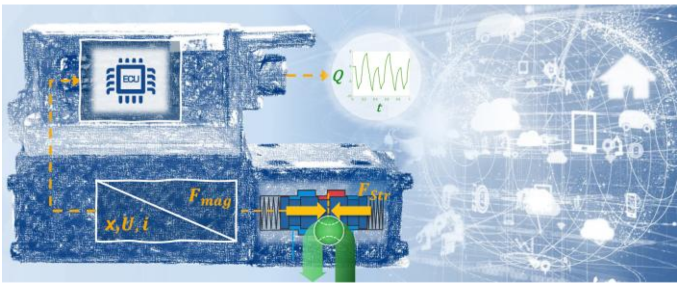


Figure 7: Schematic concept of virtual volume flow sensing, based on the force of the electromagnetic valve actuator.

In addition to soft sensors, there are other possibilities for data collection. One example is shown in [23], where simulation-based and measured data sets are used to train a condition monitoring algorithm based on machine learning. The approach is illustrated in **Figure 8** using the example of a hydraulic press. Machine learning is applied to identify patterns related to system failures (e.g., external and internal leakage). For this purpose, a database is built from both physical and virtual machines (simulation model). Subsequently, feature detection is performed, and machine learning is used to train the algorithm to recognize these features. In this research, the required amount of data and the combination of simulated and real data are also investigated. However, most algorithms are not designed to handle raw machine data directly and therefore require the data to be compressed and transformed into a smaller set of representative features. While several coding toolboxes aim to simplify feature generation through generic feature extraction methods, this work presents an enhanced procedure for automatically refining and selecting features. Moreover, an approach for condition monitoring based on neural network is shown in [24]. The study shows that a feed-forward neural network can reliably identify different operating states of a pneumatic system based on vibration, pressure, and position data. It also becomes clear that even low-cost sensors enable reliable vibration-based condition monitoring, thereby supporting the industrial adoption of such maintenance strategies.

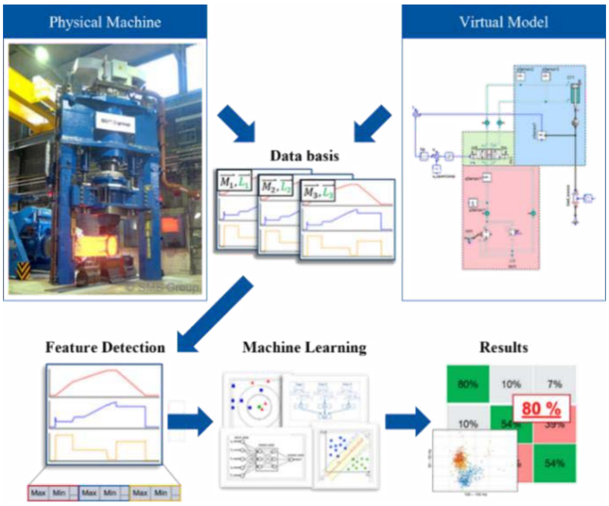


Figure 8: Collecting data from different databases to train a machine learning-based condition monitoring algorithm.

Another example of data collection for condition monitoring is given in [25]. This contribution proposes a cost-effective condition monitoring method for axial piston pumps using a single low-budget sensor capable of capturing multiple fault indicators. Data from various sensors operating under different conditions were used to detect faults such as valve plate cavitation, slipper wear, and axial clearance using machine learning algorithms.

### *4.2. Process data*

Once the data has been collected, it is transferred between devices, specifically from the physical system to the digital twin, and prepared for analysis. For example, parameters can be transferred from the real application into simulation environments. The AAS provides an interoperable interface for data, models, and related information (see **Figure 9**). Consequently, within the development process, a variety of stakeholders such as component suppliers, system manufacturers, and operators can be seamlessly integrated. At the same time, heterogeneous data sources become accessible in a standardized and interoperable manner. By employing the AAS, data can thus be exchanged and utilized consistently across different systems and stakeholders. AAS is already being used in some industry-relevant use cases, an overview of which is given in [17]. In particular, within the domain of fluid power, several research activities are already being conducted in the context of simulation-based development and parameterization [5, 26, 27], and in the field of automated commissioning [28].

