IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received March 29, 2022, accepted April 22, 2022, date of publication April 25, 2022, date of current version May 4, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3170430

Physics-Based Digital Twins Merging With Machines: Cases of Mobile Log Crane and Rotating Machine

EMIL KURVINEN[1], ANTERO KUTVONEN[2], JUHANI UKKO[3], QASIM KHADIM[4], YASHAR SHABBOUEI HAGH[4], SURAJ JAISWAL[4], NEDA NEISI[4], VICTOR ZHIDCHENKO[4], JUHA KORTELAINEN[5], MIRA TIMPERI[2], KIRSI KOKKONEN[2], JUHA VIRTANEN[5], AKHTAR ZEB[5], VILLE LÄMSÄ[5], VESA NIEMINEN[5], JUKKA JUNTTILA[5], MIKKO SAVOLAINEN[5], TUIJA RANTALA[5], TIINA VALJAKKA[5], ILKKA DONOGHUE[2], KALLE ELFVENGREN[2], MINA NASIRI[3], TERO RANTALA[3], ILYA KURINOV[4], EERIK SIKANEN[4], LAURI PYRHÖNEN[4], LEA HANNOLA[2], HEIKKI HANDROOS[4], (Member, IEEE), HANNU RANTANEN[3], MINNA SAUNILA[3], JUSSI SOPANEN[4], (Member, IEEE), AND AKI MIKKOLA[4]

[1]Materials and Mechanical Engineering, Department of Mechanical Engineering, University of Oulu, 90570 Oulu, Finland
[2]School of Engineering Science, Lappeenranta-Lahti University of Technology LUT, 53850 Lappeenranta, Finland
[3]School of Engineering Science, Lappeenranta-Lahti University of Technology LUT, 15140 Lahti, Finland
[4]Department of Mechanical Engineering, School of Energy Systems, Lappeenranta-Lahti University of Technology LUT, 53850 Lappeenranta, Finland
[5]VTT Technical Research Centre of Finland, 02044 Espoo, Finland

Corresponding author: Emil Kurvinen (emil.kurvinen@oulu.fi)

This work was supported by the Business Finland Digibuzz-LUT and Digibuzz-VTT Projects under Grant 4329/31/2019 and Grant 4437/31/2019.

ABSTRACT Real-world products and physics-based simulations are becoming interconnected. In particular, real-time capable dynamic simulation has made it possible for simulation models to run in parallel and simultaneously with operating machinery. This capability combined with state observer techniques such as Kalman filtering have enabled the synchronization between simulation and the real world. State estimator techniques can be applied to estimate unmeasured quantities, also referred as virtual sensing, or to enhance the quality of measured signals. Although synchronized models could be used in a number of ways, value creation and business model development are currently defining the most practical and beneficial use cases from a business perspective. The research reported here reveals the communication and collaboration methods that lead to economically relevant technology solutions. Two case examples are given that demonstrate the proposed methodology. The work benefited from the broad perspective of researchers from different backgrounds and the joint effort to drive the technology development towards business relevant cases.

INDEX TERMS Multibody simulation, finite element method, Kalman filter, state estimation, parameter estimation, physics-based simulation.

I. INTRODUCTION

The importance of managing information and data in the manufacturing industry has consistently grown and is already more responsible for the competitiveness of enterprises than the management of material or financial flows [1]. Modeling, simulation and enterprise information systems have developed rapidly and started to integrate leading to the recent introduction of digital twins, which are the virtual representations of physical assets. Digital twins of higher maturity level [2], [3] such as those employed in the automotive or aviation domains [4], [5] are not only providing a simple visualization or access point to machine Internet of Things (IoT) data but are also supporting multiple product processes across

The associate editor coordinating the review of this manuscript and approving it for publication was Laxmisha Rai.

the lifecycle. Mature digital twins can draw from multiple data sources [6] combining and contextualizing data with its operational environment [7] and supporting decision making through real-time simulation[1] [8].

The ultimate aim for the scientific field of real-time simulation is to advance to the singularity point where a seamless fusion and synchronicity of both virtual and physical assets is achieved. This will trigger a radical reorganization of industrial business[2] wherein digital twins serve as the requisite scaffolding for interorganizational knowledge flows and the realization of collaborative data collection, processing, analytics, and exploitation on the ecosystem scale. Already, we are seeing increases in the virtualization of work; *i.e.*, work performed in virtualized environments [10], [11]; making use of digital twins in product development and production ([2], [12], [13]; implementing sophisticated industrial automation and collaborative robotics [14]; and developing new ways to collaborate and perform industrial design, planning, and implementation [15]. Digital twins have evolved from mere simulation models to tools that enable the study of real product behaviors in virtual environments. Physics-based simulation enables developing virtual prototypes that are subject to real-life physical constraints [16] while real-time capability extends the use of simulation to further product lifecycle stages. Computationally effective dynamics modeling opens the possibility for, *e.g.*, fault and state identification, problem root source debugging, and predictive maintenance [17]. State-of-the-art simulation models can also account for system hydraulics in real-time [18] and therefore respond to user inputs as well. In the mobile heavy machine industry, *e.g.*, earth-moving equipment, this gives the operator the needed awareness and control over the stresses and loads on the equipment.

Digital-twin use is growing across a variety of businesses, domains and ways to enhance company performance [19], [20]. Digital-twin enabled virtual learning, standardized working environments, resource optimization, and operational efficiency can provide value for the company's users and staff members [19]. Companies increasingly use digital twins to enhance operational flexibility and gain a view to their performance and operating conditions based on real-time data [19] that can be leveraged to enable better decision-making in operations such as condition monitoring, function simulation, evolution simulation, dynamic scheduling, predictive maintenance, and quality control [20]. Additionally, the real-time data made available by digital twinning facilitates the monitoring and optimization of operations [20], [21], the development of more innovative products, the realization of more effective service programs [22], the diversification of business models, and more effective value creation [23].

Digital twin technologies can also be seen as enablers for new innovations in the era of digital transformation. Aheleroff *et al.* [24] presented the Human, Technology, and Process framework (see Figure 1) where establishing good relationships and a balance among these aspects would lead to achieving the highest organizational efficiencies. In the digital space, the Digital Clone represents humans, the Digital Twin and Digital Thread symbolize processes. Combined, the three aspects cover the entire product development lifecycle. This framework illustrates how a fully digital system should function to support humans in achieving innovation, scalability, and autonomy [24].

The digital twin approach makes use of information coming from broad spectrum of viewpoints [19] that passes through different departments and stakeholders with systematic methodologies that can enable processes to be automated at a high level. From the technical point of view, the challenge is that it is necessary to enable and exploit data flows across many integrated systems to automate products and processes at a high level. While data interoperability questions can be solved, the exploitation of the data and analytics requires a multidisciplinary understanding that is facilitated at multiple levels. More specifically, extracting value from data in business processes requires that 1) the information is shared to the right teams and persons at the right time in a usable and understandable form, 2) cross-functional teams are supported within the organization, and 3) cross-organizational capabilities, processes, and policies exist to support the collaborative use of data. From the viewpoint of data use and sharing, there must be sufficient cybersecurity, latency, and trust as well as clearly defined data needs, flows, and responsibilities.

In this research, two case examples are given that demonstrate the proposed methodology. They were designed to use the virtual sensor concept to add both technical and business value. While numerous case examples of digital twin applications can be found in the state-of-the-art literature (see *e.g.*, [4]), the process used to achieve the received benefits has not been previously described. Here, in addition to presenting the two case examples, the steps taken to accomplish the planned goals are also described. The focus is especially on leveraging the physics-based simulation, which is synchronized with the actual products, to enable the full potential of virtual world information. The work was carried out in close cooperation among innovative companies and research organizations by multidisciplinary researchers from a broad spectrum of backgrounds. The participating companies, comprising multiple SMEs and midcap-sized companies, are listed in the ending Acknowledgements. The structure of the following text is as: Section II describes the methodologies from a technical viewpoint: simulation models, Kalman filters, connectivity, connection to back-end, the used digital twin framework concept and machine learning. In addition, the value creation and utilization of digital twins in benefits to business are described. In Section III, two case

[1]Here, simulation refers to computational dynamics based on multibody system dynamics and its application to intelligent machines in real-time simulation.

[2]Similar future scenarios have been envisioned by researchers of blockchain governance (see *e.g.*, Lumineau *et al.* [9]). In fact, these two technology trends intersect and may end up accelerating the transformation.

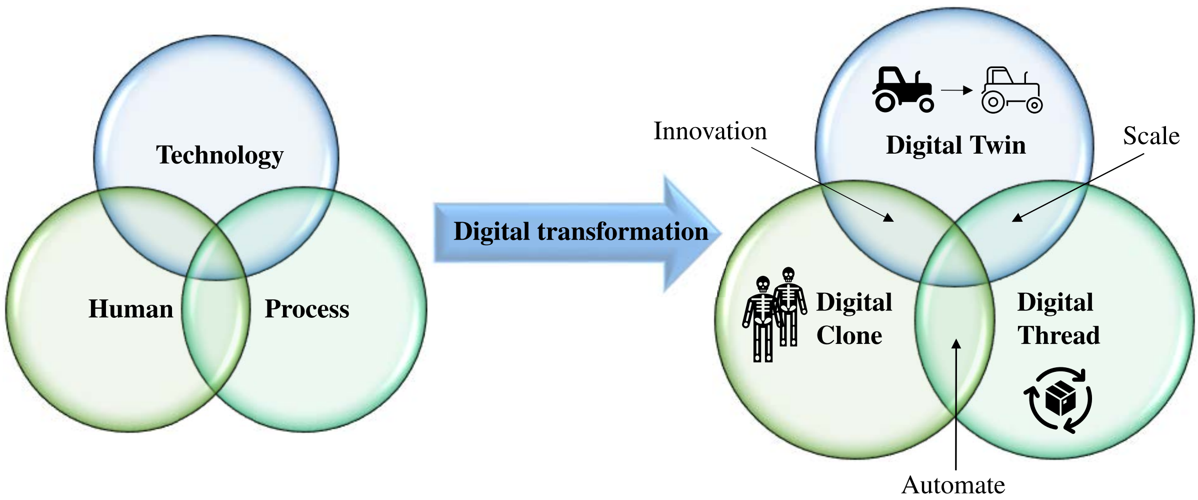


FIGURE 1. Digital transformation in humans, technologies, and processes (adapted from [24]).

studies are presented, where the virtual sensor application is demonstrated. Section IV present a discussion about the solutions and their business viewpoints. Section V summarizes the results of the study.

II. METHODS

The foundation of a digital twin is the mathematical model of the physical system. There are a variety of different methodologies to construct this model, and selecting the right one is case dependent. In this section, common methods are evaluated for physics-based simulation that is capable of providing relevant information with low latency, *i.e.*, can provide real-time evaluation of the system or accept alternative offline-taught data for specific identification tasks. In physics-based simulation, two methods are widely used: MultiBody Simulation (MBS) and the Finite Element Method (FEM).

A. PHYSICS-BASED SIMULATION MODELS

Physics-based simulation models enable the virtual study of component or system behaviors. They make it possible to "experience" realistic component or system behaviors. This capability has been widely used in the product design phase, *e.g.*, to explore the dynamic behaviors of prospective designs, leading to the design of products that will behave well in actual operation. Through simulation, many resonance and fatigue phenomena can be revealed in the design phase, and the product design can be modified accordingly. In the following paragraphs, the two most common simulation methods, multibody-based simulation and the finite element method, are briefly described. Either of these can be used to investigate industry application problems with high accuracy.

