# A data-driven design framework for early stage PSS design exploration

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**Abstract:** Ubiquitous and pervasive computing holds great potential in the domain of Product-Service Systems to introduce a model-driven paradigm for decision support. Data-driven design is often discussed as a critical enabler for developing simulation models that comprehensively explore the PSS design space for complex systems, linking of performances to customer and provider value. Emerging from the findings of two empirical studies conducted in collaboration with multinational manufacturing companies in the business-to-business market, this paper defines a data-driven framework to support engineering teams in exploring, early in the design process, the available design space for Product-Service Systems from a value perspective. Verification activities show that the framework and modeling approach is considered to fill a gap when it comes to stimulating value discussions across functions and organizational roles, as well as to grow a clearer picture of how different disciplines contribute to the creation of value for new solutions.

**Keywords:** data-driven design, co-simulations, decision making, value-driven design, design space exploration, engineering design.

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## 1 Introduction

Engineering design is a decision-intensive activity (Ullman and D'Ambrosio 1995) which often peaks at the earliest phases of design (Baumann and Pfitzinger 2017). To reduce the risk and costs of rework in a later phase caused by sub-optimal decisions, it is important to frontload early-stage tasks with simulation models (Isaksson et al. 2013) to support the comprehensive exploration of the feasible design space (Green 2000). Paradoxically, while the results of these simulations are used to make design decisions on increasingly complex systems (Zeigler et al. 2018), the available modelling and simulation support is strongly mono-disciplinary, and software tools are poorly integrated (Fitzgerald et al. 2010). For instance, dynamic systems simulation, finite element analysis, and lifecycle analysis are often performed in isolation, even though there is an intuitive logical connection between these domains. When a system is composed of multiple subsystems (Bhise 2013), a more holistic view on the integration of simulation domains is needed, something that is referred to in the literature as co-simulation (Gomes et al. 2018; Sinha et al. 2001).

A major gap is seen today when it comes to co-simulate the ability of a design concept to deliver 'value' to customer and stakeholders during the front-end of a development project. The knowledge used to build the sequence of simulations model for concept assessment is often of speculative nature (see: Dorst 2006; Mocko et al. 2004). This hinders the ability to assess if a given concept will raise customer satisfaction and, in turn, revenues and provider's profitability. Intuition, instinct, gut feelings and personal experience have been observed to be primary means to link micro-level decisions (e.g., on material properties) to macro-level phenomena (e.g., customer satisfaction) (Ericson et al. 2007).

Digitalization and the Internet of Things are often discussed as game changers when dealing with the construction of relevant and reliable models for early stage design decision making (Kim et al. 2017). The opportunity to gather and analyse a large amount of data from existing solutions is seen as a major enabler in the process of identifying trends - and hence functions - to improve the trustworthiness of early simulation models (King et al. 2017; Provost and Fawcett 2013; Yu and Zhu 2016). This opportunity is often captured by the umbrella term 'data-driven design' (e.g., Labrinidis and Jagadish 2012). Several authors (e.g., Yu and Zhu 2016) have discussed how data-driven design might close the knowledge gap between how the product is realized and how this will satisfy the final users. Data-driven frameworks (Afrin et al. 2018; Tuchsen 2018) have been further proposed to support this co-simulation exercise. Existing literature shows examples of how data-driven approaches have been adopted for predicting the product performances (Zhang 2017; Zheng 2018) and to explore the available design space (Bogers et al. 2016) during concept design. An issue common to most of the proposed frameworks is their poor generalizability outside their proposed domain and/or industrial sectors. At the same time, these frameworks are often limited to the evaluation of only alternative product configurations from a performance perspective and do not support the assessment of the 'ilities' as a system (e.g., adaptability, changeability, sustainability), alternative business models in terms of different Product-Service Systems (PSS) types (Baines et al. 2007), and circular economy considerations.