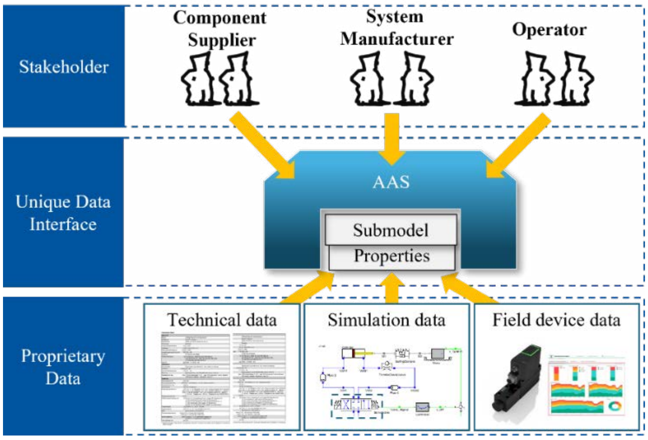


Figure 9: Integration of AAS into the product life cycle to enable a unique data interface.

## *4.3. Parameter adjustments*

After the data is transferred, it is adapted for use in a virtual environment, for example for engineering applications. Adapting parameters to specific applications, such as parameterizing simulation models within a simulation environment, represents a key step in the development process. One example of parameter adjustment occurs during the detail development phase, as described in [5, 26] and illustrated in **Figure 10** and **Figure 11**.

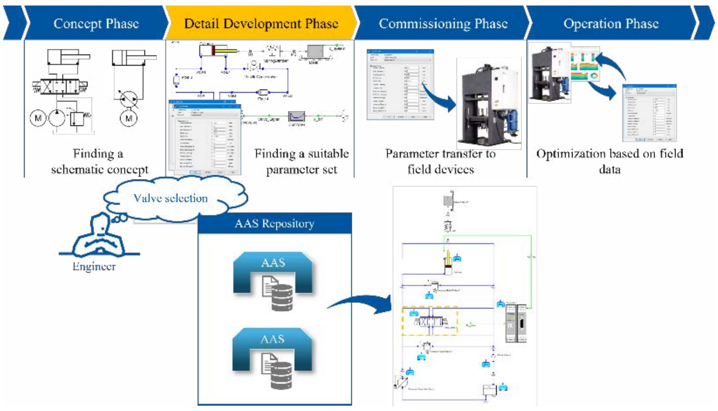


Figure 10: Exemplary use case for parameterization simulation models via AAS.

Engineers traditionally select components and set initial parameters manually by consulting various sources such as websites and data sheets, a process that is time-consuming and prone-to-errors. For example, an engineer may need to select a new valve and verify whether it has the correct size. This task usually involves clarifying the requirements and parameterization of the simulation with the relevant component data. This process can be made significantly easier using AAS.

The automatic component selection and parameterization of the simulation is described in **Figure 11** with more detail below.

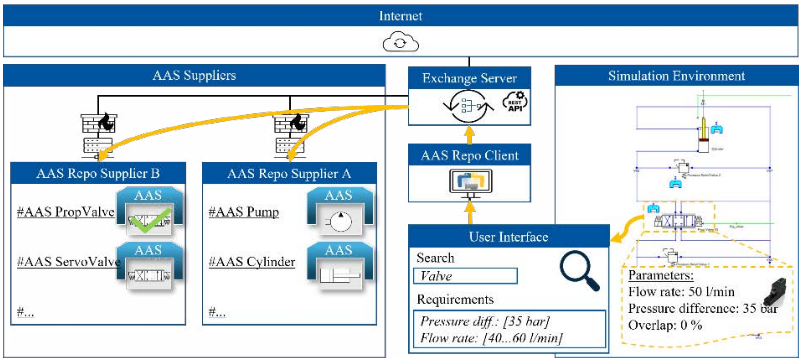


Figure 11: Parameter adjustment in the simulation-based development process.

