Forschung im Ingenieurwesen (2023) 87:1347–1370
https://doi.org/10.1007/s10010-023-00711-5

ÜBERSICHTSARBEITEN/REVIEW ARTICLES

Parameter assessment for reliability modeling of machine components using heuristic screening

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Received: 30 August 2022 / Accepted: 18 August 2023 / Published online: 25 September 2023

Abstract

For the investigation of influence of various parameters on properties and outputs of components or systems, Design of Experiments (DOE) offers the most efficient approach to create a comprehensive empirical insight into product performance. However, especially if product lifetime is treated as the investigation objective, the main focus of attention must be placed on the efficiency of testing—if only to comply with the principle of DOE, even before testing begins. Without actual test runs, a pre-selection of relevant factors influencing the target quantity can be performed here and strategically adjusted in scale compared to the subsequent method. In this work, common heuristic tools and methods are analyzed and evaluated with respect to a deliberate preselection of influencing factors versus the challenges in lifetime testing and degradation behaviors. Several factors as well as their interactions are taken into account to achieve this. For this purpose, these methods are partially extended and adapted in their focus in order to finally be made applicable in a suitable procedure. An illustration of this is also provided in a selected use case with limited empirical and experimental prior-knowledge, in which a sample of relevant influences is identified through qualitative heuristic decision making with respect to parameters that influence product lifetime.

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Gezielte Bestimmung relevanter Einflussparameter für die Zuverlässigkeitsmodellierung von Maschinenkomponenten durch heuristisches Screening

Zusammenfassung

Für die Untersuchung des Einflusses verschiedener Parameter auf die Charakteristik und Leistung von Komponenten oder Systemen bietet die statistische Versuchsplanung (Design of Experiments, DOE) den effizientesten Ansatz, um einen umfassenden empirischen Einblick in die Produkt-Performance zu erhalten. Insbesondere dann, wenn die Lebensdauer eines Produkts als Untersuchungsgröße definiert wird, muss das Hauptaugenmerk auf die Effizienz der Tests gelegt werden – was gemäß den Prinzipien von DOE jedoch bereits schon vor der experimentellen Phase selbst gilt. Dazu kann zugleich eine Vorauswahl relevanter Einflussfaktoren (Screening) auf die Zielgröße ohne tatsächlich ausgeführte Tests erfolgen und bezüglich deren Umfang strategisch für die experimentelle Phase angepasst werden. In dieser Arbeit werden gängige heuristische Werkzeuge und Methoden im Hinblick auf eine gezielte Vorauswahl von Einflussfaktoren gegenüber den Herausforderungen bei Lebensdauer-Erprobung und Degradationsverhalten analysiert und bewertet. Dabei werden mehrere Faktoren sowie deren Wechselwirkungen berücksichtigt. Bestehende Methoden werden darin teilweise erweitert und in ihrer Anwendung angepasst, um schließlich in einem geeigneten methodischen Ablauf eingegliedert zu werden. Zuletzt wird der vorgeschlagene methodische Ablauf an einem ausgewählten Anwendungsbeispiel mit begrenztem empirischem und experimentellem Vorwissen veranschaulicht. Es wird gezeigt, dass mittels qualitativer heuristischer Entscheidungsfindung so eine kennzeichnende Vorauswahl relevanter Einflussparameter auf die Lebensdauer für die Versuchsphase identifiziert werden kann.

Abbreviations

BG	Best-Guess Approach
CAD	Computer-Aided Design
CBA	Cost-Benefit Analysis
DOE	Design of Experiments
DM	Decision-Making
DSM	Design-Structure-Matrix
EOL	End-of-Life
FBD	Function Block Diagram
FEA	Finite-Element-Analysis
FMEA	Failure Mode and Effects Analysis
FSD	Functional Specification Document
FTA	Fault-Tree-Analysis
L-DOE	Lifetime-DOE
M7	Seven Management Tools in QM
MCDM	Multiple-Criteria Decision-Making
OFAT	One-Factor-At-A-Time Approach
Q7	Seven Quality Tools
QM	Quality Management
RS	Requirement Specification

1 Introduction

The comprehensive understanding of a full set of parameters that defines the essence and behavior of a system or process while it is in or out of operation, as well as the knowledge of parameter impacts on measured quantities are powerful advantages for efficient design and quality engineering. This allows products to be engineered to an optimal design for their future load—without causing oversizing or unexpected failure issues in use. Test-engineers ideally utilize established tools here: the selection of suitable experimental designs for the investigation of the full-set of parameters and the consideration of test-power to identify and evaluate correlations within the set variables. This applies in particular to the service life and reliability as key characteristics of a product. Observing systems or processes, hereafter equally summarized under the term *System*, during their operation is thus an important part in the learning process to understand the respective system performance. It is precisely the lack of this understanding that can lead to undesirable warranty costs or high design costs. However, to further understand the exact cause-effect relationships of a system, a deliberate and experimental modification of the influencing variables to the system and an observation of the resulting effects on target properties such as lifetime must be performed, compare [1].

Corresponding to Fig. 1, the relationships among influencing variables, disturbance variables, and target variables through the input and output of a system are shown in a schematic representation of a system under investigation, the P-diagram [2]. With regard to a methodical investigation of the system performance with this blackbox approach, a distinction is made between controllable and uncontrollable inputs for influencing and disturbing variables. For testing, adjustable and controllable inputs are collected under the term *Factors*, where these correspond, e.g. to controllable variables such as frequencies, temperatures or forces. On the other hand, all those influencing parameters, some of which would be adjusted under laboratory conditions but are not actively controlled in their entirety, add up to *Co-factors*. For instance, these can be disturbance variables from the environment, the wear of a test

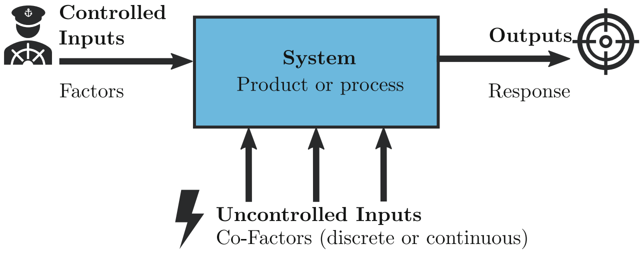

Fig. 1 Parameter diagram (P-Diagram): schematic representation of a system or a process under investigation regarding its inputs and outputs

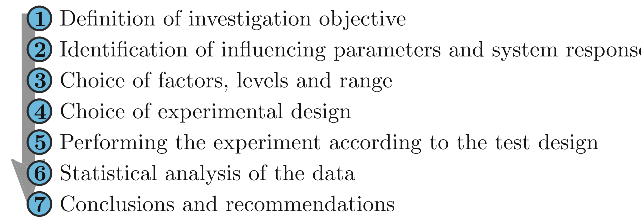

Fig. 2 DOE steps, adapted from [1, 5]

bench or measurement errors. Ultimately, the system *Response* serves as the observable output, which is a measurable quantity that ideally changes negligibly or with statistically significant effects depending on factor modifications. Exemplary, these are the service lifetime, the wear behavior, the strength of a product or the capability of a process [1, 3, 4].

The choice of input factors for an observation of the system response is usually made within a careful selection of test runs during experimentation. Here, it is necessary to clarify how influential the input factors are and to what extent their combination balance affects the robustness of the output towards a nominal target value or even against simultaneous variations of co-factors. For each test run and the examination of several factors, first a specific combination of factor *Levels* is set and then examined through the systems response.

Design of Experiments (DOE) [1, 6, 7] offer cardinal benefits in the study of such system responses as a function of multiple factors. Within this methodology, a *Factorial* experimental design may be carried out in which the factor levels are changed together over various test runs. For each combination of variations, the system response is therefore observed and the effects are evaluated with respect to the factor levels and, primarily, to their interactions. However, in the process it may happen that the effort increases immeasurably despite the most efficient DOE, if it is not clear beforehand how the parameter set and the system are to be meaningfully delimited. It is also in the nature of things that this effort multiplies in time within testing lifetime. More specifically, when the number of factors is too high, the full factorial design is even no longer feasible. In addition, there is another very decisive challenge: even if only a few factors are deliberately selected with regard to testing for service life, it is often unclear what interactions they exhibit during the test period that possibly influence the test sequence unknowingly. This requires clarity in advance.

In order to create a reasonable amount of factors for factorial experimentation, a system description with the gathering of all influencing parameters as well as their analysis towards an investigation objective (the system response) must be performed first. Subsequently, an assortment and structuring of these parameters with respect to the system response has to be carried out, compare *Step 1–3* in Fig. 2. The result, a run-down number of parameters towards the most system-relevant factors, is integrated in a suitable selection for an experimental design afterwards. Using these findings, the system response is analyzed and appropriate conclusions are formulated within the last *Step 7* according to Fig. 2 within the DOE procedure.

Accordingly, the described *Steps 2–3* are to be understood as preliminary work for an efficient test design within the context of DOE. Methodically, they can be summarized under the term *Screening*. Concluding from that, screening methods and designs serve to minimize the loss of information with as few runs as possible. For the application of a highly efficient DOE under time and cost sensitive aspects, it is therefore equally of utmost interest to design the screening strategy in the most efficient way *as well*. This includes the application of heuristic screening methods, as exemplary summarized by [8]. Heuristic screening approaches are based on a system analysis with or without specific prior system knowledge. Therefore, it might not be possible to access results and findings from experiments that could have been explicitly designed for the research objective. Heuristic screening steps are located between the definition of the investigation objective and performing of (screening) experiments, compare Fig. 3. As a rational and plausibilizing technique for decision making, heuristic methods can thus replace the experimental description of complex system interrelationships—or at least reduce the effort of the latter [8, 9].