1) MULTIBODY-BASED SIMULATION

Multibody simulation is a straightforward process of defining the dynamics of a system by deriving its equations of motion. It is especially applicable when large displacements and/or rotations occur, and bodies are connected together via joints. Computational efficiency is important when modeling complex systems, such as those prevalent in industrial applications, and real-time solutions are needed to accommodate user input, an important consideration of machine performance. For these applications, MBS is often used. A multibody system can be defined as an assembly of bodies connected using kinematic constraints [25]. Furthermore, bodies can also be indirectly connected via force elements such as springs, dampers, and actuators. The bodies can be assumed to be rigid or deformable. In general, multibody modeling approaches fall into one of two categories. They can be global formulations or formulations based on relative coordinates such as the semi-recursive formulation. In this study, the semi-recursive formulation was used. Formulations can be further categorized as open- or closed-loop systems. In the semi-recursive formulation, a closed-loop system can be converted into an open-loop system by introducing a temporary cut-joint in its kinematic loop. The equations of motion for a closed-loop system can be formulated by incorporating the cut-joint constrained equations into the dynamics of the open-loop system [26]. As demonstrated recently, the semi-recursive formulation is well suited for real-time simulation applications [10], [27], [28]. The accuracy of MBS can be improved by also addressing the deformation of bodies, which results in a more computationally intensive simulation. The Floating Frame of Reference Formulation (FFRF) can be used to describe the deformation of flexible components by adding the component's dynamics. The modal reduction technique is also used to reduce the number of degrees of freedom and enhance computational efficiency. However, in large applications (*e.g.*, an excavator) where dynamics are important, this can result in less accuracy with less realistic results if the reduction method is not properly selected.

2) FINITE ELEMENT METHOD

The finite element method is widely applied over a broad range of applications in engineering. One is rotordynamics. Rotordynamics analysis using finite elements must consider the dynamics of the entire rotating drivetrain including driver and driven shafts, connection elements, bearing systems, and support structures. For a standard electric motor rotor (often axisymmetric) operating at moderate speed, a one-dimensional (1D) beam element approach can be used. However, beam elements have limitations in high-speed applications since they do not account for deformation of the shaft cross section or for flexibility of attached component, *e.g.*, impellers or sleeves [29]. High rotating speed and high energy density make it necessary to consider additional effects such as internal stresses, contact interfaces, and temperature gradients. Using two-dimensional (2D) axisymmetric harmonic [30] or three-dimensional (3D) solid finite elements (FE) [31], [32], these effects can be modeled. Figure 2 depicts a beam and solid element-based model of a steam turbine-generator rotor.

3D-solid element-based FEM models are typically computationally expensive making the approach unsuitable for real-time applications. In rotating system applications this is usually acceptable, because the operator/user is not directly connected to machine performance. On the other hand, a beam-elements-based model can be made real-time capable using either model order reduction techniques or frequency domain solution methods [33], [34]. The performance and durability of industry-scale structures can be evaluated by applying physics-based model-driven methods or data-driven measurement-based methods. Recent research has demonstrated that combining these approaches can result in excellent simulation performance and accuracy [17]. In principle, the accuracy of calculation models correlates with the level of detail built into the structural model, *i.e.*, the number of elements used (fineness of the mesh). Despite the advances in finite element simulations and computational approaches of rotordynamics, the uncertainties related to operational loadings, manufacturing tolerances, boundary conditions, contact interfaces, and thermal gradients still present a challenge to the accurate prediction of dynamic behaviors.

On the other hand, possibilities to validate models by monitoring real data are always limited, *e.g.*, in terms of observability and the number of available sensors. To overcome this challenge a hybrid method for virtual sensing was utilized, which integrates real measurements to synchronize physics-based simulation model and exploits the model to gather data that is unavailable using traditional approaches alone. The aim of this new approach was to predict or virtually measure the dynamic response of the entire structure using a minimum number of direct measurements.

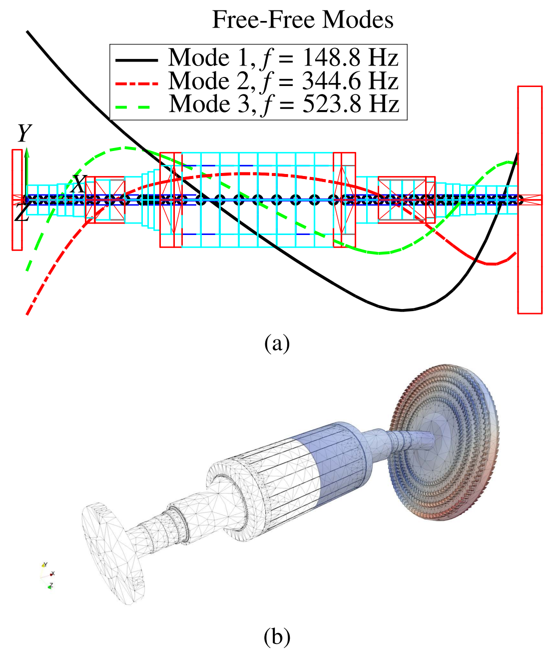


FIGURE 2. Finite element models of a 1 MW integrated steam turbine-generator rotor a) beam element model b) 3D-solid element model.

B. KALMAN FILTERS

The Kalman filter, also known as a linear quadratic estimator (LQE), was originally developed by Rudolf Kalman in the 1960's as an optimal way to solve the state estimation problem for a linear dynamic system with known Gaussian noise properties [35]. The Kalman filter is often seen as a sub solution for the linear quadratic control problem (LQG), which comprises the linear quadratic regulator (LQR) and linear quadratic estimator (LQE). Therefore, it is widely used in, *e.g.*, control engineering [36], mechatronics [37], and heat transfer [38]. However, its system linearity requirement limits the application of the original Kalman filter in multibody systems. Non-linear variants of the Kalman filter are often more suitable for multibody system problems. One of the fundamental requirements of state-space models, the basis for the Kalman filter, is to describe system dynamics using linearly independent states, *i.e.*, no state can be expressed in terms of another state. In multibody systems, requiring state independency presents a challenge, since systems are often constrained, which makes some coordinates dependent on others. To address this issue, Cuadrado *et al.* [39] proposed a method that uses coordinate partitioning to construct the system model by replacing states with independent coordinates. To estimate the states of a mechanical system, the independent coordinate method was introduced by [40]. In their approach, the independent positions and velocities of the multibody model are considered the states of the Kalman filter. With this method, a system of full coordinates can be estimated in terms of independent coordinates in both open- and closed-loop multibody models. The independent coordinate method is further extended to hydraulically actuated systems for state estimation [41] and parameter estimation [42].

In the following paragraphs, four different non-linear variants of the Kalman filter are discussed from the multibody system perspective. These include the Extended, Indirect Extended, Unscented, and Adaptive Unscented Kalman filters. Later in this manuscript, these variants are simply referred to as Kalman filters. The Kalman filters are used here to synchronize the (real-time) simulation models with the systems they represent with low complexity and a minimum number of sensors to carry out, *e.g.*, parameter estimation.

1) EXTENDED KALMAN FILTER

The extended Kalman filter (EKF) is one of the first non-linear variants of the original Kalman filter. The original Kalman filter equation consists of a state prediction term (data from the model) and a state update term (data from the measurements). Both are linear. In contrast, the EKF uses a non-linear plant model for the state prediction term and a linearized version of the non-linear plant model for the state update term. In the EKF, the state or parameter variables are propagated through the non-linear plant model analytically using the first-order Taylor series approximation [43] to compute the Jacobean of the system. In general, the EKF is applied for the simulation of nonlinear systems [44] and [45]. In the field of multibody dynamics, the EKF has been implemented in Continuous, Discrete, and Error-state formats [40] using the independent coordinate method to carry out state estimation. With the Continuous EKF, the Jacobian of the multibody plant model is computed using the state vector at the prediction stage. The resulting differential equation can be solved using forward integration in the continuous time frame [40]. However, the Discrete EKF uses the transition model of the system to compute the Jacobean of system [40] in discrete time steps. The transition model can be calculated using the time step, velocity, and acceleration vectors of the dynamic system. The Error-state EKF considers errors in the independent positions and velocities of the system as the states of the plant model [40]. Among these types, the Error-state EKF has been, in many use cases, the most efficient format [40]. It has typically been applied in an indirect filter form to state estimation for hydraulically driven systems.

2) INDIRECT KALMAN FILTER

The Indirect Kalman filter is based on the previously described Extended Kalman filter. In the indirect (error-state) filtering approach [27], [40], [46], instead of estimating the variables of interest, the errors of the variables are estimated. Here, a multibody model is run without modifications, and the indirect (error-state) filter estimates the drift of the multibody model with respect to the measurements available. After every measurement, the multibody model is corrected based on the estimated errors. This approach makes it possible to use any multibody formulation and integrator. However, some terms of the multibody formulation are generally used in the propagation of the covariance matrix of the estimation error and in the Jacobian matrix of the sensor model.

3) UNSCENTED KALMAN FILTER

As mentioned previously, the prediction stage of the Extended Kalman filter uses a first-order Taylor series approximation to analytically compute the Jacobean of the state transition matrix. This can lead to errors in the true means and covariances [43]. As a result, EKF state estimation may not be very accurate [43]. To address this problem, the Unscented Kalman filter (UKF) uses the unscented transformation method, which can approximate the true means and covariances to a third-order Taylor series for a non-linear plant model [43]. The unscented transformation method is based on calculating the sigma points of system states and propagating them through the non-linear plant model. Because it avoids using the Jacobeans of the state transition matrix, which may be unclear in many complicated heavy machines, the UKF is easier to implement. Further, the UKF does not require Jacobean sensor models in its implementation. The UKF was previously implemented in the framework of multibody system dynamics by [40].

4) ADAPTIVE UKF

The EKF and UKF are the most common Kalman filter versions used to carry out state estimation for nonlinear systems. The UKF overcomes EKF drawbacks mentioned in [47] and [48]. However, process and measurement noise statistics must be known and provided to the UKF for it to function correctly. In the real world, these statistics are difficult to determine. Mistuning covariance matrices, especially in applications that require high accuracy and a very small sampling time, can degrade performance and lead to divergence. The Adaptive UKF can provide accurate state and parameter estimation of the multibody system subject to completely unknown process and measurement noise statistics. [49]

C. LIFECYCLE, CONNECTIVITY AND FRAMEWORK, AND NEURAL NETWORK

The following paragraphs describe the information flow in industrial processes and machines including existing platforms (back-end systems), the lifecycle perspective, and an exemplary framework to exchange information in real-time. Especially with digital twins, unless a manufacturing operation is being built from the ground up, integration with an existing infrastructure is necessary.

1) LIFECYCLE OF DIGITAL TWINS

Digital twins can bring added value throughout the lifecycle of the product or system [50]. The digital twins of existing products or systems provide valuable information about operational conditions, loading, and performance. Together with the digital models, this information can be used to better design and optimize new products, to improve operations and maintenance and eventually to enable safe and efficient product or system disassembly or disposal. The lifecycle of its simulation models, required software, and computing components must all be considered part of the lifecycle of a product or system with a digital twin that relies on physics-based simulation and simulation models. If the expected lifecycle of the product or system is long, *e.g.*, several decades and the simulation approach used in the digital twin has computationally challenging features, such as advanced models of physical phenomena or system simulation, lifecycle management of the digital twin can be challenging.

For several decades, researchers have investigated and discussed how a single computer-aided design model could be used with multiple distinct engineering tools [51], [52]. The main obstacles to this data exchange challenge have been solved, mainly with the standardization of common file format, *e.g.*, the STEP-file format (standards ISO 10303, AP203, AP214 and AP242). However, issues remain with the exchange of simulation model data for multibody system simulation [53]. The application of physics-based simulation models in digital twins makes this data exchange challenge relevant over the entire lifecycle of the product. With the advent of digital twinning not only product engineers, but also users and operators make use of the simulation models. Therefore, long-term robust operation of the digital twins and preservation of the simulation models and their data become crucial. The number of individual simulation models also increases with every delivered system that has a digital twin. Any systemic issue with the digital twin, such as incompatibility with the latest computer operating systems, may affect a large fleet of digital twins and may cause a serious risk to the business.