A workflow is illustrated in which simulation data are adjusted based on parameters provided by the AAS. To enable this, a framework was developed that allows the parameterization of simulation models via the AAS. The framework is implemented using an HTTP REST API and considers manufacturer-specific safety requirements. The framework supports component selection by enabling searches in AAS Repositories provided by manufacturers to identify components that meet the desired requirements. The framework allows the definition of query criteria such as component type (e.g., valve or pump) and technical requirements (e.g., pressure difference and flow rate) specified as exact values or ranges. In the example considered in **Figure 11**, the engineer searches for a valve to ensure that the hydraulic press meets its functional requirements. Based on preliminary calculations, the engineer estimates the valve specifications, such as a nominal pressure difference of 35 bar and a flow rate of 40 to 60 l/min. Another example of adjusting parameters is shown in [29]. The contribution presents an approach for the identification, tuning, and verification of digital twins in hydraulic control systems. Another approach to parameter adjustments is presented in [30], which demonstrates a self-optimizing fuzzy PID controller for the independent control of the speeds of two non-identical electric motors. An example in the pneumatic area is shown in [31]. This contribution shows a concept for modeling and simulating the fluidic behavior of pneumatic vacuum generators. To increase the accuracy of the simulations, the approach uses instance-specific data rather than just object-specific data for the respective asset. The model and data are integrated into the digital twins of the pneumatic vacuum generators so that they can be combined with other components to represent digital twins of complete vacuum handling systems.

### *4.4. Scenario calculation and comparison*

After parameterizing the engineering applications, such as simulation models, various scenarios are calculated and compared according to the engineering objectives. Finally, a suitable configuration is selected. Therefore, parameter studies are carried out for testing new configurations, for example evaluating the performance of a new component in a hydraulic system, finding suitable settings for a controller or testing different designs of slippers in hydraulic pumps. An example of scenario analysis is shown in [32] where displacement-controlled hydraulic systems are analyzed as an energy-efficient alternative to conventional valve-controlled systems in construction machinery. Another example is shown in [33], where different geometric designs of slippers for axial piston machines are investigated. After the scenario comparison, suitable configurations are selected, such as an optimal set of parameters for a controller or the best design of a slipper. Therefore, tools are being researched that enable fast calculation of scenarios and allow efficient comparison of the results. Examples include [34, 35], in which a framework of fast computation of lubricated contacts using PINNs was developed. Conventional simulation tools are often time-consuming for extensive parameter studies and scenario comparison. Accurately representing all possible operating conditions requires many simulation cases, and in some applications, near real-time performance is even necessary for control tasks. Although extensive research has been conducted in this area, further efforts are particularly needed to accelerate calculations through AI-based approaches such as PINNs and neural networks, as well as in uncertainty management and cross-domain and cross-scale simulation.

The identified configurations and parameters are then made available again and can be used to adjust the real machine. At this stage, there is potential for an automatic transfer of parameters to the real application using tools such AAS. In **Figure 12** an overview of scenario calculation and comparison is shown. This process can be accelerated using AI-based simulation frameworks.

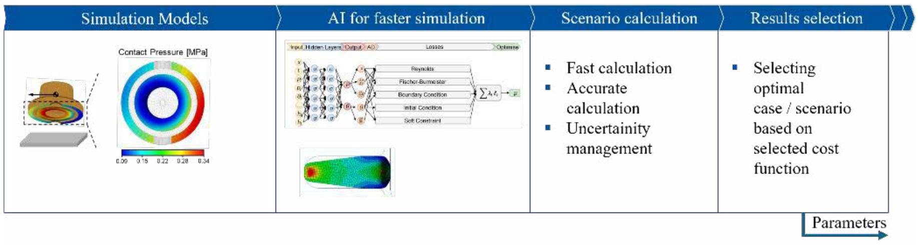


Figure 12: Scenario calculation and comparison with AI-based accelerated simulation.