The purpose of this research work is to support engineering designers in exploiting a data-driven design paradigm for early stage design. The objective of the paper is then to propose a framework that guides the design team in the development of a chain of simulations models – and related data sources - capable of exploring design space comprehensively - in terms of performances, behaviour, and generated value along the system lifecycle. The driving research question for the work can then be described as:

*How can a data-driven approach support the design exploration process for PSS concepts in early design?*

The concept of 'value' is central to the research question and to the development of the proposed data-driven framework. This is because the recent "servitization" (Vandermerwe and Rada 1988) and "service transformation" (Cavalieri et al. 2017) trends have highlighted how manufacturing companies are transforming their business nature, from being owners of competencies and resources to become integrators of a set of skills, resources, and technologies able to realize complex value creation processes. Rather than focusing on technical improvements and cost reduction, the manufacturers of products and systems are increasingly promoting the selling of the utility and performance associated with its use.

In the following sections, the paper describes how the proposed data-driven framework has been conceptualized from the analysis of the literature review and from the analysis of the empirical data. Section 2 presents the research methodology and describes how empirical data have been collected and analysed. Section 3 investigates the literature review conducted to build a theoretical background to support the proposed framework. Section 4 describes the proposed data-driven framework for design assessment and exploration. Section 5 discusses the findings from the study, while the conclusions and future work are presented in Section 6.

## 2 Methodology

The overall research effort is framed according to the Design Research Methodology (DRM) framework (Blessing and Chakrabarti 2009). DRM consists of four stages: Research Clarification (RC), Descriptive Study I (DS-I), Prescriptive Study (PS) and Descriptive Study II (DS-II). Hence, the work presented in this paper covers a review-based RC, a comprehensive DS-I and PS, and an initial DS-II. The application of DRM in this research is justified both by the complexity of the data-driven design phenomenon, and by the aim to improve (and do not merely understand) design practices. DRM is thought to be suitable when the objective is that of developing support rather than mainly explain or predict a phenomenon. The paper does not merely focus on modelling a theory of an existing situation but wants also to propose a vision of the desired situation, as well as of the support (the proposed data-driven framework) that is likely to change the existing into the desired situation and maintain this.

The Research clarification (RC) stage has benefitted from the analysis of current literature in the domain of data-driven design and PSS, as well as from the interaction with industry practitioners, process owners and experts from a range of different manufacturing sectors (from aerospace and mining to road construction and automotive).

Empirical data in DS-I have been obtained from the analysis of two case studies (Yin 2013) conducted in collaboration with multinational manufacturing companies active in the business-to-business market. Company A is a multinational food packaging and processing company based in Sweden. The company that offers packaging, filling machines and processing for dairy, beverages, cheese, ice-cream and prepared food, including distribution tools. Company B is a multinational engineering manufacturer of mobile compactors for road surfaces, also based in Sweden.

Data collection activities featured semi-structured interviews (both individual and paired interviews), regular multi-day physical co-creation workshops and the analysis of company documents. Following the guidelines for qualitative research proposed by Miles et al. (2013), interviews activities covered a variety of roles, both at managerial and engineering level, to generate knowledge from both the ‘meatiest’ cases and the ‘peripheries’. Each of the 12 interviews conducted in the 2 cases lasted for about 50 minutes. Respondents were located mainly using a snowballing technique (Warren 2002). Once the initial respondent (fulfilling the theoretical criteria) was identified, he/she helped to locate others through his/her social network. During the interviews and the workshops, the authors compiled visual representations and demonstrators of the emerging modeling concepts for data-driven design. These were used mainly as discussion triggers to identify critical topics for the development of the proposed framework. These findings were iteratively verified with the industrial practitioners in co-located research workshops and through the participation in regular debriefing activities within the research project.

## 3 Literature review: towards data-driven PSS design

A wave of change fostered by the so-called Fourth Industrial Revolution or Industry 4.0 is sweeping the manufacturing industry in recent years. The introduction of the Internet of Things has led to vertically and horizontally integrated production systems (Thoben et al. 2017). The shift from 'traditional production methods' to 'intelligent manufacturing' (Zhong et al. 2017) has been enabled by the combination of cheap and ubiquitous sensors high computational speeds, and advancements in artificial intelligence applications.