The traditional means to overcome interoperability issues is standardization. It provides the basis for a long-lasting solution to the data exchange challenge and lowers the risks of data becoming unusable and killing interoperability. The drawback of the approach is that it is time consuming and expensive, and for simulation domains such as system simulation, it is technically challenging. Standardization can be achieved, and simulation models and required simulation software can be maintained in source code using a standardized programming language such as the C or C++ language. However, this approach does not usually work with commercial simulation tools and software, because they are rarely available as source code. Depending on the application the challenge of digital twin data lifecycle management can be met by standardizing model data representation, using software source code to present the computing software and simulation model data, and making use of established simulation languages such as Modelica[3] and Julia.[4]

2) DIGITAL TWIN CONNECTIVITY TO BACK-END

Effectively integrating the digital twin into existing IT Systems brings value to both the manufacturer and operator. This increases the value of the overall business system and offers new ways to use the information and the results of simulations. The primary purpose of the digital twin is to virtually model an existing or planned real-world system as it functions within its operating environment [54]. To achieve this purpose, the digital twin relies on information that is managed by the Information Management System [50]. Given this information, the digital twin can remain aligned with reality and the analysis of systems or operations, either being developed or ongoing, and the subsequent implementation of corrections is both faster and more accurate.

In addition to representing a product or system, a digital twin can also represent manufacturing or supply chain processes. In these cases, the digital twin can provide a data bridge to the existing IT systems (ERP, CRM, PLM)[5] making information available that will enable the manufacturer, suppliers, and operators to develop an ecosystem over the lifecycle of the product or system that will improve operational efficiencies and help identify new business opportunities. The goal of implementing new digital services built on IoT data and data analytics can also benefit from adopting digital twins to simulate new services and running what-if scenarios faster than real-time to select optimal operating characteristics [55].

3) DIGITAL TWIN FRAMEWORK CONCEPT

A physics-based Digital Twin (DT) requires a computer program to run its simulation (the DT program). In some application areas (*e.g.*, manufacturing) the DT program can be executed in or near the product or system it represents with good connectivity to the sensors providing measurement data. In other scenarios, however, such as a digital twin for an off-road mobile machine, proximity and connectivity to the measurement data is a challenge. The mobile machine may operate in a harsh and remote environment, which puts demands on computer hardware reliability and makes it difficult to monitor and update the program. A cloud-based approach can be beneficial for remote scenarios. If the application is sensitive to data transmission delay, fog or edge computing could be used to move calculations closer to the data source.[6] Therefore, a DT program should be capable of running in cloud, edge, and fog computing environments on different types of hardware, and its architecture should support periodic updates and the application of security patches.

To describe, construct, and deploy physics-based digital twins in heterogeneous execution environments, a reference architecture was developed by [56]. It uses operating system-level virtualization (containerization) to implement standardized DT programs with the longevity and ability to run in different execution environments. A description of a containerized DT program is stored together with information about the actual product, its sensors, and the model used to develop the DT program. All these data are used by a digital twin management system implementing the reference architecture to execute DT programs for many instances of the actual product. The digital twin management system interacts

[3]The website of the Modelica Association: https://modelica.org/

[4]The website of the Julia programming language: https://julialang.org/

[5]Enterprise Resource Planning, Customer Relationship Management, Product Lifecycle Management.

[6]On-board execution can be considered a special case of edge computing in such scenarios.

with the back-end system, which combines the output of DT programs with other product-related data to construct digital twins that provide business value.

4) MACHINE LEARNING

Although physics-based digital twins cover most of the issues related to engineering, design and manufacturing, the operation and maintenance areas still commonly rely instead on measurement data. Decision-making in operations and maintenance should be based on enhanced situational awareness, for which connectivity of the actual digital twin implementation is crucial. From the application point of view, good connectivity means, in practice, that data should be comparable between the real and virtual worlds, *i.e.*, between measured data and data predicted by simulation. Therefore, the feature extraction, *e.g.* physical quantities, process is designed is to find relevant information from the data [57]. In large sensor networks, in addition to the problem of finding good physically meaningful features, finding the most relevant features or combinations of features is complicated. Sensitive features can also be nonphysical. Examples include autoregressive coefficients (*e.g.*, [58], [59] and some other model parameters (*e.g.*, [60], [61]).

The main premise of applying machine learning models as data-based digital twins is that a chosen model can explain the data under normal conditions. Faults, failures, damage, or anomalies are seen as outliers. To detect novel events, the machine learning system is first trained with the data taken under normal conditions. If no prior information or data on unexpected events is available, the detection problem must be solved and the novelty detection approach applied to new unseen data. Luckily, the training data from such events can be simulated effectively using the physics-based digital twins. The trained machine learning models are then used to identify and classify data, *i.e.*, to build up the enhanced situational awareness and basis for decision-making. A convenient by-product of the feature selection and classification processes in machine learning systems is the feasibility of the process to also address the minimum number of sensors and their preferable predefined locations [62]. Therefore, enhanced connectivity for the situational awareness can be maintained.

D. VALUE CREATION AND EXPLOITATION OF DIGITAL TWINS

The real-time capability of a digital twin enables it to provide additional information about system performance. This can be exploited to make better process and business decisions.

1) BUSINESS NETWORKS & ECOSYSTEM

To enhance value creation in an ecosystem-based business that includes digital twins, several prerequisites must be satisfied. Companies are aware of value co-creation endeavors in an ecosystem-based business, but they still see many challenges in fitting together the processes, operations, and goals of the different ecosystem actors. However, trust and openness, which are central building blocks in an ecosystem-based business, cannot be achieved without universal agreement as to shared goals and values. To solve this issue, *e.g.*, [63] emphasized the importance of gaining a thorough understanding of the pains, gains, and jobs of the different actors before a digital-twin solution can be applied in a collaboration ecosystem. Establishing common standards and rules and defined responsibilities are considered central preconditions for ecosystem design [64], as is the balance between the companies' own profitability targets and shared ecosystem value. Even though business ecosystem thinking should be based on mutual dependency (*e.g.* [65]), an orchestrating actor is needed to define the businesses relevant to the ecosystem. Moreover, better coordination of the membership is needed to meet the challenges of interconnectivity, interoperability, and competing interests [66].

2) SELLING DATA-BASED SOLUTIONS

Selling data-based solutions (*i.e.*, digital twins) is about selling value to the customer and understanding the customer's business, *i.e.*, value creation in the value chain. Value-based sales means finding the offering's most valuable benefit for the customer business. Only satisfying the customer's expressed needs is insufficient [67]. Selling complex data-based solutions, such as digital twins is seen as very complex because perceived and real value can be different even to different persons in the customer company. Therefore, a framework to sell a data-based solution was constructed in a previous publication [68]. The selling process for a data-based solution could be divided into parts to clarify the value from different perspectives. In addition to understanding the offered value-adding data-based solution, a salesperson must understand the customer's sub processes, processes, and business. Figure 3 shows how the understanding of the digital twin should increase with the level of ecosystem complexity.

3) VALUE CREATION

Value creation can be defined as the group of activities and processes that enforce the integration of resources and the roles of the various actors in a service ecosystem [69]. The first step in creating value with digital twins is to determine the value proposition [63]. Digital twins bring value by making it possible to share risks, skills, resources, and duties; cut expenses; increase flexibility; and finally maximize customer satisfaction [70]. The second is to analyze and define the roles of the various actors. Because each contributor will be making a unique contribution, is it important to understand and coordinate their participation to avoid unproductive misalignments between the actors and the process [63]. The third step is to analyze the network effects to understand how adding or removing contributors can affect the ecosystem as a whole [71], [72]. The final step is to establish the revenue model and determine how to best produce financial benefit.

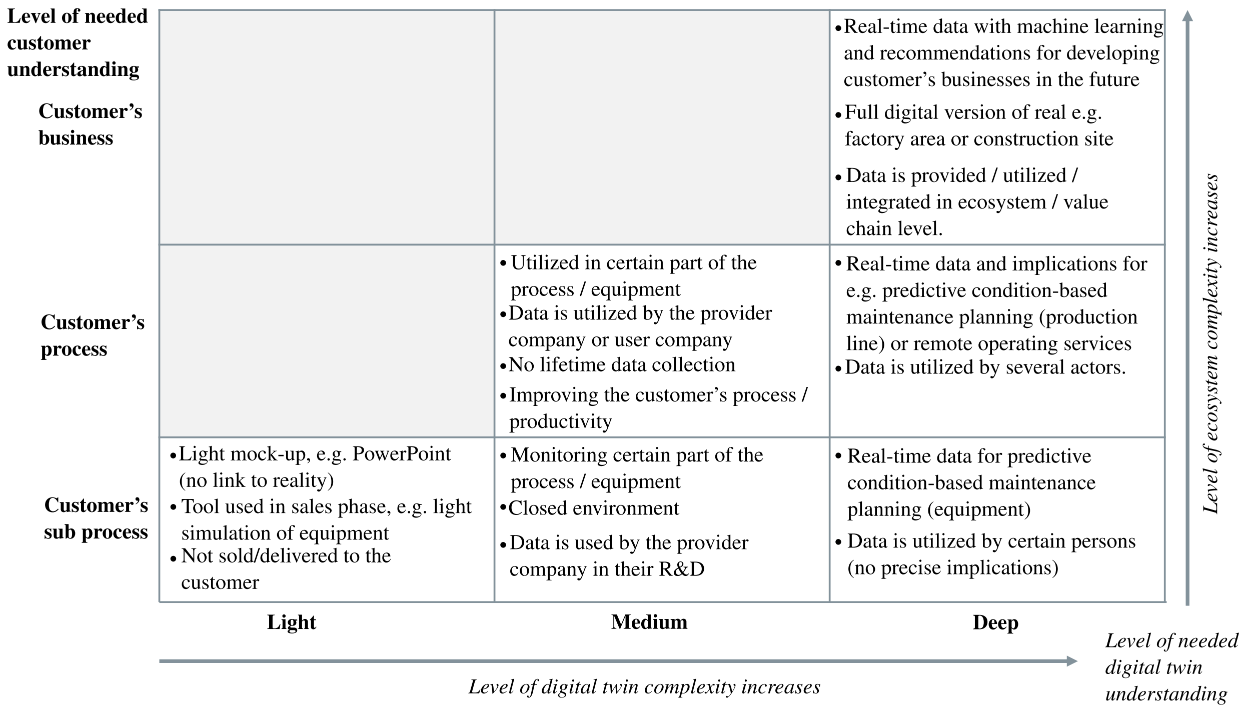


FIGURE 3. Selling a data-based solution (*i.e.*, digital twin) in B2B markets requiring different levels of customer and digital-twin understanding as ecosystem complexity increases.

III. CASE STUDIES: MOBILE LOG CRANE AND ROTATING STRUCTURE

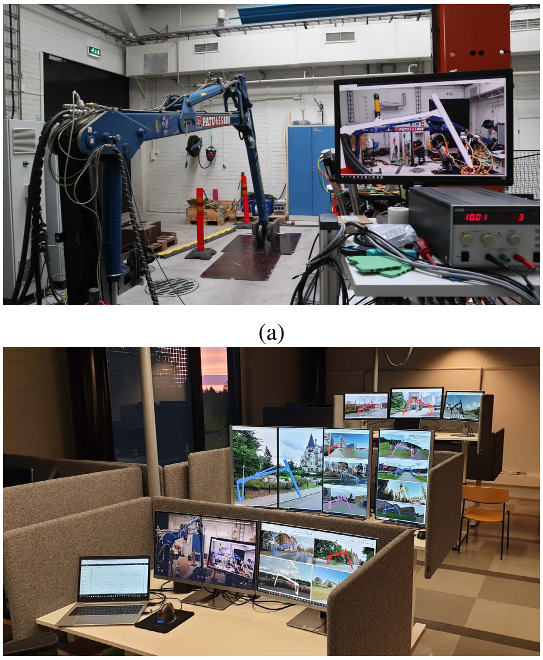
To demonstrate the proposed methodology, two case examples were investigated. For the first example, a mobile log crane was modeled with MBS-based methods and UKF was applied to estimate the states of the system. In the second case, a rotating machine was modeled using FEM-based methods, and the parameters of the system were estimated using the Kalman filter. In both examples, the simulation models were well synchronized with the actual products, which made it possible to emphasize virtual sensor capabilities [73].