Moreover, in [36] an optimization framework for hydraulic hybrid vehicles is presented. The paper introduces a simulation-based optimization approach for assessing a series hydraulic hybrid vehicle transmission, demonstrating that numerical optimization enables exploration of a wide design space and reveals trade-offs between component sizing and control strategies. This framework builds on the simulation-based optimization methodology originally introduced in [37]. Therefore, various scenarios defined by the design parameters of the hydraulic components are analyzed and systematically compared.

### *4.5. Update parameters*

Feeding the optimized parameters back into the physical system closes the information loop between the digital and physical domains. By applying these updated parameters, the system operates more accurately and reliably, improving controllability, ensuring smoother performance, and enhancing overall output. At the same time, optimizing energy efficiency reduces energy consumption, resulting in a more sustainable and cost-effective operation. An example of updating parameters is presented in [38], where deep reinforcement learning (RL), an emerging branch of machine learning, addresses complex nonlinear optimal control problems through data-driven, trial-and-error learning. In this contribution, a deep RL controller is applied to a hydromechanical system, an inverted pendulum on a cart with a hydraulic drive, demonstrating a comprehensive framework that enables training in simulation to swing up and balance the pendulum. Another example is shown in [39], where mobile off-highway machines are equipped with sensors that continuously record data such as position, inclination, power, and information about surrounding obstacles for analysis. Through sensor data fusion and modeling, this information can be enriched with geospatial data to generate semantic insights about the environment. As a result, a digital twin of the surroundings can be created, supporting geodata-based processes like digital construction planning or terrain analysis. Despite these research findings, much work remains to be done from both a scientific research perspective and an industrial standpoint. Transforming the available information into tangible benefits is a complex challenge, yet it is essential to fully realize the potential of digital twins. **Figure 13** summarizes the potentials of connecting data from real and virtual world, e.g., for the optimization of the machine controller.

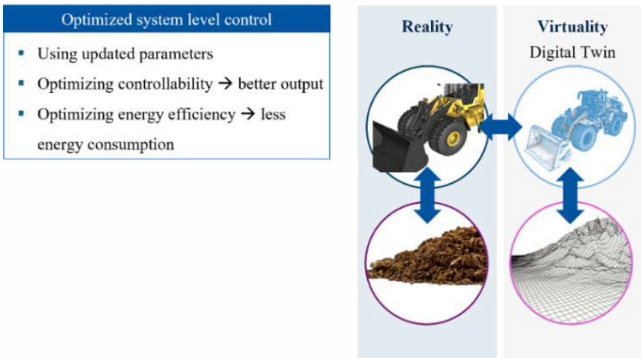


Figure 13: Transferring parameters from the virtual to the real world.

## 5. CONCLUSION

Fluid power is a key technology applied across various industries but continues to face challenges in energy efficiency, environmental impact, and digital integration. Digital twins provide a promising approach to address these issues. However, the extent of existing research in this field remains unclear. Therefore, this contribution addressed the research question: *What is the current development level of digital twins in fluid power?* To answer this question, the term "digital twin" was first derived from scientific literature. Moreover, key aspects for understanding a digital twin were identified and explained, including, for example, simulation as a physical modeling of reality and the AAS as an example for a model and data carrier. Subsequently, this contribution presents relevant exemplary research findings from the field of digital twins in fluid power.

This contribution points out the significant progress made in recent years regarding concepts and solutions for various aspects of digital twins in fluid power. In addition, there are very advanced research activities related to collecting data with digital methods, for example using machine learning or the development of soft sensors. Moreover, there are research activities concerning process data and data adjustment, especially regarding the use of the AAS. Furthermore, in terms of scenario analysis and comparing scenarios, there are increasing activities focused on using PINNs to accelerate simulations and to enable an easy comparison of different scenarios. The identified research activities underline that there are many ongoing efforts in each sub-area of the digital twin process. Building on recent advances, future research should focus on developing a unified and holistic framework for digital twins in fluid power.

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