The opportunity to exploit real-world data to improve product design, reliability and quality lies at the core of the notion of 'data-driven design'. What makes the latter to stand-out from classical performance-based analysis is the opportunity to seamlessly connect the IoT (and its massive dataset) with the design environment, so to ensure that the next generation of products, services and systems meets customers' needs even better than today's generation. Noticeably, rather than making assumptions about how a product concept will perform when operated, maintained, dismissed or recycle, the design team can extract relevant knowledge for decision making by leveraging existing data from the field. Imagine a manufacturer that monitors usage of a fleet of products operating in different markets, geographical areas or customer groups. By gathering field data, the team might come to the realization that a particular sub-system (or component) is over-engineered and unnecessary. In turn, this may lead to products that are unnecessarily costly, while still being unable to add value to customer and users. The team can use this information to modify the original design - e.g. by simplifying its architecture or installing cheaper components - reducing production costs so to reduce selling price or improve margins.

### 3.1 Towards model-based value analysis

A model-driven paradigm to support the early stages of the design of complex systems has been exercised for many years. Today, it is possible to build physical or behavioural models for almost any system/subsystem across any relevant stage of their life cycle. For instance, models produced in MATLAB, Simulink, Ansys, LS-Dyna provide engineers with quantitative data on the performances of the systems for different internal and external inputs. Through these simulations, it is possible to evaluate design alternatives to find better solutions and support design for robustness, reliability, and safety.

Model-Based System Engineering (MBSE) is a common approach in the domain of Systems Engineering (SE) to exploit domain models as the primary means of information exchange between engineers (Alemanni et al. 2011; Gausemeier et al. 2013). As described by Zeigler et al. (2018) MBSE calls for formalized models to replace documents as the fundamental building blocks of (SE). In practice, MBSE promotes the use of a 'central model' to serve as a means of coordinating system design (Cameron and Adsit 2018). This model facilitates all the activities related to requirements definition, analysis, verification and validation of a complex system since the conceptual design, throughout development, and until the later phases of its lifecycle.

Nowadays MBSE is considered a critical and indispensable capability to develop complex system requirements in a systematic manner and to enable different teams to work in a collaborative way (Madni and Purohit 2019). Yet, recent work (e.g., Cameron and Adsit 2018). has highlighted several practical challenges related to the introduction of MBSE in the organization, a major one being the MBSE inability to support a “full-system lifecycle” view (see: Madni and Sievers 2018). More specifically, literature in the domain of Systems Engineering has stressed the importance of assessing, early on, the expected value of a complex system design concepts (Collopy and Hollingsworth 2011). This means extending modelling and simulation capabilities behind traditional performances, so as to measure the ability of a system to provide value to customers and stakeholders. Collopy (2009) is among the firsts to spotlight the opportunity of developing so-called ‘value models’ to capture the long term consequence of design from a value perspective

Yet, in spite of many conceptual frameworks being proposed for Value-Driven Design (VDD) (Lee and Paredis 2014; Isaksson et al. 2015; Bertoni et al. 2017), the uptake of value modelling methodologies is still limited due to the intrinsic difficulties of capturing and measuring all the relevant aspects of value for customers - subjective and objective (Weiss 2013) – since an early design phase.

Gorissen et al. (2014) and Bertoni et al. (2015) recognize that decision-makers need enough information and data to properly understand the design “trade-off” assessment using a value model. The opportunity of exploiting data from the usage and operational stage related to the interaction between humans and the system (hardware, software, and service) holds great potential to cope with the current limitations of VDD. At the same time, VDD approaches shall make better use of data obtained from the early simulation on the design concept and use them to populate a value model to understand trade-off capabilities, performance, cost and life for a complex product. Current activities in the VDD research stream (e.g., Isaksson et al. 2015; Bertoni et al. 2017) are exploring the opportunity to apply value model in a data-rich situation, arguing that by applying a data-driven approach for value assessment it will be possible to increase the reliability and fidelity of the value model at all design levels.