A. MOBILE LOG CRANE

To demonstrate the feasibility of physics-based digital twins in the heavy equipment segment, the dynamics of a mobile log crane was modelled in independent coordinates using MBS formulations as a proof-of-concept system. MBS provides general formulations to build dynamic simulation models of industrial machines [10], [18], [28] which can be used in divergent phases of product lifecycle ranging from product development to maintenance. Using the MBS formulations in the presented case example makes it possible to reduce the number of sensors in the implementation of the digital twin. A digital twin was developed that calculated crane dynamics in real-time using position and pressure sensor data obtained from the crane hydraulic cylinders.

Meta data describing parameters of the actual crane, the sensors, the model, and software implementing the digital twin were collected and stored in a cloud system for PLM collaboration ShareAspace, which was provided by partner company Eurostep Oy. Using the digital twin framework, software was written to emulate a module within a fleet management system for heavy equipment. This module read the meta data from the ShareAspace system and executed several instances of the DT program in the Amazon web services cloud. Each instance was implemented as a Docker container[7] providing scalability for running large numbers of digital twins concurrently. The sensor data was gathered from a real crane (PATU 655) operated in the Laboratory of Intelligent Machines at LUT University. Although a single crane was used in the experiments, its sensor data were replicated to 16 instances of the DT program running concurrently in the cloud. This setup emulated digital twin execution for a fleet of machines. The results of calculations were visualized in 16 web browser windows on desktop computers at LUT University, each presenting the motion of the crane in real-time and showing the force vectors acting on the crane booms. The goal was to develop a proof-of-concept system capable of running physics-based DT programs for a fleet of machines using the proposed framework. Of particular interest wast the suitability of container technology for maintaining multiple instances of computationally intensive DT programs in the cloud and executing several DT programs on a single host. The setup demonstrated an ability to run physics-based digital twins for a heavy equipment fleet in real-time using commercially available cloud systems. Figure 4 depicts the mobile

[7] A container is a standard unit of software that packages up code and all its dependencies so the application runs quickly and reliably from one computing environment to another.



(a)

(b)

FIGURE 4. **(a) PATU 655 mobile log crane and (b) fleet of virtual models.**

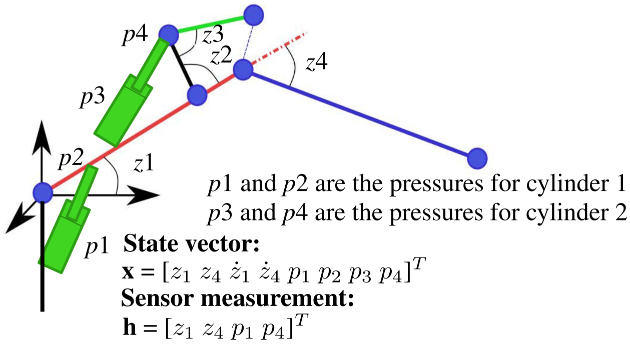


FIGURE 5. **Mobile log crane physics-based simulation model made with MBS-z_1, z_4, $\dot{z}_1$, and $\dot{z}_4$ represent the angles and angular velocities of the lift boom and outer boom, respectively. p_1, p_2, p_3, and p_4 are the pressures of cylinders 1 and 2.**

log crane and the fleet of virtual models in the digital twin framework.

Figure 5 illustrates the MBS model of the PATU 655 mobile log crane. The model is based on the crane's actual dimensions and parameters. It comprises the lift boom, the outer boom, bracket 1, bracket 2, and the system hydraulics. As Figure 5 shows, the crane is powered by two hydraulic cylinders. To demonstrate the digital twin, three MBS models were used. They were designated the real model, the plant model, and the simulation model.

Measurement of the angles z_1 and z_4 and the cylinder pressures p_1 and p_4 came from the real model. White Gaussian noise was added in the measurement data so that it replicated the actual sensor performance. The plant model differs from the real model in terms of external forces, joint tolerances, and initial conditions. The dynamics of plant model and simulation model are the same. The Unscented Kalman Filter was used to estimate the real model states. State-estimation results are discussed in the following paragraphs where the Kalman Filter was used to synchronize the plant model with the real model based on sensor measurements. Note that in this study the results of z_4 and p_3 estimation are presented. Further details of the modelling, implementation, and results of UKF in PATU 655 mobile log crane can be found in [74]. A period comprising 25 seconds of operation was considered.

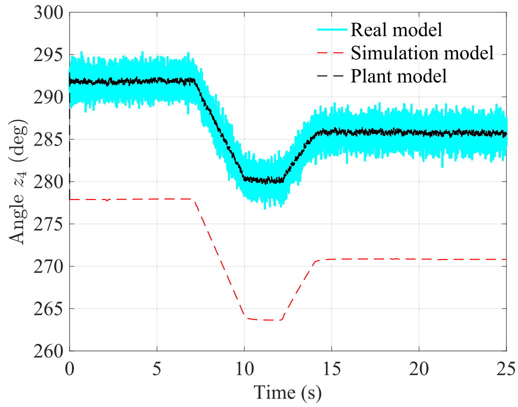
1) STATE ESTIMATION USING UNSCENTED KALMAN FILTER IN PATU 655 MOBILE LOG CRANE

Figure 6a depicts state estimation for angle z_4, *i.e.*, the outer boom angular position with respect to the lift boom. The red dashed line represents the faulty simulation model with the initial contact angle set to 277 degrees. The correct value was 292 degrees. The black dashed line represents the Kalman filter corrected value, which is aligned with the actual system. Figure 6b shows the error in the angle estimation. Similarly, Figure 6c depicts state estimation for pressure p_3 (the second cylinder piston side pressure), where the incorrect model reads 60 bar, and the Kalman filter correction pushes it to 43 bar.

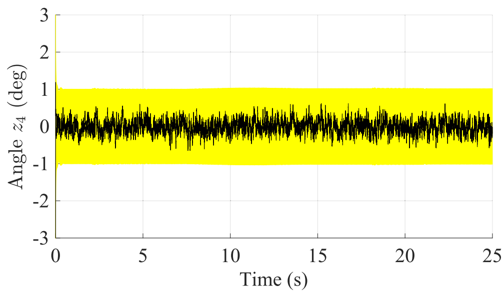
2) KALMAN FILTER IN ROTATING MACHINES

The torsional vibration demonstration example represents a proof-of-concept demonstration for the rotating machinery industry. The demo case demonstrates the feasibility of using a physics-based digital twin to identify machine state changes. For this example case, the Unscented Kalman filter was used to estimate the state of the experimental torsional vibration proof-of-concept device where an electric motor drives the main rotor via a flexible coupling as shown in Figure 7. The rotor is supported by four bearings and the vibration at the bearing locations is measured by acceleration sensors.

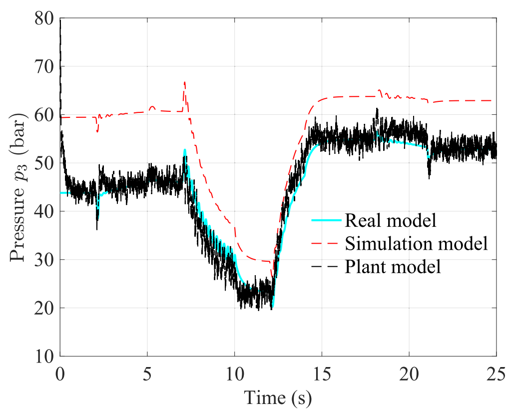
This study shows the contribution of the pedestal, *i.e.* the table where the machine is standing, movement. Higher order frequencies and support types affect recorded vibration measurement, so using raw measurement data to study system response is not the best approach. Additional signal processing steps and model updating based on measurement data are needed. The first order component of the signal is used here to provide a clearer image of system behavior during the sweep. As shown by Figure 8, vibration peaks at 7 Hz at the first order component of the signal at the rigid body mode of the pedestal. Here, pedestal movement has a significant effect on the unbalanced response. The vibration peak appears mainly at the horizontal and also slightly vertical directions. The pedestal is heavy, and the system has high stiffness in the vertical direction. Therefore, the amplitude of vibration is small. The stiffness of the supports in the attachment of the



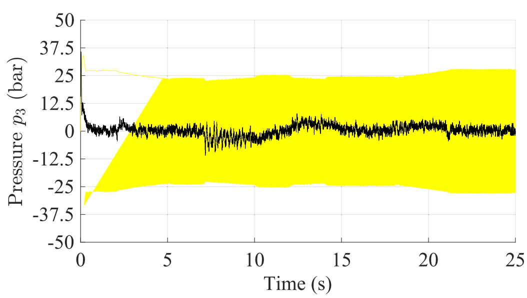
(a) Estimation of outer boom angle z_4



(b) Error in outer boom angle z_4 estimation



(c) Estimation of cylinder pressure p_3



(d) Error in pressure p_3 estimation

FIGURE 6. Estimation of z_4 and p_3 in the mobile log crane using UKF. Errors in the states in 95 % confidence interval during the estimation.

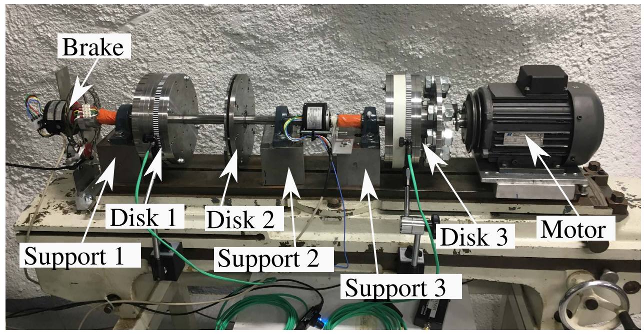
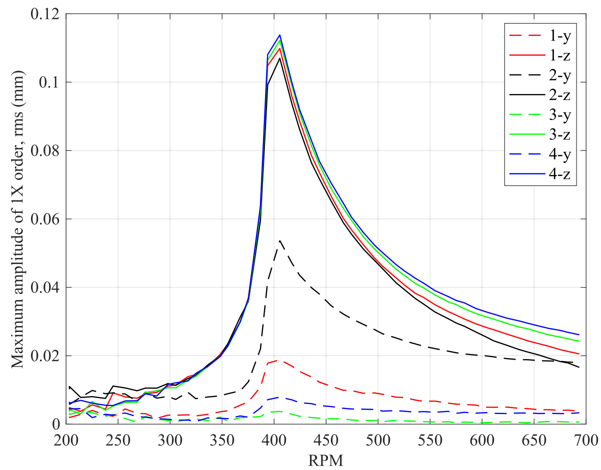
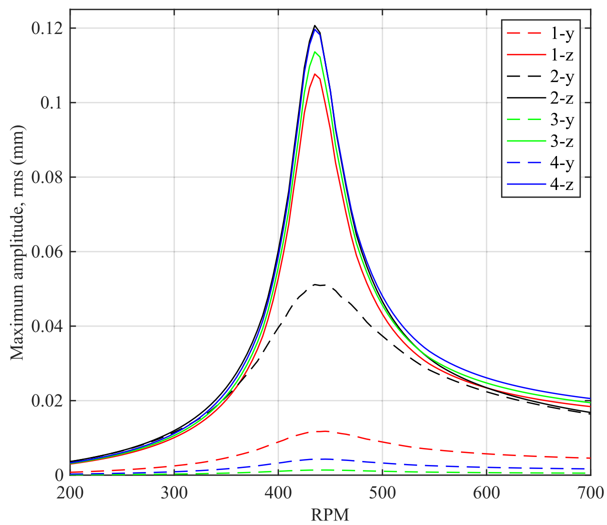


FIGURE 7. Rotating machine proof-of-concept.