1.1 The power of heuristic screening

Summarizing the above, not all heuristic screening approaches are equally suitable when it comes to establishing a holistic understanding of a system with associated failure mechanisms, lifetime and reliability. Rated against the state of science, common heuristic tools need particularly to be considered from a reliability engineering perspective and not be constrained to parameter optimization or robustness

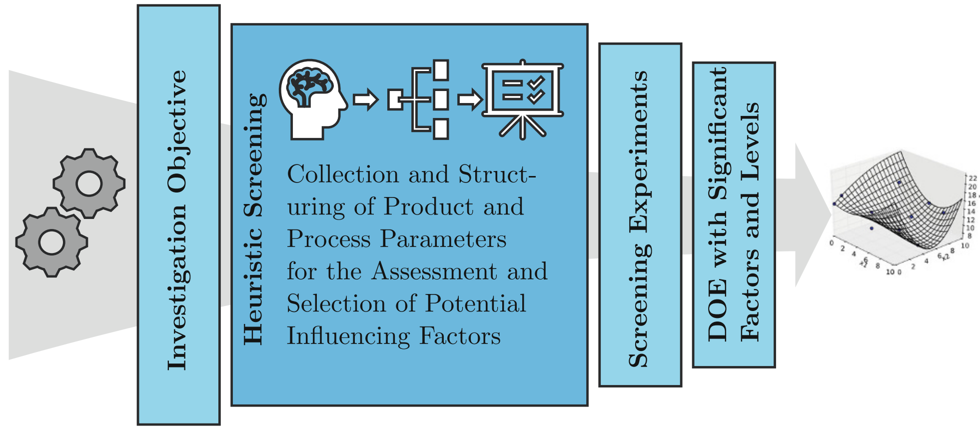

Fig. 3 Heuristic Screening Procedure in the Context of DOE

at a specific *initial* time frame. In this respect, the concept of reliability must be understood more sophisticated. According to *Bertsche* [4], the following definition applies:

> "Reliability is the probability that a product does not fail under given functional and environmental conditions *during a defined period of time*."

Thus, two main circumstances represent a demand to extend the common approaches to factor assessment and screening for reliability and lifetime as investigation objectives. On the one hand, *Kremer's* [12] extension for the factorial experimentation for model building through Lifetime-DOE (L-DOE) has proposed a method to model reliability based on a set of several lifetime-influencing factors. This addresses challenges in processing *Weibull*-distributed data within DOE. On the other hand, evolved procedures for heuristic screening instead do not explicitly target the handling of lifetime-influencing factors and their time-dependent interactions to process them into statistically based lifetime-model building [3, 8, 9, 13]. To illustrate the latter, Fig. 4 should be taken into account. The conventional methodical approach of using tools for heuristic screening usually considers the influence of factors on the initial distribution of functional characteristics, also called the (system) performance $y(t)$ (cf. Fig. 4 *A*) [2, 11]. This process is usually subsumed under the terms of

- functionality testing and
- robustness optimization.

However, especially from the perspective of reliability engineering and test planning, this consideration might directly mislead, as the performance characteristic to the state of degradation y_1 is influenced by another, differing set of influencing factors and particularly its interactions within at a later point in lifetime $t = [t_1, t_2, ..., t_n]$ (cf. Fig. 4 *B*). In addition, it may happen that this differing set of influences containing interactions also provokes other damage- and failure mechanisms, which in case of doubt cannot be compared to conclusions from the initial distribution of performance when making a reliability statement, compare Fig. 5. Thus, while an identified parameter set may be described and a failure mechanism is observed, in experiments it may technically not correspond to the expected failure mechanism *A* as shown in Fig. 5a and this may exclusively result from a supposedly omitted influence by a factor or its interaction over the lifetime. Otherwise, it remains to consider the case that in real observations even two different failure mechanisms *A* and *B* result, but the existing initial distribution of the performance $y(t)$ is one and the same—independent of which parameter set is considered, cf. Fig. 5b. In other words, the initial distribution of a system's performance may be completely independent of the process of failure of a system. The exact consideration of the influencing parameters that affect the states of the performance precisely between this period is therefore indispensable in reliability studies [10, 14].

This can be described briefly with an illustrative example: prior knowledge already describes the well investigated process of corrosion and its qualitative progression which

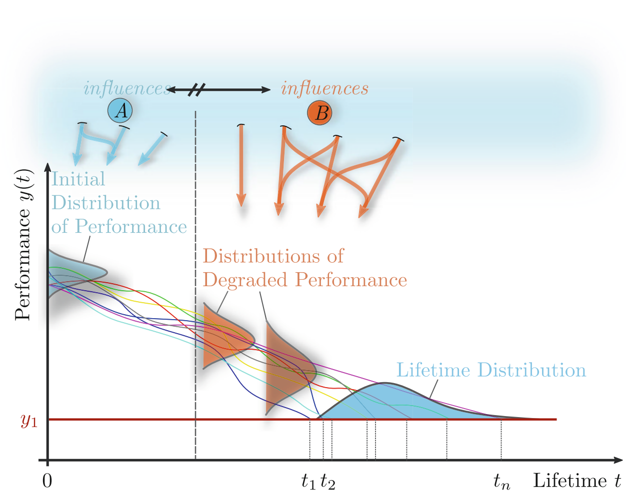

Fig. 4 Qualitative representation of the degradation of a stochastic performance characteristic y_t over the lifetime t of a system, cf. [2, 10, 11]

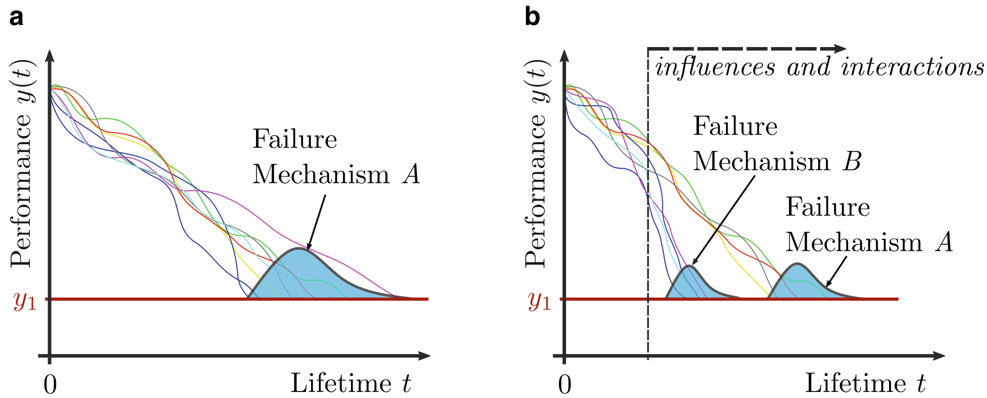

Fig. 5 Schematic illustration of the degradation of a stochastic performance characteristic y_t over the lifetime t influenced by sets of factors and interactions: **a** with one failure mechanism A; **b** with two failure mechanisms A and B

is only affected by certain combinations of temperature, amount of oxygen or saline water in advanced stages (of degraded system performance). The degradation process in an advanced stage of degraded system performance may here be accelerated into another direction and velocity depending on present influences. If an investigation into the corrosion progress of a base material has been planned without this prior knowledge, the biased neglect of information on interactions of factors mentioned above at a later point in lifetime would be severe: e.g. without temperature influence or its interactions, the process would raise a different duration or provoke varying failure mechanisms until end of life. In that sense, robustness as a initial constant of performance would not provide any incremental value as information to system performance over lifetime, as the set of affecting influences differs over various points in lifetime. This knowledge is of elementary importance for an efficient test design.

For this purpose, the definition of an enhanced method to identify varying and mutable interacting factors is mandatory. The knowledge about a variable set of influencing factors over the lifetime is elementary, especially when it comes to the planning of lifetime tests with L-DOE. Here, the efficiency of a well-designed DOE will be severely compromised by avoidable extra effort in processing factors to lifetime investigations as outlined in Sect. 1—especially while the interface between heuristic factor selection and standardized further processing for statistical DOE is unspecified. In addition to the simple distinction between normal parameters and factors affecting component lifetime, exemplary this also applies to the basic and formal requirements of experimental designs.

The present work therefore presents a comprehensive methodological approach that enables the qualitative selection of reliability-relevant factors for the application of reliability modeling through L-DOE. In this context, contrary to existing methodological procedures, two findings are pursued:

- System performance is not only considered at the beginning of the service life in terms of robustness;
- Reliability as a lifetime-distributed target variable is subject to changing influencing factors with different interactions and failure mechanisms.

For this reason, a convenient procedure for system analysis according to *Bertsche* [4] is given first in Sect. 2. An overview of the screening process in a heuristic manner follows this analysis. Consequently, established tools for this procedure (Sect. 3) and further interfaces in parameter processing within L-DOE (Sect. 4) are presented. On the basis of this explanation, a methodical procedure is proposed that enables the identification and separation of relevant influencing factors with regard to reliability and lifetime out of the body of system parameters (Sect. 5). Finally, the requirements for this procedure are examined and it is shown by means of an exemplary application that in this way an efficient and qualitative assessment of lifetime influencing and interacting factors is possible on heuristic basis (Sect. 6).

2 The system analysis

For an efficient parameter screening, the following delineates an overview of a powerful approach for system analysis. Here at least the succeeding aspects must generally be considered in order to be able to carry out qualitative and quantitative reliability considerations: the system definition, its functional description, operating conditions, the identification and classification of components and functional groups as well as the creation of a functional plan [4]. By attending to these points, a holistic understanding of the product is created, generating knowledge about the system boundaries and system structure. As this method is typically used for system analysis in the development process of a product, the application is equally effective for reliability analysis of existing systems [15].