As the complexity of design increases, due to the need for considering an increased number of subsystems and components in the design of product-service solutions, so the complexity of the modelling activity increases proportionally. In order to manage this increasing complexity, design decision support – in the form of ad-hoc frameworks – are needed to guide the design team in exploiting data to assess the value of a design. Yet, data-driven approaches for value analysis are in their infancy and lack of a systematic way to structure the value modelling exercise by exploiting the available data.

### 3.2 Data-driven design

Data-driven approaches feature a long history in the domain of engineering design. Their main goals can be described as ‘predictive’, which is to forecast the value of a given variable, and ‘descriptive’, having the objective to understand and discover patterns in the available data (Anand and Büchner 1998). Tsent and Hiao (1997) are often indicated to be the first to propose the use of data mining for the recognition of functional requirements patterns in design. Since then, the application of data-driven models in design has captured increased attention in recent years, mainly with regards to the opportunity of improving the design synthesis stage and the ability to understand customer needs and expectations (see: Bertoni 2018).

Vale and Shea (2003) are among the first to define a modification-based design framework where design solutions develop through the successive application of modification operators to the existing design. Machine learning is used to support synthesis by guiding the solution search process using past experience that is self-learned by on-going observation. In this approach data are accumulated through observations and machine learning is applied to learn relevant relationships between the design objectives, constraints and modification operators. Song and Kusiak (2009) describes the application of data mining algorithms to historical sales data, extracting knowledge from that data, and using it to manage product diversity. In this work, the knowledge (rules) extracted from the historical purchase data was used to infer customers' future buying patterns, thus allowing producers to meet customer requirements and to manage efficiently the enterprise's resources. Later, Wickel and Lindemann (2015) propose a data-driven approach to help companies in improving their decisions in engineering change processes by discovering new patterns and structures through the use of machine learning algorithms. Nie et al. (2018) lately describe the combined use of MATLAB and Simpack, as well as of surrogate modelling, to support the design of railway vehicles under the data-driven paradigm.

Digital technologies have long been described as critical enables to help companies in the journey towards service-based business (Neu and Brown 2008). Ubiquitous and pervasive computing holds great potential in the domain of Product-Service Systems (PSS) to introduce a model-driven paradigm for decision support. For instance, the ability to record a large quantity of data about hardware use, service performances, and human-product interactions is believed to dramatically enhance decision making at different levels of the enterprise (strategical, tactical and operational) and along the entire lifecycle of the PSS (see: Bertoni 2018). Geng et al. (2012) illustrate an interesting example of the application of data-driven approaches in the domain of Product-Service Systems. In their work, they propose an apriori-based association rule mining algorithm for aiding PSS conceptual design. In their work, the authors describe how parameter translating rules are extracted from historical PSS design data, providing the designers with sufficient knowledge to aid analysing parameter translation between two adjacent domains and to decrease the subjectivity and complexity of the decision-making process. Another example of the application of a data-driven paradigm in PSS is provided by Lützenberger et al. (2016). The authors provide a methodology and an example of how information gathered from sensors embedded in consumer products (in this case, a washing machine) can be used to retrieve improved design requirements for next-generation PSS hardware. Based on the sensor data from the washing machine and the user feedback, the authors exemplify both how the product can be adapted to consumer needs and also services can be created/supported. Additional contributions have focused at a more operational level to propose mining techniques suitable for product development tasks. Woon et al. (2003), for instance, propose the use of the so-called Product Development Miner (PDMiner) to mine weblogs efficiently and effectively and, in this way, design faster products by discovering the relationships among parts and assemblies. An interesting recent contribution given the objective of this paper is the Predictive Life Cycle Design (PLCD) design framework proposed by Ma and Kim (2016). PLCD enables engineering designers to optimize a product design - adjusting product attributes, the selling prices and production quantities of new and reman product – by considering the current and future demand for a product through data trend mining. The framework enables the engineering team to eventually identify the product design that is expected to maximize the total profit over the entire product life cycle.