(a)



(b)

FIGURE 8. First order response, a) measurement, b) simulation.

bearing to the pedestal also affects system response in the simulation model.

The capability of the Kalman filter to determine the corrected state based on measurement data was tested. The FEM model has 50 dofs. The states considered were displacement, velocity, and acceleration in the different degrees of

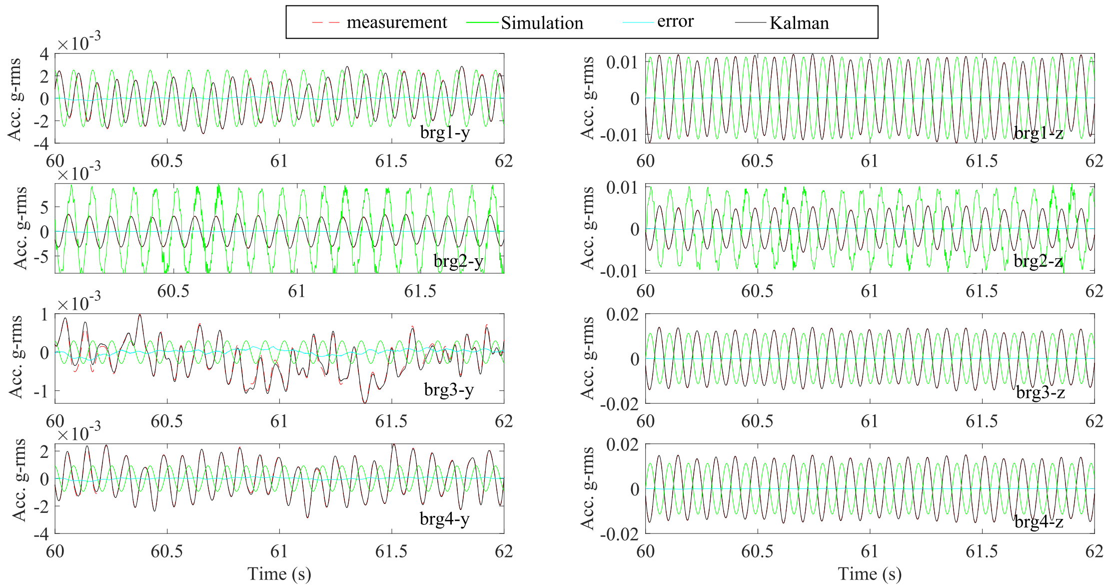


FIGURE 9. Kalman filter results for estimation of acceleration at bearing location (Acc.: acceleration).

freedom of the model. The 8 sensors provided measurements of horizontal and vertical displacement at the bearing location. Figure 9 gives the results of the acceleration predicted by the Kalman filter. The figure shows the Kalman filter correction to be good even though the simulation model has a considerable difference with respect to the measurement data and the full model was used.

IV. DISCUSSION

Digitalization is developing rapidly, especially in the more innovative industrial companies that are seeking new solutions and new ways of generating value. Figure 10 depicts the concept for structuring information and making use of physics-based simulation technologies to create value in products and in decision making. In the conceptual approach, the simulation models are designed so they can be operated in parallel with actual product operation. This makes it possible to use information gathered by the physics-based simulation model to gain a deeper understanding of product behavior, which can be used, for example, in decision making. This is especially relevant in products that are highly customized or unique, where substantial operational data is not available prior to customer use. The depicted concept can be utilized in several ways, and it considers both value creation and technical aspects. Section 3 described two examples cases based on this concept.

A. BUSINESS CASES RELATED TO PROOF OF CONCEPTS

A digital twin based on a real-time simulation model and a Kalman filter offers several benefits. When the actual product and the simulation model operate in synchronization, insights gained from the physics-based simulation, *e.g.*, forces and inertias, can be used directly to assess loads and therefore the damage to the system. In the product development phase, the justification for using these types of models, instead of building and testing actual prototypes, includes faster time to market and other economic benefits. Redesigns and modifications can be made in hours instead of the weeks or even months required to redesign and modify an actual prototype. The Kalman filter based model makes it possible to explore the applicability of different materials and components or how best to optimize energy efficiency. Parameters such as these are especially significant in supporting the transition to digital twins, *i.e.*, digitalization and green transformation, because their effects can be quantified and compared prior to introducing a new product to manufacturing. Marketing and sales also benefits. The new modeling approach not only saves time, but also provides competitive advantage. The mobile log crane and rotating machine case examples illustrated how simulation makes it possible for the user (potential customer) to experience, engagingly and realistically, the performance of a new machine system. Users can participate in development of the model, influence system specifications, and ultimately experience the operation of various machine options. The Kalman-filter-based simulation models promise to provide new intelligent solutions such as production optimization. Moreover, the simulation models promise to provide new intelligent solutions such as production optimization. For example, they can produce real-time data and automatically control and adjust processes, therefore improving energy efficiency and productivity. In operation, the simulation models support decision making by enabling more efficient working cycles and lower fuel consumption. They can create value by enhancing employee safety and improving the ergonomics of workplace operations. Automated and resource-saving models may lower costs and therefore enhance the effectiveness of operations, units, and entire companies. The models help to prevent the breakdown of

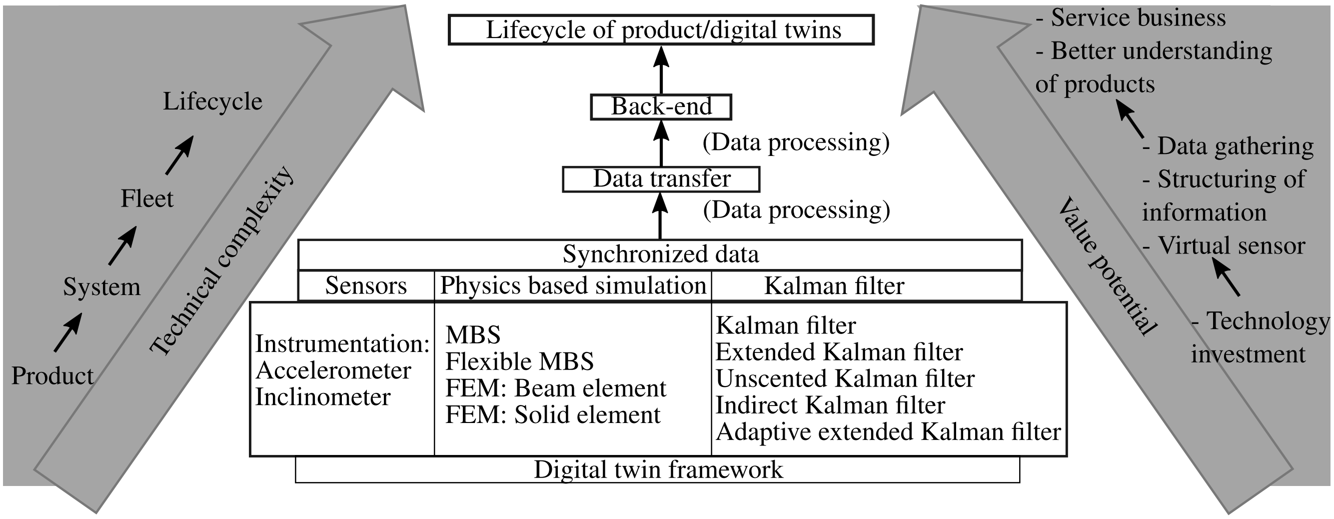


FIGURE 10. Advanced simulation tools and data processing techniques to create value in products.

machinery and ensure optimal operation. In addition, because digitalization is demanding also from the supply network perspective, the virtual product can act as a central node connecting the different actors and operators within a complex network and therefore be concrete and able to quantify the value distribution along the network of suppliers, *i.e.*, ecosystem participants. For an operator of, *e.g.*, mobile heavy machinery, the new digitalized environment enables heads-up-display solutions, the real-time processing and analytics of fused IoT and simulation data.

B. FUTURE TECHNICAL AND BUSINESS PERSPECTIVES

While the concept and solutions are promising, working methods need to be developed further. In particular, technology adaptation and organizational structures are challenging issues that must be addressed when going forward with digitalization. Education must also do its part to support the methodologies behind digitalization and digitalization-enabled opportunities. Further research and development are needed to explore the methods for specific cases and increasing robustness. Trust in the estimations given by the combination of actual product and physics-based simulation must continue to be cultivated. The digital twin concept requires cross-disciplinary collaboration and the formation of multidisciplinary teams to take full advantage of the potential of digitalization. Currently, many organizations in the industrial companies are not ready to fully provide this support. A digital twin should be built so that personnel changes do not affect its effectiveness, *e.g.*, similar concept as in IT and software development, such as the agile working routines, could be beneficial.

V. CONCLUSION

The research reported here explored technical aspects of merging machinery with a physics-based digital twins based on Kalman filter techniques and how a successful implementation can create value. Two industrial case examples were exercised to demonstrate the proposed methodology. The first, a mobile log crane, is applicable for the heavy mobile machinery industry, where many leading companies are pioneering digitalization and acting as innovators for technology adaptation. The second case example considered a rotating machine. In rotating machinery, unexpected failures are still causing problems. In the research, the broad viewpoint was explored, including the identification of potential value creation from the interviews and then ability to adapt technology based on the real needs in the industry. The novelty of the research is with the conceptual methodology, which can be applied to solve cross organizational challenges, and by introducing new ways to approach digitalization and capture the enabled opportunities. Further research is needed to identify and capture similar value in more traditional and less innovative industries.

ACKNOWLEDGMENT

The authors would like to thank the following participating companies for sharing their knowledge and viewpoints: Eurostep Oy–Leo Torvikoski, Process Genius Oy–Jani Akkila, Janne Pekkala, Mevea Oy–Tero Koskipalo, Novatron Oy–Juuso Mäkinen, Raute Oyj–Roope Eskola, Sandvik Mining and Construction Oy-Arto Vento, Wärtsilä Finland Oy–Tero Lokasaari, 3D Talo Finland Oy–Tatu Säisä, and Kone Oyj–Henri Wenlin.

REFERENCES

[1] A. Sääksvuori and A. Immonen, *Product Lifecycle Management*, 3rd ed. Berlin, Germany: Springer, 2008.

[2] I. Donoghue, L. Hannola, J. Papinniemi, and A. Mikkola, "The benefits and impact of digital twins in product development phase of PLM," in *Proc. IFIP Int. Conf. Product Lifecycle Manage.* Cham, Switzerland: Springer, 2018, pp. 432–441, doi: 10.1007/978-3-030-01614-2_40.

[3] B. R. Barricelli, E. Casiraghi, and D. Fogli, "A survey on digital twin: Definitions, characteristics, applications, and design implications," *IEEE Access*, vol. 7, pp. 167653–167671, 2019, doi: 10.1109/ACCESS.2019.2953499.

[4] C. K. Lo, C. H. Chen, and R. Y. Zhong, "A review of digital twin in product design and development," *Adv. Eng. Informat.*, vol. 48, Apr. 2021, Art. no. 101297, doi: 10.1016/j.aei.2021.101297.

[5] H. Aydemir, U. Zengin, and U. Durak, "The digital twin paradigm for aircraft review and outlook," in *Proc. AIAA Scitech Forum*, 2020, p. 0553, doi: 10.2514/6.2020-0553.

[6] J. Autiosalo, J. Vepsalainen, R. Viitala, and K. Tammi, "A feature-based framework for structuring industrial digital twins," *IEEE Access*, vol. 8, pp. 1193–1208, 2020, doi: 10.1109/ACCESS.2019.2950507.