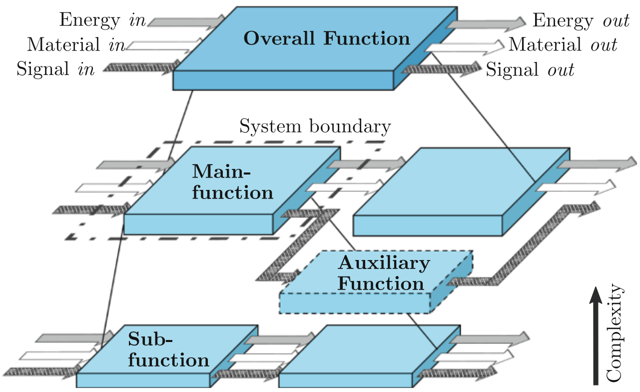

Fig. 6 Function structure including overall functions, main functions, auxiliary functions and subfunctions, adapted from [16]

While the functions of systems describe a unique interrelationship between the input and output variables, the classification of these variables by three conversions is established standard: *Energy*, *Material* and *Signal* [16]. Both individually and in combination, they perform functionalities which, in turn, result in failure or damage when not fulfilled. To allow a more precise analysis and identification of functionalities and derived failure mechanisms, the selection of variables according to [16] can be accurately completed along the proposed function databases according to [17]. Eventually, this makes the consideration of failure mechanisms of an arbitrary system even more individual. Each variable needs to be qualitatively and quantitatively describable and measurable within a system boundary to be defined. Therein, a reasonable system boundary is based on the definition of component structures and the objective of investigation. The choice of the system boundary must be made depending on the consideration of possibly relevant components and interfaces. With regard to the investigation objective, a system boundary that is too broad can generate too much complexity, whereas a boundary that is too narrow might impair quality of the solution. If one crucial functionality of a system is accurately isolated by the system boundary within the FDB, then its associated failure mechanism can be optimally stressed, caused and illuminated using EOL testing. The black box approach, similar to the P-Diagram shown in Fig. 1, provides one method of representation for this. Here, the function remains described only on the basis of inputs and outputs. A probable approach to specify these functions and their structures is the division to sub-functions according to the structural design of a product and the degree of function complexity in relation to the overall system. This gives the black box approach a higher resolution. Main functions and auxiliary functions are then graphically represented in a structured way via the types of flow (energy and direction, material and direction, signals and direction) within the system boundary and according to their interrelationships, compare Fig. 6.

The creation of a holistic, comprehensive Function Block Diagram (FBD) succeeds with the help of all available resources, which may include the following information acquisition methods [9, 15, 18–21]:

- Design documents and checklists;
- Technical drawings and sketches;
- Calculation and design protocols;
- Computer-Aided Design (CAD) data;
- Finite Element Analysis (FEA) data;
- (Process) flow charts;
- Manufacturing documents;
- Assembly documents;
- Handling guidelines;
- Work and test plans;
- Checklists;
- (Expert) interviews;
- Previous (experimental) investigations;
- Previous qualitative reliability analysis: e.g. Failure Mode and Effects Analysis (FMEA) or Fault-Tree-Analysis (FTA);
- Functional Specification Documents (FSD);
- Requirement Specifications (RS);
- Appraisal data;
- (Customer) complaints;
- Field data;
- Cost-Benefit Analysis (CBA).

Now within the FBD, single functions are more precisely characterized and abstracted using Boolean Functions or General Valid Functions. General Valid Functions are derived from the characteristics type, magnitude, number, location or time of the energy-conversion, material-conversion or signal-conversions. They are classified into the options *Change*, *Vary*, *Connect*, *Channel* and *Store* [16]. Combined with information about the structure of functions as well as their arrangement via components, all functionalities are uniquely defined in this way. In the sense of a reliability analysis this can represent the basis for the consideration of the structure in case of non-fulfillment of product functions and features. Further alternative forms of representation through a systems analysis are complemented by working-, constructional- and system-interrelationship approaches, see [18].

Based on this system analysis, subsequently the complete identification of variables that influence system functionality, and in particular lifetime and reliability, is enabled. Thereby, it has to be clarified which failure mode has a significant influence on the lifetime and is to be tested exclusively in the lifetime investigation. According to Fig. 1, this step also determines which functionality as a complement to the failure mode is to serve as the objective of investigation.

3 Heuristic parameter screening methods

The following is an overview of applicable and well-documented tools adaptable for the handling of system parameters and lifetime-influencing factors within heuristic screening procedures. Different from statistical analysis in the context of screening experiments, heuristic screening methods are based on an understanding of causal interrelations and plausibilization. They are supportive in the search for a solution of an investigation objective and generally offer good prospects of success for this, but cannot ensure that a solution found corresponds to its optimal solution [15]. In this context, there might not be explicit experimentally recorded knowledge about influences on an investigation objective (lifetime, reliability) existent, but at most general empirical values and expert knowledge about the system behavior. The procedure thus follows the use of logical thinking and rationality in the interpretation of evidence [8, 19].

This section is structured in such a way that first the entire selection of tools is shown and described. This entirety does not claim to be complete to its full extent for all available tools, but very comprehensively covers the most relevant state of the art within the authors estimate. These tools can be arranged correspondingly in *Step 2 and 3* of Fig. 2. The following forms the basis for an appropriate methodical arrangement of tools in a practicable flow scheme. In accordance with a logical structure, this first follows the gathering of influencing variables through information acquisition, then followed by their structuring and eventually an assessment in relation to the investigation objective at the end, compare Fig. 7. Tools listed therein are particularly examined and described in the subsequent subsections and eventually evaluated in Sect. 4 in terms of their applicability and combinability for L-DOE.

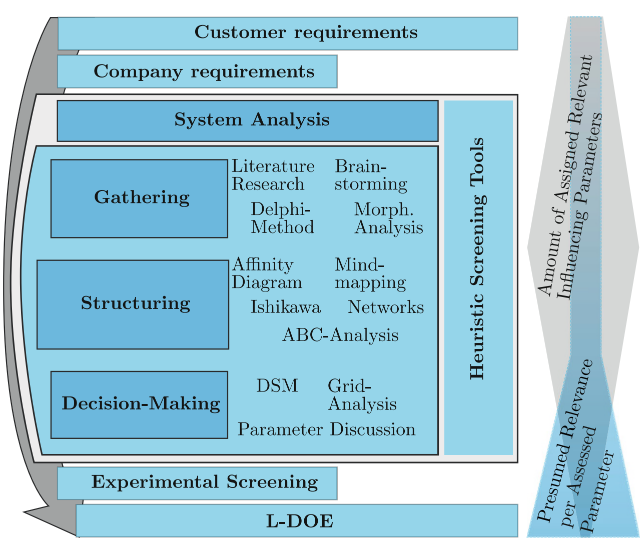

Fig. 7 Heuristic Screening Procedure in the Context of DOE, cf. [8, 12]

3.1 Information acquisition and gathering of system parameters

The holistic collection of influencing parameters, inputs and outputs of a system and its subsystems, factors, co-factors and system responses is first of all about not omitting any system parameters and interactions. It is about unprejudiced identification of all system parameters and features first, not about assessing their relevancy. Thus, the perspective is set to a bird's eye view in order to identify the entirety of variables as neutrally, objectively and unbiasedly as possible. For this procedure, the overview and structure of a properly designed FBD provides a suitable basis. Above all, however, an appropriate breeding ground for identifying the system parameters results from the exchange and discussion with experts and moderators based on this. This exchange can be enriched by using a number of tools and methods:

3.1.1 Literature research

The literature research offers the first basis in the methodical procedure for the moderator or model builder, who would like to experimentally carry out and manage the system investigation with regard to the investigation objective. This does not only apply with regard to the investigation of lifetimes, but is inevitably connected with the scope of the *Seven Management Tools* (*M7*) and *Seven Quality Tools* (*Q7*) in the context of quality management (QM) [22–24]. In particular, these provide an overview of further established tools and contexts for system analysis and idea collection, thus providing an overarching method itself. As these are to be applied methodically, available sources of information as also listed in Sect. 2 must be analyzed in full. Furthermore, it is advisable to consult relevant subject-specific standard literature and overviews of recent publications in order to analytically collect existing parameters from already collected findings on possible and definitive influencing factors.

3.1.2 Brainstorming

As a creativity technique for groups of up to ten people, Brainstorming offers a mostly time-scheduled approach to intuitively and associatively find ideas and system variables for an investigation objective together. Here, an evaluation or classification during the collection of ideas is explicitly dispensed with in order to generate a flow of new ideas and thus to be productive and efficient in the procedure [8, 15]. The documentation of ideas can be as diverse as the modification of the original method itself and partly imply the latter: the method may be used in presence or via electronic meeting systems and collaborative real-time editors; as a variation in the sense of Brainwriting, in which the participants sequentially complete their respective associations on a number of sheets of paper, each with one buzzword already written down; or for instance as ABC-Brainstorming, which structures solution ideas alphabetically and thus triggers them.

3.1.3 Delphi-method

The Delphi-Method follows the approach of interviewing selected experts. These experts are asked individually and independently to give their ideas and opinions on a questionnaire that has been developed by a moderator. The moderator first compiles the questions and then the answers, finally evaluates this questionnaire statistically. This process is carried out several times while its results are averaged. In this way, subjective and extreme individual estimates are removed and a more representative information value is generated [15].