## 4 Developing a data-driven framework for PSS design

The results from the literature review and empirical study have brought to the definition of a data-driven framework to support engineering teams in exploring - early in the design process - the available design space for PSS from a value perspective. Figure 1 provides an overarching view of the and illustrates the sequence of simulation activities - and the associated flow of data – needed to be performed to support value assessment activities along the concept design stage.

The framework is composed of 6 main layers, corresponding to the main outcomes of the associated simulation models. These have been defined to highlight, on the one end, the generic product lifecycle phases (See: www.capgemini.org). On the other end, the definition of the layers has been inspired by the main layers point circular economy system strategies described by (MacArthur 2013). Data are gathered at each layer to support the definition of relevant simulation models able to represent the contribution of each design from a value perspective. Several sources have been identified and mapped in the framework with regards to the main data items to be considered in the value modelling activity. These primarily include sensor data collected from production processes and during the usage phase of existing hardware. Information stored in internal and external databases, e.g., originating from manual reports and other activities, is also included in the framework as a secondary data source. Eventually, the outcomes from previous modelling activities (e.g., the results of CAx models and more) provides further information to define and populate the chain of simulation models at each step.

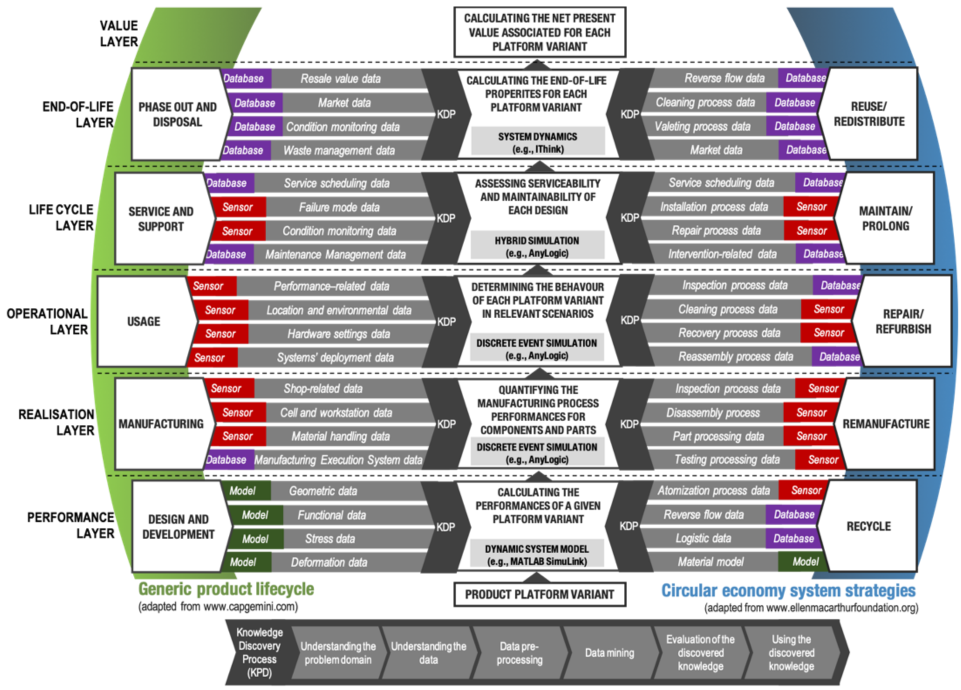


**Figure 1: The generic data-driven design framework for early stage PSS design exploration.**

The Knowledge Discovery Process (KDP) featured in the framework is adapted from the work of Kulin et al. (2016) and describes all the necessary steps to transform data into knowledge when dealing with new knowledge in large datasets. Initially, the design team must state the specific piece of knowledge needed to populate the simulation model at each layer. This statement must then be explicitly formulated as a data science problem, describing how the collected data can be used to define the input to the simulation model. As explain by Kulin et al. (2016), data must then be collected - according to the definition stated – and explored so to validate both the dataset and the formulation of the data science problem from the previous step. In the pre-processing phase, the raw data must be transformed into a format suitable for feeding into machine learning algorithms. This phase foresees four main sub-steps: data cleaning, data integration, data transformation, and data reduction. The goal of the Data Mining phase that follows is that of training the algorithms to solve the knowledge discovery problem that was identified and formulated in step 1. The performance of previously trained data algorithms must be then evaluated so to select the best performing model. Eventually, the functions, expressions and other outputs from the KDP process are turned into relevant inputs for the simulation models at each layer.