[7] W. Z. Bernstein, T. D. Hedberg, Jr., M. Helu, and A. B. Feeney, "Contextualising manufacturing data for lifecycle decision-making," *Int. J. Product Lifecycle Manage.*, vol. 10, no. 4, pp. 326–347, 2017.

[8] M. Saunila, J. Ukko, J. Heikkinen, R. S. Semken, and A. Mikkola, "Creating value with sustainable production based on real-time simulation," in *Real-Time Simulation for Sustainable Production*. Evanston, IL, USA: Routledge, 2021, pp. 1–9, doi: 10.4324/9781003054214-1.

[9] F. Lumineau, W. Wang, and O. Schilke, "Blockchain governance—A new way of organizing collaborations?" *Org. Sci.*, vol. 32, no. 2, pp. 500–521, 2021, doi: 10.1287/orsc.2020.1379.

[10] S. Jaiswal, P. Korkealaakso, R. Åman, J. Sopanen, and A. Mikkola, "Deformable terrain model for the real-time multibody simulation of a tractor with a hydraulically driven front-loader," *IEEE Access*, vol. 7, pp. 172694–172708, 2019, doi: 10.1109/ACCESS.2019.2956164.

[11] L. Hannola, A. Richter, S. Richter, and A. Stocker, "Empowering production workers with digitally facilitated knowledge processes—A conceptual framework," *Int. J. Prod. Res.*, vol. 56, no. 14, pp. 4729–4743, 2018, doi: 10.1080/00207543.2018.1445877.

[12] M. Li, A. Milojević, and H. Handroos, "Robotics in manufacturing—The past and the present," in *Technical, Economic and Societal Effects of Manufacturing 4.0*. Cham, Switzerland: Palgrave Macmillan, 2020, pp. 85–95, doi: 10.1007/978-3-030-46103-4_4.

[13] I. Palomba, D. Richiedei, A. Trevisani, E. Sanjurjo, A. Luaces, and J. Cuadrado, "Estimation of the digging and payload forces in excavators by means of state observers," *Mech. Syst. Signal Process.*, vol. 134, Dec. 2019, Art. no. 106356, doi: 10.1016/j.ymssp.2019.106356.

[14] S. Vorotnikov, K. Ermishin, A. Nazarova, and A. Yuschenko, "Multi-agent robotic systems in collaborative robotics," in *Proc. Int. Conf. Interact. Collaborative Robot.* Cham, Switzerland: Springer, 2018, pp. 270–279, doi: 10.1007/978-3-319-99582-3_28.

[15] A. Kostis and P. Ritala, "Digital artifacts in industrial co-creation: How to use VR technology to bridge the provider-customer boundary," *California Manage. Rev.*, vol. 62, no. 4, pp. 125–147, Aug. 2020, doi: 10.1177/0008125620931859.

[16] M. C. Becker, P. Salvatore, and F. Zirpoli, "The impact of virtual simulation tools on problem-solving and new product development organization," *Res. Policy*, vol. 34, no. 9, pp. 1305–1321, Nov. 2005, doi: 10.1016/j.respol.2005.03.016.

[17] D. Bobylev, T. Choudhury, J. O. Miettinen, R. Viitala, E. Kurvinen, and J. Sopanen, "Simulation-based transfer learning for support stiffness identification," *IEEE Access*, vol. 9, pp. 120652–120664, 2021, doi: 10.1109/ACCESS.2021.3108414.

[18] N. Alaei, E. Kurvinen, and A. Mikkola, "A methodology for product development in mobile machinery: Case example of an excavator," *Machines*, vol. 7, no. 4, p. 70, Nov. 2019, doi: 10.3390/machines7040070.

[19] Y. Lu, C. Liu, K. I.-K. Wang, H. Huang, and X. Xu, "Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robot. Comput.-Integr. Manuf.*, vol. 61, Feb. 2020, Art. no. 101837, doi: 10.1016/j.rcim.2019.101837.

[20] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, and A. Y. C. Nee, "Enabling technologies and tools for digital twin," *J. Manuf. Syst.*, vol. 58, pp. 3–21, Jan. 2021, doi: 10.1016/j.jmsy.2019.10.001.

[21] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, "Digital twin-driven product design, manufacturing and service with big data," *Int. J. Adv. Manuf. Technol.*, vol. 94, nos. 9–12, pp. 3563–3576, Feb. 2018, doi: 10.1007/s00170-017-0233-1.

[22] R. Söderberg, K. Wärmefjord, J. S. Carlson, and L. Lindkvist, "Toward a digital twin for real-time geometry assurance in individualized production," *CIRP Ann.*, vol. 66, no. 1, pp. 137–140, 2017, doi: 10.1016/j.cirp.2017.04.038.

[23] Y. Lu and X. Xu, "Cloud-based manufacturing equipment and big data analytics to enable on-demand manufacturing services," *Robot. Comput.-Integr. Manuf.*, vol. 57, pp. 92–102, Jun. 2019, doi: 10.1016/j.rcim.2018.11.006.

[24] S. Aheleroff, X. Xu, R. Y. Zhong, and Y. Lu, "Digital twin as a service (DTaaS) in industry 4.0: An architecture reference model," *Adv. Eng. Informat.*, vol. 47, Jan. 2021, Art. no. 101225, doi: 10.1016/j.aei.2020.101225.

[25] J. G. de Jalon and E. Bayo, *Kinematic and Dynamic Simulation of Multibody Systems: The Real-Time Challenge* (Mechanical Engineering Series), 1st ed. New York, NY, USA: Springer-Verlag, 1994, p. XVI and 440, doi: 10.1007/978-1-4612-2600-0.

[26] J. Cuadrado, D. Dopico, M. Gonzalez, and M. A. Naya, "A combined penalty and recursive real-time formulation for multibody dynamics," *J. Mech. Des.*, vol. 126, no. 4, pp. 602–608, 2004, doi: 10.1115/1.1758257.

[27] S. Jaiswal, R. Aman, J. Sopanen, and A. Mikkola, "Real-time multibody model-based heads-up display unit of a tractor," *IEEE Access*, vol. 9, pp. 57645–57657, 2021, doi: 10.1109/ACCESS.2021.3072452.

[28] Q. Khadim, E.-P. Kaikko, E. Puolatie, and A. Mikkola, "Targeting the user experience in the development of mobile machinery using real-time multibody simulation," *Adv. Mech. Eng.*, vol. 12, no. 6, 2020, Art. no. 1687814020923176.

[29] G. Genta and M. Silvagni, "On centrifugal softening in finite element method rotordynamics," *J. Appl. Mech.*, vol. 81, no. 1, Jan. 2014, doi: 10.1115/1.4024073.

[30] L. Hu and A. Palazzolo, "An enhanced axisymmetric solid element for rotor dynamic model improvement," *J. Vibrat. Acoust.*, vol. 141, no. 5, Oct. 2019, Art. no. 051002, doi: 10.1115/1.4043411.

[31] J. Oh, B. J. Kim, and A. Palazzolo, "Three-dimensional solid finite element contact model for rotordynamic analysis: Experiment and simulation," *J. Vib. Acoust.*, vol. 143, no. 3, Jun. 2021, Art. no. 031007, doi: 10.1115/1.4048556.

[32] E. Sikanen, J. E. Heikkinen, and J. Sopanen, "Shrink-fitted joint behavior using three-dimensional solid finite elements in rotor dynamics with inclusion of stress-stiffening effect," *Adv. Mech. Eng.*, vol. 10, no. 6, 2018, Art. no. 1687814018780054, doi: 10.1177/1687814018780054.

[33] T. Choudhury, E. Kurvinen, R. Viitala, and J. Sopanen, "Development and verification of frequency domain solution methods for rotor-bearing system responses caused by rolling element bearing waviness," *Mech. Syst. Signal Process.*, vol. 163, Jan. 2022, Art. no. 108117, doi: 10.1016/j.ymssp.2021.108117.

[34] P. Koutsovasilis and M. Beitelschmidt, "Model order reduction of finite element models: Improved component mode synthesis," *Math. Comput. Model. Dyn. Syst.*, vol. 16, no. 1, pp. 57–73, Mar. 2010, doi: 10.1080/13873951003590214.

[35] S. G. Mohinder and P. A. Angus, "Applications of Kalman filtering in aerospace 1960 to the present [historical perspectives]," *IEEE Control Syst. Mag.*, vol. 30, no. 3, pp. 69–78, Jun. 2010, doi: 10.1109/MCS.2010.936465.

[36] Y. Zhang and Q. Xu, "Adaptive sliding mode control with parameter estimation and Kalman filter for precision motion control of a piezo-driven microgripper," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 2, pp. 728–735, Mar. 2017, doi: 10.1109/TCST.2016.2569567.

[37] M. Soltani, M. Bozorg, and M. R. Zakerzadeh, "Parameter estimation of an SMA actuator model using an extended Kalman filter," *Mechatronics*, vol. 50, pp. 148–159, Apr. 2018, doi: 10.1016/j.mechatronics.2018.02.001.

[38] Y. Oka and M. Ohno, "Parameter estimation for heat transfer analysis during casting processes based on ensemble Kalman filter," *Int. J. Heat Mass Transf.*, vol. 149, Mar. 2020, Art. no. 119232, doi: 10.1016/j.ijheatmasstransfer.2019.119232.

[39] J. Cuadrado, D. Dopico, A. Barreiro, and E. Delgado, "Real-time state observers based on multibody models and the extended Kalman filter," *J. Mech. Sci. Technol.*, vol. 23, no. 4, pp. 894–900, Apr. 2009, doi: 10.1007/s12206-009-0308-5.

[40] E. Sanjurjo, M. Á. Naya, J. L. Blanco-Claraco, J. L. Torres-Moreno, and A. Giménez-Fernández, "Accuracy and efficiency comparison of various nonlinear Kalman filters applied to multibody models," *Nonlinear Dyn.*, vol. 88, no. 3, pp. 1935–1951, May 2017, doi: 10.1007/s11071-017-3354-z.

[41] S. Jaiswal, E. Sanjurjo, J. Sopanen, J. Cuadrado, and A. Mikkola, "State estimator based on an indirect Kalman filter for a hydraulically actuated multibody system," *Multibody Syst. Dyn.*, vol. 54, pp. 373–398, Feb. 2022.

[42] Q. Khadim, M. Kiani-Oshtorjani, S. Jaiswal, M. K. Matikainen, and A. Mikkola, "Estimating the characteristic curve of a directional control valve in a combined multibody and hydraulic system using an augmented discrete extended Kalman filter," *Sensors*, vol. 21, no. 15, p. 5029, Jul. 2021, doi: 10.3390/s21155029.

[43] E. A. Wan and R. Van Der Merwe, "The unscented Kalman filter for nonlinear estimation," in *Proc. IEEE Adapt. Syst. Signal Process., Commun., Control Symp.*, Oct. 2000, pp. 153–158, doi: 10.1109/ASSPCC.2000.882463.