3.1.4 Morphological analysis

Morphological analysis originally uses decomposition of an existing system into subsystems, whose individual solutions are first found and defined, and then combined into a new composition of permuted subsystem-solutions within product development [15, 25]. With the help of this procedure for structuring a system, sub-problems and in particular their influencing variables can be identified. According to [15, 26], the first step is the analysis of the design factors, and therefore parameters that influence the overall system response. Doing so, the method results in an morphological overview of influencing parameters identified for a specific investigation objective.

3.2 Structuring system parameters

Using the methods mentioned in the previous subsections among others, systems can now be analyzed for the entirety of their influencing parameters (also *Inf. Pa.*), inputs with interactions and outputs, and a collection of these can be created that covers as much of the full parameter data as possible. At least, it can be assumed that all supposedly relevant parameters have been identified to this step. If these are now to be structured on the basis of a deeper understanding of the system, further tools are available. The structuring thus not only enables a clustering into parameter groups, but can also identify and visualize their mutual influence. Particularly in the case of interactions of factors that influence service lifetime, this is a decisive advantage that corresponds to the idea of DOE [1, 5, 12]. Above all there are exemplary phenomena in this context that cannot be described trivially in physical terms, such as aging effects or other changes in material properties that can significantly influence lifetime, cf. Fig. 5.

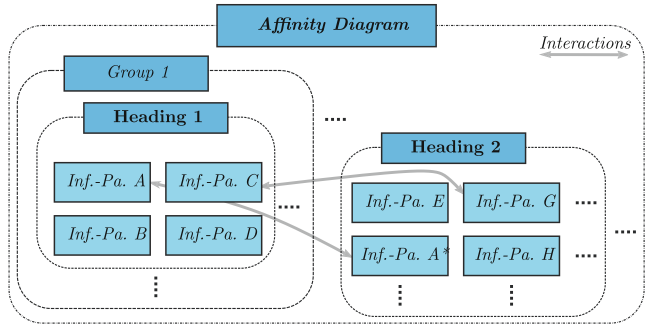

Fig. 8 Affinity Diagram containing interactions, adapted from [8, 15]

Below, the most popular and practicable tools are selected:

3.2.1 Affinity diagram

The Affinity Diagram builds a part of the *M7* and is designed for transparent representation of relationships between a large number of inputs [9, 23]. Starting from Brainstorming activities, collected ideas of influencing parameters are numbered and grouped by assigning them adequate headings. Afterwards an evaluation follows, whereby a subject can also be assigned to several groups, compare Fig. 8. This procedure is suitable as preparation of the data for an Ishikawa diagram (see Sect. 3.2.3). Once the assignment of the ideas to groups is completed, the result is presented graphically grouped on a board. Here, interactions among each other may be added [8]—particularly when they are required within lifetime investigation. Individual groups can further symbolize branches of the Ishikawa.

3.2.2 Mind-mapping

In heuristics, Mind-Mapping serves as a structuring method for the clear presentation of complex qualitative information and is also stated in the *M7* [9, 23, 27]. The type of structure results from the individual situation of the investigation objective. The starting point (root) might be the investigation objective itself, while branches symbolize criteria such as influencing parameters and groups of them. A connection of these is done by nodes as long as they are related to each other. Preferred attributes are weighted to

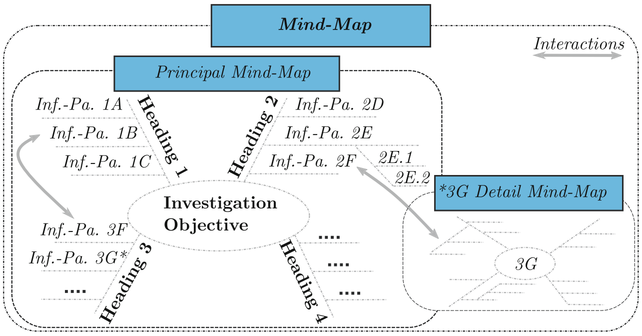

Fig. 9 Mind-Map containing interactions, adapted from [8, 15]

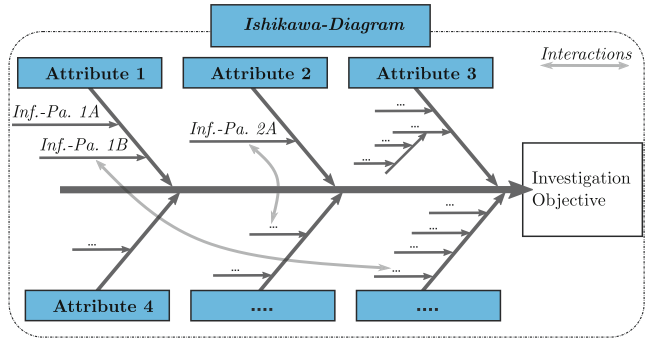

Fig. 10 Ishikawa-Diagram containing interactions, adapted from [1, 8, 15]

higher levels, while less influential parameters are build up lower branch levels [15]. Thus, the number of branches at a node to a higher-level influence parameter branch represents the intermediary relevancy with respect to the root. With regard to the investigation objective, less influential parameters are thus only indirectly switched over more relevant factors. The branching level of the parameters and their interconnection thus structures the parameter data in interrelations and relevancy, compare Fig. 9. Mind-mapping therefore serves as a gathering *and* structuring method. By means of the tools Brainstorming and Delphi-Method described in Sects. 3.1.2 and 3.1.3, collected values can directly be arranged in that way. In this layout, two special features may also be taken into account: in case of a strong loss of clarity, it is possible to display and further refine individual branches in more detailed mind maps; if interactions between influencing variables exist and are to be visualized, they will be cross-referenced with arrows. If a representation of the collected parameter set by an Ishikawa-Diagram (see Sect. 3.2.3) is too complex, the mind map will serve as a practicable preparation stage, in order to represent collected parameter groups individually therein for the use through Ishikawa afterwards [8].

3.2.3 Ishikawa-diagram

The Ishikawa-Diagram, also known as cause-effect diagram or fishbone diagram, is used for the detailed structuring of attributes with regard to a target variable, meaning influence parameters with respect to an investigation objective. The structuring is done by means of arrows. Here, too, the parameters are divided into clusters or groups and assigned to the objective via their main criterion. Originally this clustering is done by the *6M* attributes: *Man*, *Material*, *Machine*, *Method*, *Measurement* and *Mother nature* (environment). Further, a reasonable choice of main causes and influences depends on the respective problem to the investigation objective and can be freely determined accordingly [1]. In addition, a combination with the Brainstorming method (see Sect. 3.1.2) is also possible here to trigger cluster-specific idea generation. If prior knowledge of cause-effect relationships is known, these will also be specifically marked with arrows, see Fig. 10. This might be recommended, especially in case of expected interactions from which correlations (towards the investigation objective reliability) can be derived [8].

3.2.4 Interdependence networks

Within networked thinking, impact processes of system components or functions are analyzed. Here, also according to *M7*, a *Relation-Diagram* is usually created in order to be able to structure supposed causal relationships that are subordinate to a complex situation [23]. In particular, interactions of influencing variables are also considered. Therefore, all relevant functions, facts, influences and interrelationships are collected. The creation of the diagram based on ideas about influencing factors from, for instance, Brainstorming and their interactions can be carried out individually and interactively by networked thinking participants. Methods from *Graph-Theory* and *Network Technology* allow to structure them in order to map the interrelationships completely and graphically with respect to the specific direction of effect, intensity and time aspects in *Interdepen-*

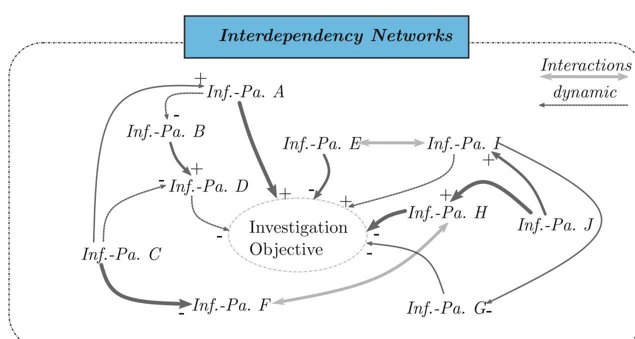

Fig. 11 Interdependence Network containing interactions, adapted from [15, 28]

dence + Networks (expandable to *directed graphs/digraphs* and/or *Bayesian Networks*) [20, 21, 28], compare Fig. 11.

Therein, directions of effects do not only indicate the orientation, but possibly their net contribution amount (+/−) on related influencing factors and the target variable. The representation of temporal aspects, on the other hand, can be done by variation of contour shapes of the connecting arrows, which symbolize the influence variable interactions. An evaluation of the intensity of the interaction between influencing factors and their relevance with respect to the target variable is to be handled by an evaluation scale, which can range, e.g. from 0 (no or negligibly low intensity) to 1 (low intensity), 2 (strong intensity) and 3 (very strong intensity) [29]. A procedure scheme stated in summary in [15] includes and arranges the following ordered points:

- Delimitation of the problem, whereby a system to be examined is to be considered from the respective view of different disciplines;
- Determination of the network, which is defined by the relations, interactions and positive (+) as well as negative (−) loopbacks of the idea elements;
- Capture of the dynamics, in which the temporal component is integrated;
- The interpretation of behavior possibilities, in order to consider different scenarios;
- The steering possibilities, which describe the statics of different influencing variables;
- Steering interventions, in order to capture manipulation possibilities regarding the system.

3.2.5 ABC-analysis

In order to simplify the complexity of a set of influencing parameters, the ABC analysis serves as an ordered classifier for influences [1, 23]. Here, too, the number of parameters can be structured in their relevance according to the Pareto principle and via expert knowledge or documented experience. The classification can be used to support the Decision Making (DM).