### 4.1 Performance layer

Previous research in the domain of complex system design (e.g., Isaksson et al. 2013) has shown that new products, sub-systems, and components are seldom radically new designs, but rather incremental improvements of a given product platform. Evans et al. (2007) further highlight how a platform strategy can be a significant enabler to create high-performing PSS, thanks to the opportunity of customizing and contextualizing system-level solutions to fit many sets of different needs. As also pinpointed by Evans et al. (2007) a platform-based approach allows derivative products to be developed with more variety, shorter schedules, and lower costs. The data collected from the empirical investigation support these considerations, further revealing that the necessity to comply with a number of requirements – e.g., manufacturing commonality, logistics and supply chain management – considerably limit the design team's freedom to develop radical solutions. Hence, early in the design process, the assessment of a PSS hardware kicks-off from the identification and further development of such a platform. From this, a number of platforms ‘variants’ (i.e., design configurations) are tested for ‘suitability’ for the targeted PSS business models. A product platform during early design is typically described by a functional diagram and by a fully parametric CAD model, which also contains rules for the automatic generation of alternative topological variants of given platform design. Multiple configurations are generated through a Design-of-Experiment (DoE) routine (Bertoni et al. 2018), and each of them features its own physical and engineering characteristics, which may change during the design process until a final concept is chosen (Logan and Smithers 1993).

The Performance layer represents the first step in the value analysis. The objective is to calculate the specific performances (e.g., acceleration, speed and fuel consumption for a vehicle) associated with a give platform variant. This information is, in turn, exploited at the Operational, Life Cycle and End-of-Life layer of the framework, in order to assess the expected behaviour of the machine and its contribution to the creation of value for both customers and other stakeholders. To estimate performances at this layer, a Dynamic System (DS) simulation is developed in the MATLAB environment. The differential or algebraic equations underlying the DS simulation are defined in a way so that the main engineering characteristics of each platform variant can be treated as a variable. Several functional attributes needed to define the equations in the MATLAB environment are derived from the CAD description, such as the mass of a sub-system or component, its geometrical features and more. These equations may further contain constant factors, coefficients, and other constraints, which are typically extracted from the company database or from the existing product in use. The simulation model further interacts with other software (CAE, FEM, numerical computing platform etcetera) (referred to as clients) that run specific models needed to assess different aspects of the studied concept.

### 4.2 Realization layer

The main purpose of the Realisation layer is to raise awareness among design decision-makers about the lead time, energy cost, equipment investment and other factors associated with the production of a given platform variant. A Discrete Event Simulation (DES) model is deployed to quantify the ability of a design to meet the production goal, as well as to spotlight unforeseen bottlenecks and production issues. The simulation model takes as input geometrical data from CAD, such as for example, the number of components in a system (affecting manufacturing and assembly cost), estimated mass (affecting logistics in the manufacturing operations), component size and more. Sensor data are gathered at the shop floor, cell and workstation level to feed the simulation model with relevant functions to simulate the behaviour of the machine in operation. The Manufacturing Execution Systems (MES) provides further information related to the throughput of the production process and to its planning that is used to guide the value modelling activity. This layer further incorporates a simulation model that accounts for the opportunity to bring end-of-life products back to good-as-new. Remanufacturing refers to the industrial process whereby used products referred to as ‘cores’ are restored. Sensor data from the restoration facilities can be collected and analysed to provide an assessment of how the product would fit a circular strategy based on the remanufacturing model.