[44] A. R. Ghiasi, A. A. Ghavifekr, Y. S. Hagh, and H. SeyedGholami, "Designing adaptive robust extended Kalman filter based on Lyapunov-based controller for robotics manipulators," in *Proc. 6th Int. Conf. Modeling, Simulation, Appl. Optim. (ICMSAO)*, May 2015, pp. 1–6, doi: 10.1109/ICMSAO.2015.7152248.
[45] Y. S. Hagh, R. M. Asl, A. Fekih, H. Wu, and H. Handroos, "Active fault-tolerant control design for actuator fault mitigation in robotic manipulators," *IEEE Access*, vol. 9, pp. 47912–47929, 2021, doi: 10.1109/ACCESS.2021.3068448.
[46] E. Sanjurjo, D. Dopico, A. Luaces, and M. Á. Naya, "State and force observers based on multibody models and the indirect Kalman filter," *Mech. Syst. Signal Process.*, vol. 106, pp. 210–228, Jun. 2018, doi: 10.1016/j.ymssp.2017.12.041.
[47] H. Bonyan Khamseh, S. Ghorbani, and F. Janabi-Sharifi, "Unscented Kalman filter state estimation for manipulating unmanned aerial vehicles," *Aerosp. Sci. Technol.*, vol. 92, pp. 446–463, Sep. 2019, doi: 10.1016/j.ast.2019.06.009.
[48] S. Razvarz, R. Jafari, and A. Gegov, "Leakage detection in pipeline based on second order extended Kalman filter observer," in *Flow Modelling and Control in Pipeline Systems*. Cham, Switzerland: Springer, 2021, pp. 161–174, doi: 10.1007/978-3-030-59246-2_8.
[49] Y. S. Hagh, R. M. Asl, and V. Cocquempot, "A hybrid robust fault tolerant control based on adaptive joint unscented Kalman filter," *ISA Trans.*, vol. 66, pp. 262–274, Jan. 2017, doi: 10.1016/j.isatra.2016.09.009.
[50] M. Grieves and J. Vickers, "Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems," in *Transdisciplinary Perspectives on Complex Systems*. Cham, Switzerland: Springer, 2017, pp. 85–113, doi: 10.1007/978-3-319-38756-7_4.
[51] S. D. Urban, J. J. Shah, and M. Rogers, "An overview of the ASU engineering database project: Interoperability in engineering design," in *Proc. 3rd Int. Workshop Res. Issues Data Eng.: Interoperability Multidatabase Syst. (RIDE-IMS)*, Apr. 1993, pp. 73–76, doi: 10.1109/RIDE.1993.281942.
[52] J. Fowler. (1995). *Step for Data Management, Exchange and Sharing*. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.107.2051&rep=rep1&type=pd
[53] M. González, F. González, A. Luaces, and J. Cuadrado, "Interoperability and neutral data formats in multibody system simulation," *Multibody Syst. Dyn.*, vol. 18, no. 1, pp. 59–72, Jun. 2007, doi: 10.1007/s11044-007-9060-8.
[54] M. W. Grieves, "Virtually intelligent product systems: Digital and physical twins," in *Complex Systems Engineering: Theory and Practice*. Amer. Inst. Aeronaut. Astronaut., 2019, doi: 10.2514/4.105654.
[55] I. Donoghue, L. Hannola, and A. Sääksvuori, "Implementing digital twins to enhance digitally extended product-service systems," in *Real-Time Simulation for Sustainable Production*. Evanston, IL, USA: Routledge, 2021, pp. 121–131, doi: 10.4324/9781003054214-13.
[56] V. Zhidchenko, E. Startcev, and H. Handroos, "Reference architecture for running computationally intensive physics-based digital twins of heavy equipment in a heterogeneous execution environment," *IEEE Access*, to be published.
[57] I. Guyon, S. Gunn, M. Nikravesh, and L. A. Zadeh, *An Introduction to Feature Extraction*, vol. 207. Berlin, Germany: Springer, 2008.
[58] S. Hoell and P. Omenzetter, "Sequential projection pursuit for optimal transformation of autoregressive coefficients for damage detection in an experimental wind turbine blade," *Proc. Eng.*, vol. 199, pp. 2226–2231, Jan. 2017, doi: 10.1016/j.proeng.2017.09.188.
[59] K. K. Nair, A. S. Kiremidjian, and K. H. Law, "Time series-based damage detection and localization algorithm with application to the ASCE benchmark structure," *J. Sound Vib.*, vol. 291, nos. 1–2, pp. 349–368, Mar. 2006, doi: 10.1016/j.jsv.2005.06.016.
[60] W. Caesarendra and T. Tjahjowidodo, "A review of feature extraction methods in vibration-based condition monitoring and its application for degradation trend estimation of low-speed slew bearing," *Machines*, vol. 5, no. 4, p. 21, Sep. 2017, doi: 10.3390/machines5040021.
[61] P. Potočnik and E. Govekar, "Semi-supervised vibration-based classification and condition monitoring of compressors," *Mech. Syst. Signal Process.*, vol. 93, pp. 51–65, Sep. 2017, doi: 10.1016/j.ymssp.2017.01.048.
[62] J. Junttila, "Operational state recognition of a rotating machine based on measured mechanical vibration data," M.S. thesis, Arcada Univ. Appl. Sci., Helsinki, Finland, 2021.
[63] J. Meierhofer, S. West, M. Rapaccini, and C. Barbieri, "The digital twin as a service enabler: From the service ecosystem to the simulation model," in *Proc. Int. Conf. Exploring Services Sci.* Cham, Switzerland: Springer, 2020, pp. 347–359, doi: 10.1007/978-3-030-38724-2_25.
[64] K. Kokkonen, L. Hannola, T. Rantala, J. Ukko, M. Saunila, and T. Rantala, "Digital twin business ecosystems: Preconditions and benefits for service business," in *21st CINet Conf., Practicing Continuous Innov. Digital Ecosyst.*, 2020.
[65] E. Autio and L. D. Thomas, "Tilting the playing field: Towards an endogenous strategic action theory of ecosystem creation," in *World Scientific Reference on Innovation: Open Innovation, Ecosystems and Entrepreneurship: Issues and Perspectives*, vol. 3. Singapore: World Scientific, 2018, pp. 111–140, doi: 10.1142/9789813149083_0005.
[66] K. Lenkenhoff, U. Wilkens, M. Zheng, T. Süße, B. Kuhlenkötter, and X. Ming, "Key challenges of digital business ecosystem development and how to cope with them," *Proc. CIRP*, vol. 73, pp. 167–172, Jan. 2018, doi: 10.1016/j.procir.2018.04.082.
[67] H. Terho, A. Haas, A. Eggert, and W. Ulaga, "'It's almost like taking the sales out of selling'—Towards a conceptualization of value-based selling in business market," *Ind. Marketing Manage.*, vol. 41, no. 1, pp. 174–185, 2012, doi: 10.1016/j.indmarman.2011.11.011.
[68] T. Rantala, T. Valjakka, K. Kokkonen, L. Hannola, M. Timperi, and L. Torvikoski, "Selling the value of complex data-based solution for industrial customers," in *Proc. Work. Conf. Virtual Enterprises*. Cham, Switzerland: Springer, 2021, pp. 345–353, doi: 10.1007/978-3-030-85969-5_31.
[69] R. F. Lusch and S. Nambisan, "Service innovation: A service-dominant logic perspective," *MIS Quart.*, vol. 39, no. 1, pp. 155–176, Mar. 2015, doi: 10.25300/MISQ/2015/39.1.07.
[70] T. Chekfoung, D. Sunil, and G. Binita, "Conceptualising capabilities and value co-creation in a digital business ecosystem (DBE): A systematic literature review," *J. Inf. Syst. Eng. Manage.*, vol. 5, no. 1, 2020, doi: 10.29333/jisem/7826.
[71] A. Asvanund, K. Clay, R. Krishnan, and M. D. Smith, "An empirical analysis of network externalities in peer-to-peer music-sharing networks," *Inf. Syst. Res.*, vol. 15, no. 2, pp. 155–174, Jun. 2004, doi: 10.1287/isre.1040.0020.
[72] A. Hein, M. Schreieck, T. Riasanow, D. S. Setzke, M. Wiesche, M. Böhm, and H. Krcmar, "Digital platform ecosystems," *Electron. Markets*, vol. 30, pp. 87–98, Nov. 2019, doi: 10.1007/s12525-019-00377-4.
[73] J. Heikkinen, E. Kurvinen, and J. Sopanen, "Added value from virtual sensors," in *Real-Time Simulation for Sustainable Production*. Evanston, IL, USA: Routledge, 2021, pp. 90–101, doi: 10.4324/9781003054214-10.
[74] Q. Khadim, Y. Shabbouei Hagh, L. Pyrhönen, S. Jaiswal, Z. Victor, K. Emil, J. Sopanen, A. Mikkola, and H. Handroos, "State estimation in a hydraulically actuated log crane using unscented Kalman filter," *IEEE Access*, to be published.

EMIL KURVINEN was born in 1988. He received the M.Sc. (Tech.) and D.Sc. (Tech.) degrees in mechanical engineering from the Lappeenranta University of Technology (LUT), in 2012 and 2016, respectively. In 2014 and 2015, he visited the University of Virginia as a Fulbright Visiting Scholar researching active magnetic bearings. From 2016 to 2017, he has served as an Engineer in structural dynamics at FS Dynamics Finland Ltd. In 2017 and 2021, he was as a Postdoctoral Researcher at LUT. He is currently a Machine Design Professor at the University of Oulu. He has a solid background in machine design, especially in the design, simulation, and analyzing of rotating machines. His research interests include rotating machines, especially high-speed machines, digital twins and integration of industrial engineering, and management to technology.

ANTERO KUTVONEN received the M.Sc. (Tech.) and D.Sc. (Tech.) degrees from the Lappeenranta University of Technology, in 2007 and 2012, respectively. He is currently working half time as a Grant Coach and a Half Associate Professor at the School of Engineering Science, LUT University, Lappeenranta, Finland. He is working with project preparations and research on topics: innovation management, sustainable-oriented innovation, and open innovation. His research interests include digital twins and sustainability related topics, where technology and business joint efforts generates additional value.

JUHANI UKKO received the D.Sc. (Tech.) degree from LUT University, in 2009. He is currently a Professor at the Department of Industrial Engineering and Management, School of Engineering Science, LUT University. He is also an Adjunct Professor at Tampere University. In recent years, he has managed and participated in research projects related to digital transformation in companies and society. His work has been published in journals, such as *Information Systems Frontiers*, *Computers in Industry*, the *International Journal of Operations and Production Management*, and the *International Journal of Production Economics*. His current research interests include performance measurement, operations management, digital transformation, digital services, and corporate sustainability performance.

QASIM KHADIM was born in Pakistan. He received the B.Sc. degree in industrial and manufacturing engineering from the University of Engineering and Technology, Lahore, and the M.Sc. (Tech.) degree from the Department of Mechanical Engineering, Lappeenranta University of Technology, Finland, and the Ph.D. degree in mechanical engineering from the Lappeenranta University of Technology. He is currently working as a Postdoctoral Researcher at the Lappeenranta University of Technology. His current research interests include multibody system dynamics, hydraulics, state estimation, parameter estimation, user experiences, non-linear Kalman filters, optimization methods, real-time simulation, and vehicle dynamics.

YASHAR SHABBOUEI HAGH received the M.Sc. degree in control engineering from the University of Tabriz, Iran, in 2016. He is currently a Junior Researcher with the Laboratory of Intelligent Machine, Department of Mechanical Engineering, LUT University, Finland. He is working on synergetic control theory, state and parameter estimation of servo-hydraulic systems, multibody dynamic systems, and digital twin concepts. His research interests include fault detection and diagnosis systems, fault tolerant controls, sliding mode controller, synergetic control, nonlinear Kalman filtering, and robotic manipulators.

SURAJ JAISWAL was born in Kolkata, India, in July 1991. He received the B.E. degree in production engineering from Jadavpur University, Kolkata, in 2013, and the M.S. and D.Sc. degrees in mechanical engineering from the Lappeenranta-Lahti University of Technology LUT, Lappeenranta, Finland, in 2017 and 2021, respectively. From 2013 to 2015, he worked as a Design Engineer with Tata Consultancy Services Ltd., Kolkata. Since 2016, he has been working as a Researcher at the Lappeenranta-Lahti University of Technology LUT. He is currently a Postdoctoral Researcher at the Laboratory of Machine Design, Lappeenranta-Lahti University of Technology LUT. His research interests include multibody dynamics, hydraulic actuators, Kalman filters, friction modeling, and real-time simulation.