3.3 Heuristic assessment tools for system parameters

Based on customer and company requirements for parameter influence analysis as mentioned prior and subsequent methods for the identification, gathering and structuring of influence parameters in Sects. 3.1–3.2, there is now the demand to analyze the structured selection heuristically. As a result, the set of collected influencing parameters should be reduced to a substantial and manageable amount of factors. Here it is important not to resort explicitly to experimental investigations, since they will be delineated again later in Sect. 5. Analysis and DM on parameters affecting service life shall be carried out under a heuristic approach. The idea of a rational consideration of relevant influencing factors *and* interactions for the analysis by DOE with regard to an investigation objective and without the effort-intensive prior-experimentation on product lifetimes (experimental screening), is also pursued using following tools and methods. In addition to countless existing methods summarized by [30], among others, DM is feasible both in the context of DM for influencing variables in the preparation of experimental investigations with respect to *one* investigation objective, as well as via Multiple-Criteria Decision-Making (MCDM) for several target variables [8]. In the context of the present work, this might only be mentioned in terms of its existence. In the following, we will continue to focus on DM with *one* investigation objective, since statistical methods based on empirically and experimentally determined data are mostly used for MCDM, and this might not be consistent with a purely heuristic plausibility approach.

3.3.1 Design-Structure-Matrix (DSM)

The DSM is defined by a $N \times N$-matrix. Within the present work, in both dimensions the entirety of N collected influencing parameters is listed in the same order. In addition, the investigation and target parameter y may be included in an extra column. Within here, it is heuristically assessed whether or to what extent an influence parameter n_i has an estimated effect y_{ij} on the target variable y via another interacting influencing parameter n_j. The assessment can be conducted within a team of experts in two ways: existent or nonexistent (*binary*); or by an evaluation scale already introduced in Sect. 3.2.4 (*numerical*). Especially when using a numerical interaction strength scale, this can vary over successive iterations or be quantified specifically depending on the individual use case. In this approach, it is important to note that although the observations and intensities are estimated interactions that could theoretically follow a symmetry $y_{ij} = y_{ji}$, nevertheless, they must be estimated individually on a line-by-line basis. Mirroring along the principal diagonal of the DSM is thus disturbed with one individual estimation and decision each—which might be quite advantageous. Moreover, it may happen that one influencing parameter causes noise and thus influences another one, but not vice versa [20, 31]. Unsymmetrical entries $y_{ij} \neq y_{ji}$ may also indicate noticeable deviations, uncertainties, or questionable estimates which leads to a subsequent discussion of a following demand for individual experimental screening [8]. If just the existence of interactions has to be identified in the DSM without evaluating specific intensities y_{ij}, these can directly be derived from undirected graphs, like node-link diagrams, created according to 3.2.4.

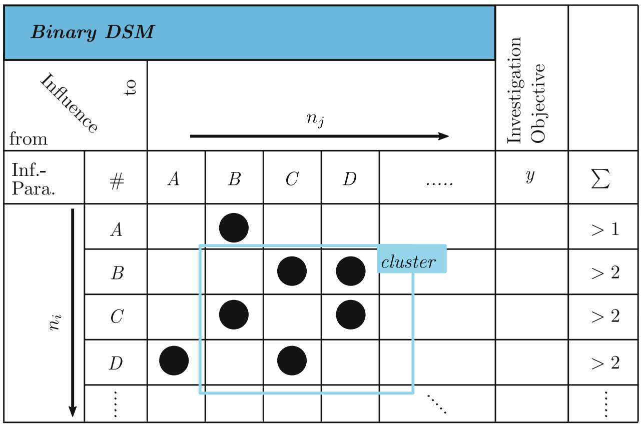

Fig. 12 Binary DSM, adapted from [8, 12, 20]

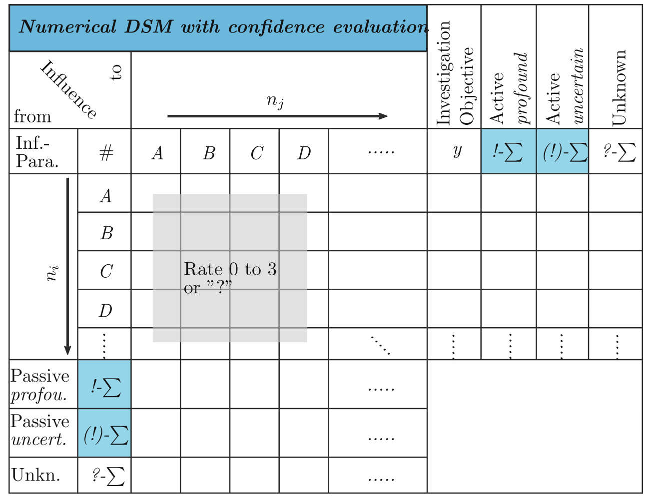

Fig. 13 Numerical DSM with estimation statement confidence, adapted from [8, 20]

A partitioning analysis can be applied to the DSM, in which rows and columns are reordered so that related interactions form groups around the main diagonal. This grouping is understood as *clustering*, whereby, e.g., influencing parameters (in general criteria) within individual components (in general domains) of a system need to be identified and visualized. On this way structural characteristics can be discovered and subsequently examined (experimentally) in more detail with regard to interactions. However, clustering is only one of several structure analysis methods and is mentioned here additionally to other options, computational analysis through feedback loops and machine learning algorithms, as it is graphically clear and manageable for the user [20]. Nevertheless, the sum of interaction existences of the influencing parameters with respect to the investigation objective then provides information about the relevancy of the influence with respect to the system response to be investigated [12]. A decision about the selection of most relevant influencing parameters can thus be made qualitatively by ranking them according to the amount of cases that occur, compare Fig. 12.

An evaluation of numerical estimated intensities in the DSM, on the other hand, is discussed in the following section. Once the DSM has been completed and appropriately visualized, experts and workers related to it should review and discuss the model. In this way, the DSM can be validated on the basis of heuristic assessment through expert know-how [20, 31].

3.3.2 Grid-analysis

Within the Grid-Analysis, the DSM (Sect. 3.3.1) is evaluated with respect to estimated intensities for parameter interactions and presumed overall influences on the investigation objective. As already mentioned in Sect. 3.2.4, an evaluation might be carried out line by line and individually for each parameter combination with an evaluation scale for the influence impact intensity from 0 to 3. For the Grid-Analysis, the DSM is extended by a line for a passive sum and a column representing an active sum, compare Fig. 13. The row sum of the DSM yields the active sum, the column sum gives the passive sum. The active sum represents the estimated total interrelation strength of a row-specific influencing parameter towards the other respective influence variables with an ultimate effect on the target variable (the investigation objective). At the same time, the passive sum represents the expected total effect of the influence variables on the column-associated influencing parameter. In addition, the line-by-line evaluation can be extended via weightings for estimation statement confidence. In this way, a separate active and passive sum is formed via an assigned confidence of statement, which is based more on intuitive decisions—compared to the evaluation, whose estimation statement confidence is based on justifiable and well-founded information. If, in addition, only insufficiently reliable information is available, question-marks can be entered in the assessment columns for the estimates. A high active sum amount of question marks for single influencing parameters in the sum-column for question-marks consequently indicates a need for targeted research or investigation (by experimental screening).

The evaluation is carried out in a diagram for grid analysis, on the ordinate of which the active sum is plotted and the passive sum is covered by the abscissa. The grid is further divided into four quadrants. High sum values are found in a quadrant that is defined as *critical*. A high active but low passive sum describes the quadrant *active*. The *inert* area includes low active and passive values, whereby lower active

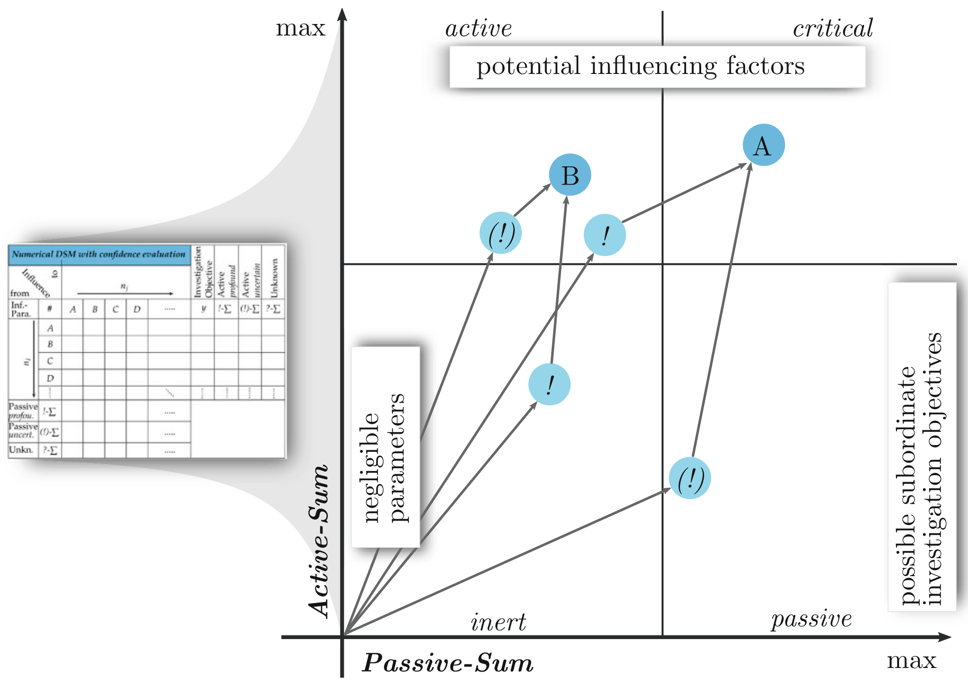

Fig. 14 Grid-Analysis based on a Numerical DSM with estimation statement confidence—exemplary with two influence parameters A and B and their specific active and passive sums, adapted from [8, 20]

values are found in the *passive* quadrant—compare Fig. 14. The coordinates of an influencing parameter placed in this diagram is finally determined by its individual values for the active and passive sum. If the grid analysis is supplemented by confidence distinctions (uncertain "(!)" or profound "!" information), the coordinates (active and passive sum) of an influencing parameter based on overall information are supplemented by support vectors, whose arrowheads point to the coordinates of each uncertain and profound active and passive sum numbers, which result in each case from active and passive co-ordinates for well-founded or intuitive information/confidence. The points that consider the confidence are then connected to the ordinary, overall-information coordinate points containing the cumulative sum values. With this visualization a more sensitive estimation is enabled, whether profound knowledge or only intuition leads to a final classification of the respective influencing parameter.