### 4.3 Operational layer

The Performance layer renders geometrical-, physical- and performance-related data that can be exploited in the simulation environment to assess the behaviour of a design concept in the usage phase. The ability to quantify the value creation opportunity for customers and users is of behemoth importance for guiding early stage design decisions towards value optimization. The Operational layer foresees the creation of several usage simulation models, that are iteratively refined during the development process. These models take a more ‘system-level’ view compared with those deployed in the previous step and consider the interaction of the proposed hardware with both humans and other machines. These models consider evolving contextual conditions in the scenario and evaluate the performances of a given hardware-service package in a given timeframe. The simulation model is also designed and configured to estimate the impact of refurbishing operations on the overall usage process highlighting the changes in performances triggered by the opportunity of updating the system components.

The framework shown in Figure 1 proposes the use of a Discrete Event Simulation Environment (DES) approach to quantify the usage-related performances of a design. The main reason to approach scenario simulation with DES is that it considers the stochastic nature of the usage scenario parameters, providing realistic predictions of how the PSS hardware will operate. Also, since the simulation verifies a limited number of moments during the simulation time, the run results are compressed and more efficient. Previous research (e.g., Bertoni et al. 2016) has also shown that DES models are preferred 'boundary objects' for the design team, mainly because they are intuitive to understand across the organizational roles and functions, facilitating negotiations and knowledge sharing across individual and disciplines., This has shown to have with beneficial effects for decision-making during the early stages of the design process.

Sensors data are collected and analysed from the usage process to support the definition of the general layout, the relationships between objects/entities and the functions in the DES model. These include all relevant performances-related data for the hardware in operation, including its geographical location and other environmental data influencing the use of the hardware in given scenarios. Hardware settings data and information about which systems are deployed at any given time are also important information to be collected so to define relevant functions for the simulation model. A module at this layer further accounts for the feasibility and associated benefit/cost of repairing or refurbishing the hardware to its desired level of performance. While process-related data – e.g., related to cleaning and recovering operations – may be gathered from sensors, other relevant inputs, such as information about the inspection and reassembly process are typically recorded by the service technician and stored in a database.

### 4.4 Life cycle and End-of-life layer

Research (e.g., Fadeyi et al. 2017) shows that PSS are characterized by heavy product usage, which requires higher product serviceability. Customers expect service procedures to be carried out with the absolute minimum disruption of product use. Serviceability and maintainability must then be built into the hardware already during the earliest phases of design, configuring the product platform variant in such a way to ease service provision.

Simulation activities at this layer aim at quantifying the costs and efforts needed to ensure the proper availability of the PSS hardware throughout its entire lifecycle. As shown by Sassanelli et al. (2016) the serviceability efficiency of the design is typically determined considering each disassembly operation and item removal. This focus on 'disassembly operations' justifies the adoption of a DES approach – which can be possible scaled-up to exploit hybrid model capabilities - to evaluate different maintenance strategies, by incorporating all the maintenance operational settings such as asset location, spare part levels, labour availability, travel time to asset, etc. in the simulation model. The use of DES is further justified from previous research focusing on the application of simulation in maintenance research (see: Alrabghi and Tiwari 2015).

Sensor data capturing the conditions of the hardware in operation (e.g., vibration, temperature and more for a vehicle) are considered critical in the proposed framework to identify those changes that indicate the development of a fault. Additional data are gathered and analysed to determine functions that can predict failure modes. Service scheduling data, as well as data from the Computerized Maintenance Management Information System (CMMIS), are an additional source of information to populate the simulation model at this layer. Noticeably, the model further assesses the feasibility and the economic viability of maintaining and prolonging the life of the hardware. Information about the speed and quality of repair is fed into the model to inform decision-makers about the extent to which a proposed platform variant can be serviced and maintain along its lifecycle.

Historical data stored in internal and external databases can be mined and analysed to obtain important information about the performances of a given design during the phase-out and disposal phase. One important aspect in this respect is the opportunity to assess the resale value of hardware by extracting relevant functions that describe how different components (and their status) influence prices and purchaser decisions in the second-hand market (Chowdhery and Bertoni 2018). Condition monitoring data, as well as other data from the targeted markets, are of interest to define the structure and the expressions governing the simulation model at this step. The simulation model at the end-of-life layer requires further information about the key performance indicators of the reverse logistics chain, as well as data from cleaning/valeting processes.