NEDA NEISI received the D.Sc. (Tech.) degree in mechanical engineering from the Lappeenranta University of Technology, Finland, in 2020. Afterward, she started to work as a Postdoctoral Researcher at the Laboratory of Machine Dynamic, LUT University. Her research interests include the bearing modeling, analyzing vibration measurement, and state-space observer.

VICTOR ZHIDCHENKO received the Candidate of Sciences degree from Samara National Research University, Russia, in 2008, and the D.Sc. (Tech.) degree from LUT University, Lappeenranta, Finland, in 2019. He is currently working as a Postdoctoral Researcher with LUT University. His research interests include computer simulation, cyber-physical systems, digital twins for heavy equipment, big data, cloud computing, and the Internet of Things.

JUHA KORTELAINEN received the M.Sc. (Tech.) degree from the Helsinki University of Technology, in 1995, and the D.Sc. (Tech.) degree in virtual design on the subject of semantic data model for multibody system modeling from the Lappeenranta University of Technology, in 2011. He was an Engineering Analyst with a private consulting company. From 1998 to 2001, he was a Researcher with the Helsinki University of Technology, focusing on computational research of internal combustion engines. Since 2002, he has been with VTT Technical Research Centre of Finland as a Research Scientist, a Senior Scientist, the Research Team Leader, and a Principal Scientist. Since 2014, his research work has been focused on the process industry domain. He is also responsible for guiding the research in engineering design at VTT Technical Research Centre of Finland. He is currently a Principal Scientist and a Principal Investigator with VTT Technical Research Centre of Finland, focusing on systems engineering and simulation research and digital engineering design. His background is in mechanical engineering and computational product development.

MIRA TIMPERI received the M.Sc. (Tech.) degree from LUT University, in 2021, where she is currently pursuing the Ph.D. degree with the Department of Industrial Engineering and Management. Her research interests include digital twins, sustainable and competitive business, industrial service development, and service-related business models.

KIRSI KOKKONEN received the M.Sc. (Tech.) and D.Sc. (Tech.) degrees from LUT University, in 2007 and 2014, respectively. She is currently working as a Postdoctoral Researcher at the Department of Industrial Engineering and Management, LUT University. She is working as a Project Researcher and as a Teacher on topics: innovation management, strategic management, and engineering ethics. Her research interests include industrial service development and service business models, value networks and business ecosystems, and entrepreneurship.

JUHA VIRTANEN received the M.Sc. degree from the Helsinki University of Technology (currently Aalto University), in 1997. He is currently working as the Research Team Leader of the Dynamic Components and Systems Team, VTT Technical Research Centre of Finland. The team he is leading is working with different research activities in field of machine dynamics, especially focusing on computational analyses integrating experimental data. He is responsible for customer activities, research project planning, and research team scientific road-map planning. His research interests include multiphysical fluid-structure interaction with transient shock scenarios, especially relating to the underwater explosion phenomenon.

AKHTAR ZEB is currently a Research Scientist at VTT Technical Research Centre of Finland Ltd., Finland. His current research interests include engineering knowledge management, semantic data modeling, data harmonization, data management of digital twins, and applications of AI and machine learning in engineering design.

VILLE LÄMSÄ received the M.Sc. degree from the University of Kuopio, Finland, in 2005. He is currently pursuing the Ph.D. degree in combined use of digital twins and machine learning in industrial applications. From 2006 to 2011, he worked as a Researcher with the Department of Applied Mechanics, Aalto University, Espoo, where he studied machine learning and probabilistic modeling solutions for structural analyses and condition monitoring. He is a Research Scientist at VTT Technical Research Centre of Finland Ltd. He is experienced in physics-based simulations and data analyses for ships and propulsion systems. He has published 14 scientific papers, nine written as the lead author. In addition, his current research interests include simulation-based static and dynamic analyses for engineering applications, feature engineering, and data analyses for engineering-based big data applications.

VESA NIEMINEN received the M.Sc. (Tech.) degree in applied mechanics from the Helsinki University of Technology, in 2009. He is currently working as a Senior Scientist at the Dynamic Components and Systems Team, VTT. He is working on numerical and experimental structural analyses, model validation and updating, structural optimization, and fatigue analysis. During his career, he has worked in a number of consulting and development projects for industry as well as research projects, where his responsibilities have included mainly structural dynamic analyses of complex structures, including also multiphysics simulations. His main research interests and expertises include integration of experimental and numerical analyses, such as virtual sensing techniques.

JUKKA JUNTTILA received the M.S.E. and M.S.E. degrees. He currently works as a Research Scientist at VTT Technical Research Centre of Finland Ltd. He has over ten years of experience in structural analyses of rotating machines and other dynamic mechanical structures using finite element method. He has also come across research topics, such as internal combustion engine technology, experimental structural analytics, topology optimization, additive manufacturing, and laser scanning during his studies and his career at VTT. In addition, he has worked as a volunteer with homeless and orphan children in La Paz, Bolivia, during a sabbatical year in the early 2010s. During the last few years, he has broadened his expertise into the fields of big data analytics, machine learning, and systems simulation.

MIKKO SAVOLAINEN received the M.Sc. degree from LUT University. He is currently working with the Dynamic Components and Systems Team, VTT. He is working on dynamic analysis. His research interests include vibrations and fatigue.

TUIJA RANTALA received the B.Sc. degree from the Tampere University of Applied Sciences, in 1999, and the M.Sc. degree in industrial engineering and management from the Tampere University of Technology, in 2005. She currently works as the Research Team Leader of the Data-Based Asset Management and Business Models Team, VTT, on cognitive production industry research area. Lately, she has studied digital twins, service robotics, big data, the Internet of Things (IoT), digitalization, mergers and acquisitions (M&A) as enablers for new business, and related challenges for B2B companies. She has over 15 years of experience as a Project Manager and a Researcher in company assignment and research projects on diverse topics related to new B2B business creation. Her main research interests include new business creation and business-to-business (B2B) sales.

TIINA VALJAKKA received the M.Sc. degree in industrial management from the Lappeenranta University of Technology and the M.Sc. degree in operations and production management from Michigan Technological University. She currently works as an Operations Support Manager in foresight and data economy research area at VTT. She has carried out several research and commercial projects developing inter-organizational collaboration and published articles in the research areas of business networks and collaboration. Her expertises cover network integration and value co-creation in business-to-business relationships.

ILKKA DONOGHUE is currently a Postdoctoral Researcher at the School of Engineering Science, LUT University, Finland. His research interests include intelligent product-service systems and the role they play in developing sustainable business ecosystems.

KALLE ELFVENGREN is currently an Associate Professor with the School of Engineering Science, LUT University, Finland. His research interests include process development in the health-care sector, management of technology, and risk management.

MINA NASIRI received the D.Sc. degree in industrial engineering and management from LUT University, in February 2021. From 2016 to 2021, she was a Researcher at LUT University. Her works have been published in different journals, such as *Technovation*, *Information Systems Frontiers*, *Technology Analysis and Strategic Management*, *Sustainable Development*, *Computers in Industry*, and *Journal of Cleaner Production*. Her research interests include digitalization, digital supply chain, digital transformation, digital innovation, corporate sustainability, smart technologies, performance measurement and management, operations management, and sustainable strategies.

TERO RANTALA received the D.Sc.Tech. degree. He is currently a Postdoctoral Researcher at the School of Engineering Science, LUT University. He has previously published in journals, such as *European Journal of Operational Research*, *Technovation*, *Journal of Cleaner Production*, *Information Technology and People*, and *Education and Work*. His current research interests include performance management and measurement in digital business environments and sustainable business contexts.

ILYA KURINOV received the B.S. degree in mechanical engineering from the Saimaa University of Applied Sciences and the M.S. degree in mechatronics from the Lappeenranta University of Technology. He is currently pursuing the Ph.D. degree with the Machine Design Laboratory, LUT University. His research interests include application of multibody system dynamics and machine learning algorithms in automation of mechatronic machines.

EERIK SIKANEN received the M.Sc. degree in mechanical engineering and the D.Sc. (technology) degree from LUT University, Lappeenranta, Finland, in 2014 and 2018, respectively. He is currently working as a Postdoctoral Researcher with the Laboratory of Machine Dynamics, LUT University. He is mainly concentrating on three-dimensional solid finite element modeling of high-speed machinery and systems, including contact and thermomechanical effects. His research interests include high-speed rotor dynamics analysis and general vibration dynamics of rotating machinery.

LAURI PYRHÖNEN received the B.Sc. and M.Sc. degrees in mechanical engineering from Aalto University, Finland, in 2017 and 2020, respectively. From 2019 to 2021, he was working on analysis and verification of power electronics in various positions at Danfoss Editron. He is currently working as a Junior Researcher with the Laboratory of Machine Design, LUT University, Finland. His main research interests include state and parameter estimation and multibody system dynamics.

LEA HANNOLA is currently an Associate Professor with the Department of Industrial Engineering and Management, Lappeenranta University of Technology, Finland. Her research interests include innovation management, especially product, service, technology, and systems design methods, and sociotechnical aspects in manufacturing and smart factories.

HEIKKI HANDROOS (Member, IEEE) received the D.Sc. (Tech.) degree from the Tampere University of Technology. He has been a Professor of machine automation with the Lappeenranta-Lahti University of Technology, since 1992. He has been a Visiting Professor with the University of Minnesota, Peter the Great St. Petersburg Polytechnic University, and the National Defense Academy, Japan. He has published about 250 international scientific papers and supervised around 20 D.Sc. theses. He has held several positions of trust in the American Society of Mechanical Engineers. He has led several important domestic and international research projects. His research interests include modeling, design, and control of mechatronic transmissions to robotics, and virtual engineering.

HANNU RANTANEN is currently a Professor of industrial engineering and management at the Lappeenranta University of Technology. He has published more than 100 scientific papers. His research group, The Performance Management Team has extensive knowledge and experience of performance measurement, analysis, and construction of measurement systems for a variety of purposes. His team specialize in measurement and management of multifold aspects and dimensions of performance in many contexts. His research provides in addition to scientific contribution practical tools and methods for companies and other organizations. His current research interests include performance measurement and management, both in private and public sector, for example latest survey deals with the obstacles restraining productivity improvement.

MINNA SAUNILA received the D.Sc.Tech. degree. Since 2018, she has been a Docent of the School of Business and Economics, University of Jyväskylä. She is currently an Associate Professor at the Department of Industrial Engineering and Management, School of Engineering Science, LUT University. Recently, her research projects have been related to digitization of services and production. She has previously published her works in *Technovation*, *Computers in Industry*, *Journal of Engineering and Technology Management*, and *Technology Analysis and Strategic Management*. Her research interests include performance management, innovation, service operations, and sustainable value creation.

JUSSI SOPANEN (Member, IEEE) was born in Enonkoski, Finland, in 1974. He received the M.Sc. degree in mechanical engineering and the D.Sc. (technology) degree from LUT University, Lappeenranta, Finland, in 1999 and 2004, respectively. He was a Researcher with the Department of Mechanical Engineering, LUT University, from 1999 to 2006. He was a Product Development Engineer of electric machine manufacturing with Rotatek Finland Ltd., from 2004 to 2005. From 2006 to 2012, he was a Principal Lecturer in mechanical engineering and the Research Manager of the Faculty of Technology, Saimaa University of Applied Sciences, Lappeenranta. He is currently working as a Professor with the Machine Dynamics Laboratory, LUT University. His research interests include rotor dynamics, multibody dynamics, and the mechanical design of electrical machines.

AKI MIKKOLA received the Ph.D. degree in machine design, in 1997. Since 2002, he has been working as a Professor with the Department of Mechanical Engineering, Lappeenranta University of Technology, Lappeenranta, Finland, where he is currently leading the research team of the Laboratory of Machine Design. He has been awarded five patents and has contributed to more than 90 peer-reviewed journal articles. His research interests include machine dynamics and vibration, multibody system dynamics, and biomechanics.