In the case that all influencing variables and interactions with respect to the target variable have been correctly captured at this point, exemplary the DSM might be symmetrical, all points are placed on the first bisector of the grid diagram. However, since this condition is impossible to determine by means of heuristic estimation, the points will deviate vertically upwards from this bisector due to stronger individual estimates for intensity to a direct effect on the target variable and by further deviate omni-directionally due to uncertainties in general. Finally, the following interpretations can be made:

- *Inertial* parameters tend to take a subordinate role in interrelations and effects for the investigation and might be neglected;
- *Active* factors represent a strong interaction with other parameters and effect on the investigation objective;
- *Critical* parameters are characterized by a high degree of influence on the target variable but also by substantial dependence;
- Parameters that are strongly influenced without mutual influence are taken into account as *passive* parameters in such a way that they are not directly changed in testing, but may be well recorded and recognized as subordinate investigation objectives by measurements.

A division of the quadrants can also be done according to different strategies. Either the intervals of the abscissa and ordinate are halved at the mean value of the sums, the division is done depending on the cluster-distribution of parameter points or the quadrant shares are based on a limitation according to the Pareto principle, where a ratio of e.g. 20% to 80% for active values is taken into account and defined [8]. The classification of the influencing parameters collected according to Sect. 3.2 thus provides an estimation of parameter relevance on a heuristic basis. The respective assigned parameter-class thus implies a qualitative estimation of the influence strength on the target parameter and the effort of forthcoming experimental investigations.

3.3.3 Influencing parameter discussion

On the basis of these tools for the evaluation of collected influencing variables and subsequent DM from previous sections, now it must be elaborated *which set and amount of influencing parameters* from the heuristic assessment is to be investigated further in experimental screening or even be directly processed to experimental design.

A consideration is made here in particular by detailed discussion and some boundary conditions: specialized expert knowledge in team exchange, the weighing of decisions on the basis of uncertainties or profound information, as well as the consideration of benefit versus effort. In particular, here a fluent crossover to DOE strategies is encountered at the latest when it comes to the definition of experimental factors and the determination of their levels, the discriminatory test power, and the choice of experimental design. A transition to this is therefore examined in a dedicated manner in the following sections.

4 Boundary conditions in parameter assessment for reliability modeling

With the overview in Sect. 3 of not just available but also practicable tools to heuristic screening of influencing parameters for the experimental investigation with respect to the objective lifetime/reliability through L-DOE, we clarify here the interface for further processing of the assessed parameters in the same. Existing literature however does not specify this interface in detail with the corresponding requirements, which may methodically lead to a loss of efficiency. Additional methods for the heuristic parameter screening are quite available after [15, 19, 20], however, they are not classified as probable or extended enriching. If now the partly simultaneous, partly sequential processing of parameters in screening and test designs needs to take place, two aspects in particular will be fundamentally considered: requirements both for a subsequent experimental screening process in general *and* for processing to experimental designs and reliability modeling. With respect to influencing parameters, both boundary conditions pursue the following central objective:

> *The selection of only the principal set and acceptable amount of factors from the body of system parameters for the application of L-DOE.*

In [1, 3, 7–9] topic related procedures are generally illustrated using exemplary case studies. Even the historical creator of the DOE methodology *Fisher* used illustrative examples in [6], as this of course is much more transparent. Thus also here both aspects have been validated against a case study briefly outlined in Sect. 6 and are therefore discussed and evaluated with respect to the tools presented in Sect. 3. First, however, an overview is explained abstractly:

4.1 Overall requirements in the screening process

Qualitative requirements that are valid for both heuristic and experimental screening as well as for the assessed parameters within can be outlined as follows:

- ***Transparency***: when it comes to comprehensibility in the screening process, a reproducible, clear and transparent documentation and representation of the information and idea acquisition, structuring and assessment process for parameter information is required both for the further course after the heuristic steps and for that itself. This applies as well to the comprehensibility of causal interrelationships and the justifications for the selection process as to graphical visualizations. Documenting the procedure for the acquisition of information according to Sect. 3.1, this should be trivial by using standards for the protocolling of sources used, responsible persons, partners, contents and results. If it comes to structuring (Sect. 3.2), the tools are to be selected more carefully. Options from the network analysis and graph theory for the representation of relations and interactions are to be selected attentively in particular with large and complex system structures [15, 28]. Bayesian Networks e.g. can be a probable tool in computational processing, but above a certain system size they probably can only be represented graphically in an unclear and unmanageable way. Also the possibility to use different information and interpretation levels is limited by the choice of the visualization method for certain structures. It is therefore advisable here to choose a method that is clear through form, color, size, type, etc. to visualize parameter influencing structures clearly;
- ***Accuracy***: generally meaning that the selected influencing parameters must be reproducibly adjustable and measurable, i.e. they have to be qualitatively and/or quantitatively describable and transferable to an experimental investigation [8, 9]. As far as possible, this also implies that the choice is made in favor of continuous parameters. Otherwise, a supposedly relevant influencing parameter can be identified in a methodological manner, but still its interaction and effects cannot be recorded statistically [24, 32];
- ***Effectiveness***: obvious and yet always in conflict of interest—the procedure for parameter assessment by heuristic and experimental screening should be target-oriented, so that a reduction of the system parameter body is actually provided for the investigation in further processing. Individual tools from Sect. 3 possibly then classify several influencing parameters as equally relevant in high

and lower importance ranks. Thus, further tools would have to be applied simultaneously for the same screening steps to break this equality and differentiate parameter relevancy;

- ***Applicability***: for reliability modeling of systems or products, the assessed influencing factors and possible interactions need to be significantly influential to system lifetime and be recognized as such in the screening. Otherwise they can also be neglected within experimental design. On a qualitative level and in addition to the system analysis tools presented in Sect. 2, information can be obtained by analyzing literature for well-documented failure modes and system-specific damage mechanisms across varying operating conditions and load spectra [1, 7]. This will first lead to potentially relevant influencing parameters as failure root causes and provide then a framework for structuring factors further influencing them. On a quantitative level, root-cause depending effects and their stochastic interferences must be statistically detectable and describable.

4.2 Requirements for parameter processing in L-DOE

When screening parameters for and within L-DOE, several other details must be considered. Essentially, these are also trade-offs between information gain and effort. However, their perspective classification in the heuristic screening already influences how many of the parameters, which were collected, structured and ordered according to relevance (compare Sect. 3), are processed further into the experimental design procedure. Thus, as in the previous section, relevant considerations are abstracted in the following:

- ***Prior Knowledge***: Depending on the intended depth of knowledge and the prior knowledge, experimental designs are adaptable to a correspondingly reduced number of factors, if already known and significant main effects and occasionally interactions can be integrated into the model building. Finally, the information content of a selection of factors is already considered.
- ***Intended Depth of Comprehension***: Another qualitative aspect in the context of further processing of a selection of parameters to investigation factors is the intended target understanding of the system. Supposedly, this can be classified via the extremes of basic research and specific detailed research of system behavior. If, for example, only physical main effects are of interest in the system investigation, possibly interaction effects can be neglected, which leads to a reduction of both factors and test runs by factor combinations. If only a linear regression model is to be created, two levels are sufficient—if a low-order polynomial relation between input and output variables is assumed, at least three levels have to be considered over an appropriate amount of factors [1];
- ***Cost and Time***: in general, the application of tools and heuristic measures is under the aspects of cost and time, too—if these can be reduced with acceptable trade-off, it increases efficiency. When dealing with experiments on product lifetime, it is essential to place them under monetary and temporal proportions. First, the scope of the investigation must be considered here. If required, testing duration and test capacities are to be taken into account as a function of the amount of influencing factors estimated to be relevant, the boundary conditions of the test plan to be used and thus of the amount of resulting test points is decisive. Exemplary for a full factorial design with m levels, there are

$$n = r \cdot m^k \tag{1}$$

runs required for r replications of the experimental design with k factors [1]. Costs and time therefore increase rapidly over r and k. Further conditions are defined by the desired type of data in the results on which reliability modeling is to be performed: *complete* data, *right*- and *interval-censored* data. Inevitably, the corresponding demand influences the runtime again. Both aspects are very product and system specific and therefore individual. For both aspects, however, certain strategies for estimating the trade-off are present that can be considered for management [33]. From this, the scope which fits best the available budget and time schedule can be derived, and which loss of information is to be expected when reducing the number of parameters and specimen [12];
- ***Levels and Level Changes***: Handling levels and ranges of factor values is essentially necessary for succeeding an experimental investigation and depends on the type of their spacing and the relation to their standard stresses (e.g. field loads, load collectives, accelerated loads and stresses). Thus, if factors are to be recorded heuristically as relevant, they are in any case subsequently confronted with a critical evaluation in this regard. Two aspects in particular must be taken into account here:
  1. in the first place, factor levels chosen actually need to cause an EOL event or significant and utilizable wear characteristic for the specimen. Using the analysis of degradation characteristics, for instance, wear can be statistically evaluated in terms of lifetime [1, 10];
  2. the level spacing needs to cause a significant effect on lifetime (or degradation) as the investigation objective in L-DOE and is clearly identifiable even under a random error ϵ by statistical hypothesis testing against a previously defined significance level α. Depending on statistically distributed result variables per factor

level, each with a mean value μ, two hypotheses about the conjecture of the resulting $\mu_{1,2}$ are usually formulated for this purpose, where holds:

$$H_0 : \mu_1 = \mu_2; \tag{2a}$$
$$H_1 : \mu_1 \neq \mu_2. \tag{2b}$$

Accordingly, it is decisive to create a test design in which, in particular, there is a suitably low probability β for the so-called null hypothesis H_0 (Eq. 2a) *not* being rejected when it is false (called *type-II error*) [1, 3]. This eventually describes the significance of a test design and is therefore denoted by

$$Power = 1 - \beta. \tag{3}$$

The power of a test design is therefore an essential quality feature and must be evaluated against feasible factor levels;