### 4.5 Value layer

The simulation results obtained at the different layers are eventually used to populate a Net Present Value (NPV) – or, alternatively, a Surplus Value (SV) - function at the Value layer. NPV and SV are monetary models that calculate the long-term profitability of a design concept, in a similar fashion to what proposed in the Value-Driven Design literature for the evaluation of complex systems (Soban et al. 2012; Cheung et al. 2012; Monceaux et al. 2014). The function compares cash inflows and outflows over a period of time considered relevant by the design team. The definition of the cost items follows the model for the Total Cost of Ownership proposed by the PROTEUS Tool book (Finken et al. 2013). From here, cost areas are shortlisted, distinguishing between items considered to be priorities, negligible or not assessable when developing the cost engineering approach. Importantly, separate value models are developed to account for alternative PSS business model types. In doing so, revenue data are calculated by considering, for instance, the effective utilization of the PSS hardware, its availability in the different PSS types, its flexibility in operation and more. The NPV model results are used then to identify the most valuable combination of features for the hardware given alternative business models.

## 5 Discussion

The research presented in this paper foresees several iterations loops where the qualitative researcher moves back and forth between design and implementation to ensure congruence among question formulation, literature, recruitment, data collection strategies, and analysis. The proposed data-driven framework shall be considered the outcome of such initial iterations and a first step towards the elaboration of a more comprehensive guidelines to support the design exploration activity for Product-Service Systems using models. The main benefit of this ‘frontloading’ exercise is to raise awareness among decision-makers of the long-term consequences of their design decisions in alternative business scenarios.

Verification activities have foreseen the involvement of industrial practitioners, academic experts, and other stakeholders, and has been conducted through the development of increasingly complex demonstrators to progressively validate the emerging modelling concepts. Debriefing activities with the partner company in the project indicate that the application of the proposed model-based approach may leverage communication among the different disciplinary teams involved in the early stages of PSS design. By combining models – and using data to raise their reliability and maturity – each individual in the design team may grow a clearer picture of how different disciplines (from engineering to management) contribute to the creation of value for new sol. The opportunity to link engineering characteristics and ‘performances’ to value are considered a critical capability by practitioners. They recognize that in the fuzzy front-end, design decision-makers also lack the ability to communicate why their work is ‘good’, and, hence, to deliberate about the most value-adding design. The application of the proposed framework and modelling approach is considered to fill a gap when it comes to stimulating value discussions across functions and organizational roles. Importantly, the ability to leverage the value negotiation early in the design process is considered critical to keeping the focus on the underlying business case when developing products and ‘hardware’, which is to justify why a proposed technology, material or design is ‘good’ in the light of the targeted PSS type.

## 6 Conclusions

The selection of PSS design concepts is an iterative process, which requires systematic support that is able to adapt to the pool of information and knowledge available during decision events. The data-driven framework presented in this paper shall be considered a step forward toward a larger research effort whose purpose is to create a data-driven platform for value-based decisions in PSS conceptual design. This contribution illustrates the initial finding from this iterative research process, pinpointing the model chain, techniques and data sources that need to be introduced in the PSS design process to assess the value of solution concepts already in an early phase. Noticeably, the proposed framework is generic enough to be applied across industrial sectors and PSS types, and it is meant to provide a reference upon which to further investigate the benefits of simulation models in data-intensive environment for early stage decision making, to ultimately push forward the state of the art and the state of the practice of data-driven design.

The overall purpose of this work is to use data-driven models to capture and represent ‘value’ aspects and link these to the engineering design process. Future research will focus on the further development of the proposed framework by gathering and collecting empirical evidence from a broader range of industries and case studies. Enlarging the number of cases will allow to further build a theory on the topic of data-driven design, identifying key variables, describing their linkages and why relationships exist.

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