- ***EOL/Degradation***: Reliability modeling via lifetime testing by DOE typically calls for EOL testing. If the supposedly investigated service life exceeds the available time frame of the experimental investigation or if test runs cannot be suitably accelerated in time, a damage progression, also with scaled loads, of a defined degradation feature up to a set limit value (pseudo-lifetime) can be investigated. Briefly described, operating times present on this can then be extrapolated to the expected lifetime via the remaining functional capability [1, 10]. Consequently, only parameters whose main effects and interaction effects are relevant to the lifetime and degradation of a system are to be considered as investigation factors. In particular, this includes factors that explicitly provoke random failures as well as wear failures and (negatively) influence the reliability of the system [4];
- ***Design Resolution***: Unlike the set of runs described in Eq. (1) for a full factorial design, only a subset or *fraction* of the possible runs is performed in a fractional factorial design. In case of limited resources or many factors, this is a good choice as the fractional factorial design consequently requires fewer runs. For this reason they are particularly suitable for early phases of investigation, in which many factors are to be investigated for effect strength in experimental screening. However, this also means that main effects directly resulting from factors or effects of 2-way factor interactions are confounded/aliased and not consistently separable from effects of higher-order interactions—they cannot be estimated separately from each other anymore. For a number of p parameters added to a fractional factorial design, this results in

$$n = r \cdot m^{k-p} \tag{4}$$

runs. The degree of this aliasing is determined by the design resolution. Thus, the risk of misinterpretation is characterized and differs for the most common resolutions as listed below:
  1. *Resolution III*—main effects are mutually un-aliased, but confound with 2-factor interactions;
  2. *Resolution IV*—main effects are un-aliased—mutually and with 3-factor interactions, but confound with 3-factor interactions and 2-factor interactions are mutually confound;
  3. *Resolution V*—main effects and 2-factor interactions are mutually un-aliased each, but 2-factor interactions are aliased with 3-factor interactions and main effects are aliased with 4-factor interactions.

  Thus, fractional factorial designs can be suitable for experimental screening as well as for a DOE plan, depending on the study objective [1, 3]. Here, too, the decision influences the final choice of the heuristically structured influencing parameters and must therefore be incorporated into the DM at an early stage;
- ***Investigation Objective Reliability***: with the intention to implement lifetime or reliability modeling by L-DOE, the definition of lifetime as a statistically distributed parameter with confidence interval has to be considered. Reliability $R(t)$, as a function and in relation to lifetime, therefore indicates the probability P that the random variable τ exceeds a time value t on the (positive) time axis $[0, t]$:

$$R(t) = P(\tau > t). \tag{5}$$

It forms the compliment to the probability of failure $F(t)$, which is defined as a function of a specific distribution type (e.g. *Weibull*) and its corresponding probability density function $f(t)$ [4]:

$$F(t) = 1 - R(t); \tag{6}$$
$$f(t) = \frac{dF(t)}{dt}. \tag{7}$$

The distribution characteristic of reliability, failure probability and lifetime is therefore significantly dependent on randomly occurring damage mechanisms of the system under investigation. These, in turn, are triggered by a selection of influencing factors and, in particular, their interactions, which have to be identified and pre-selected for L-DOE. In order to investigate the end of lifetime and thus the reliability of an object, it is therefore in the nature of things that time-intensive investigations are necessary by means of EOL testing. Of course, these have to be manageable with finite capacities. The choice of the appropriate parameters for this is, in contrast to all other objectives investigations, considered to be even more crucial. This decisive relation can be directly highlighted again with a review of Fig. 4.

4.3 Tool-performance in heuristic screening for L-DOE

With the bullet points collected in the previous sections, a brief classification of the tools presented in Sect. 3 is enabled in terms of each of their performance. As described in Sect. 1.1 at the beginning, this is to be done from the perspective of reliability and thus lifetime as the objective of the investigation. For this purpose, a qualitative classification in three levels is chosen with evaluation of the most suitable and performant (*excellent* = "+"), the quite practicable and realizable (*good* = "○") as well as unsuitable (*poor* = "-") options. Entries left free mark an assignment that is not possible or meaningful regarding considerations to boundary conditions mentioned in Sect. 4. The classification as shown in Table 1 is based on the requirements and referred to respective literature referenced in each subsection.

Accordingly, heuristic tools for gathering influencing parameters in information acquisition (compare Sects. 3.1.1, 3.1.2, 3.1.3, 3.1.4) can be recognized as directly applicable to requirements in the screening process, and for the most part, they are also suitable for this purpose. Furthermore, indications of emerging efforts by costs or factor adjustability as well as effects on reliability as the investigation objective can be detected with these. This refers in particular to the detection of known interactions.

Structuring tools (compare Sects. 3.2.1, 3.2.2, 3.2.3, 3.2.4, 3.2.5) also cover the main demand through screening and L-DOE. They are able to process L-DOE know-how and target reliability/lifetime as the investigation objective. However, the options for efficient and clear representation of the influencing factors as well as their interactions differ. Mainly with varying transparency and effectiveness in documentation, these tools can identify and document lifetime-influencing parameters as well as their interactions.

Eventually, only evaluations by DM tools (compare Sects. 3.3.1, 3.3.2, 3.3.3) are used to fully implement clear specifications from experimental designs: for instance, the maximum number of test runs implementable and the consideration of test capacity available as fixed constraints for parameter reduction. The evaluation and estimation of trade-offs to the investigation of reliability is transparently implemented here.

The applicability of the tools as well as the influence parameters to be analyzed are to be measured conclusively on the basis of more or less all boundary conditions at the same time. Reliability and lifetime as target parameters require special handling due to their time dimension and manifold dependencies (also due to parameter interactions). This has to be clearly differentiated from simple process target parameters and therefore has to be taken into account decisively.

5 Procedure for Heuristic Parameter Assessment in L-DOE

After the previously presented overview of available tools for reliability parameter assessment by heuristic screening and subsequent requirements from boundary conditions for screenings and test designs, a recommendation for action to the procedure can now be created. For this, first a delimitation to existing procedures and considerations is given. Finally, the tools are organized methodically in order to enable the addressing of emerging discussion aspects for individual applications in a suitable way.

5.1 Distinction to Taguchi and Shainin

Adjoining DOE methods, the parameter identification and a quantification of the quality loss function through the formation of matrix experiments with confounded factors as well as a final statistical evaluation was significantly coined by *Taguchi* and became known under his name. This builds substantially on classical DOE [6] and extends the same in terms of *robust* system evaluation [3, 13]. In contrast, there are methods from *Shainin*, whose essential goal is the *reduction of variation* in measurable target variables, but which also significantly extend classical DOE methods. They, in turn, gradually use *Multi-Vari Charts/Pairwise Comparison/Component Search* for ten to 20 parameters, *Search for Variables* for six to twelve parameters, *Full Factorial Test Designs* for up to six parameters, and *Process Comparisons/Scatter Plots* for up to four parameters for the reduction of a parameter set [3, 7, 13]. Both methodologies form the documented standard approaches to parameter reduction in literature. They are well documented in PhD theses [8, 9] and standard references [3, 7, 13] that takes them further, but are not associated with potentially time-consuming lifetime and reliability investigations. Additionally, the most significant drawback of the presented approaches is obviously the use of experimental investigations for the initial screening procedure from the very beginning, which is in conflict with the stated purpose of the present work. As already indicated in Fig. 4, only initial distributions of a system characteristic and not the reliability as a property over lifetime are examined with this. Moreover, the use of experimental procedures for parameter assessment

Table 1 Performance evaluation of tools shown in Sect. 3 according to criteria in Sect. 4.

	Transparency	Accuracy	Effectiveness	Applicability	Prior Knowledge	Intended Comprehen.	Cost & Time	Levels & L. Changes	EOL/ Degradation	Design Resolution	Invest. Obj.: $R(t)$
Literature Research (3.1.1)	+	+	+	+			+	+	+		+
Brainstorming (3.1.2)	o	o	-	o			+	o	o		+
Delphi-Method (3.1.3)	+	+	o	+			-	+	+		+
Morphological Analysis (3.1.4)	+	-	o	o			o	-	o		
Affinity Diagram (3.2.1)	o	o	-	+	+	-	o	+	+		+
Mind-Map (3.2.2)	+	o	-	o	+	o	o	o	o		o
Ishikawa-Diagram (3.2.3)	+	o	o	+	+	o	+	o	o		+
Interdependency-Networks (3.2.4)	-	o	o	+	+	o	+	o	+		+
ABC-Analysis (3.2.5)	o		o	+	+	+	+	+	+		-
DSM (3.3.1)	+		+	+	+	+	+	o	o	o	+
Grid-Analysis (3.3.2)	-		+	+	+	+	+	o	o	o	+
Parameter Discussion (3.3.3)	o		+	+	+	+	+	+	+	+	+

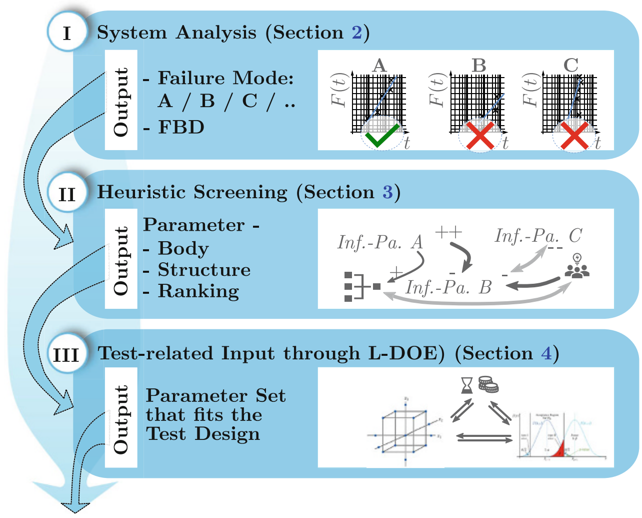

Fig. 15 Methodical approach for parameter assessment

defeats the method-performance and does not correspond to a heuristic screening. Furthermore, variation adjustment and robustness improvement also do not heuristically evaluate a state that is time-varying over the lifetime. Even when specifically applied in L-DOE, this significantly degrades the efficiency of screening, where heuristic methods could substantially remedy the situation. The subsequent outlined, however, generates the opposite. As a complement to this, therefore the following demonstrates a more comprehensive approach targeting reliability.

5.2 Heuristic procedure for parameter assessment

For an organizational overview of the procedure, first Fig. 7 is taken up again in order to explain the line of action with regard to a consideration of influencing factors and interactions on lifetime and reliability. Here, initially a system analysis is carried out, which is the basis for gathering, structuring and evaluation of influencing parameters within parameter screening. Subsequently, subject-specific facts and notes on strategies from the subject area of test design are taken into account in the DM.

5.2.1 (I) System analysis

The system analysis follows the steps described in Sect. 2 with the result of an FBD. Based on the generated information, all reliability-relevant information is bundled and evaluated here. This also includes the consideration of already detected failure data and mechanisms. If these are available, information about operational and utilization states that have generated failure mechanisms can be derived. If these vary, parameters influencing service life can at best already be assigned to the documented failure modes. If failure mechanisms can be explained by trivial fatigue processes or by early failures and not by the effect and interaction of influencing factors over the lifetime (degradation), these can be eliminated from consideration, cf. Fig. 15 *I*. For failure mechanism consideration and *Weibull* analysis also see [4, 10]. From the system analysis, we thus draw the basis for understanding the system's behavior in the event of failure.

5.2.2 (II) Influencing parameter assessment

Emerging from system analysis we now obtain the parameter set. The task here is to select suitable tools to reduce this set by means of a rational heuristic approach, so that subsequently we have robust chains of reasoning, cf. Fig. 15 *II*. The result should be a greatly reduced number of influencing factors that exclusively have a relevant influence on lifetime and the degradation process.

5.2.3 (III) Test-related input through L-DOE

The set of influencing parameters must now be adjusted to a manageable amount, by extending or further reducing them in number. The measures described in Sect. 4 serve as a basis of evaluation for this purpose. The goal is to meet the requirements of a user-defined test design by the number of factors to be examined, cf. Fig. 15 *III*. For test design evaluation also see [1, 3, 7].

With these clearly specified objectives defined in the sequence of the methodological procedure, a suitable approach can now be proposed using the evaluation made in Table 1, which is shown below:

Based on a profound system analysis and the definition of framework conditions for an investigation of the target variable (Sect. 2), as well as with the tools presented in Sect. 3, a methodical procedure for the heuristic collection, structuring and DM in parameter assessment for L-DOE is summarized in the following—see Fig. 16. The boundary conditions shown in Sect. 4 form the conceptual and procedural basis for this and derive primarily by requirements from experimental design for reliability.

Built on the knowledge gained in the course of this work, a comprehensive system analysis as described in Sect. 2 is recommended first of all aiming towards a solid foundation to service life investigations by means of L-DOE—irrespective of the intended scope for knowledge gain. In this, the complete system structure is to be recorded objectively and abstracted in an FBD for analysis. Information and sources gathered and documented therein should also provide insight into customer and company requirements. The model creator is then called upon. A literature search is rated as irreplaceable and obligatory here. The user is simultaneously required to form an inter-

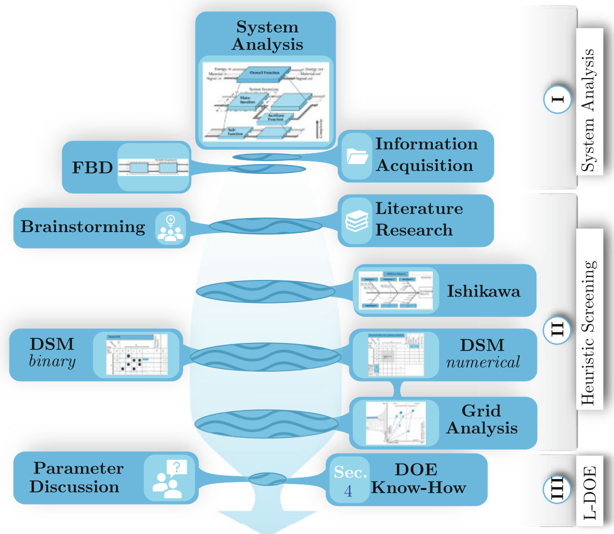

Fig. 16 Procedure of Heuristic Screening for L-DOE, representative volume of the body of considered parameters

disciplinary team of experts and to guide them through all the methods listed in Sect. 3.1, at least, however, through moderated Brainstorming. In addition to the usual procedure for examining standard target variables, it is explicitly elementary in these steps to support the identification of directly influencing parameters *and* possible interactions towards *lifetime* and *various failure mechanisms*.

With regard to DM, structuring is particularly important for a transparent presentation of the main influences *and* interactions in a network of influences to lifetime, that can at most have effects on the investigation objective *reliability*. For this reason, two requirements are assessed as necessary: a clear presentation of the cause-effect relationships *and* their effect on the target variable. Taking into account the attributes transparency, accuracy, and effectiveness required in Sect. 4.1, tools like Affinity Diagrams, Mind-Maps, or Directed Graphs are considered helpful, but not most targeted. In contrast, an Ishikawa-Diagram according to Sect. 3.2.3 has the characteristic to combine freely nameable and domain-specific advantages of a Mind-Map and an Interdependency Network and to make *more specific interactions graphically visible* over several levels of interpretation at the same time, compare Table 1. An Ishikawa diagram extended in this way therefore combines the advantages of the other representation and structuring methods with regard to the target variable reliability.

In case of DM, the authors recommend decision-making based on findings from Ishikawa and solid (L-)DOE know-how as far as stated in Sect. 4. A consideration of time effort and the level of detail allows an individual preference for a binary DSM or a numerical DSM in combination with Grid-Analysis. From experience, binary DSMs can considerably strengthen the reliability of argumentation for known systems, where well-founded expert knowledge about the system behavior is already available, but they do not generate surprisingly new insights. A profound Grid-Analysis, on the other hand, is advisable for unknown systems, where qualitatively heuristically recorded influencing variables are analyzed.

At first, simply formulated management queries according to Sect. 4.2 are to be clarified:

- what is already known and what is to be understood in which depth?
- can parameter interactions already be classified in terms of their actual effect size?
- which budget and which time frame is available for the investigation and know-how gain?
- how may the factors be managed, if selected?
- can the distributed variable lifetime be adequately described with the present parameter selection?

In case of doubt, such a rational approach to the selection of the most relevant influencing factors to reliability can only be confirmed by experimental screening regarding statistically significant effects on lifetime. In any case, however, this is a holistic, rational approach to the initialization of the most efficient (L-)DOE.

6 Case study

Within the scope of a project for reliability modeling of a timing belt drive, the procedure presented here is exemplified. On the basis of literature research, expert know-how, several publications and experimental investigations present, a large number of influencing factors and findings were available and classified according to Sect. 2. Eventually, a specific FDB (cf. Fig. 6) was created through system analysis, which was the basis for further investigations. The timing belt was isolated from its environment with regard to its top function of power transmission via the interfaces of frictional and friction-locking circumferential force, form-fit axial force and thermal and tribological disturbance parameters. In turn, failure mechanisms were investigated for the loss of the top function, whose influencing factors had to be determined. A team of experts was enabled to brainstorm and classify parameters within the procedure of an ABC-Analysis afterwards as stated in Sect. 3.1. These methods were chosen for a quick classification, since Brainstorming (cf. Sect. 3.1.2) was carried out efficiently and goal-oriented on the basis of good empirical information. The lack of transparency and accuracy within this step has been compensated by the structured documentation with the help of an ABC-Analysis (cf. Sect. 3.2.5), according to the assessment in Table 1. Here, initial ideas and findings on interactions that could influence running time of the belts

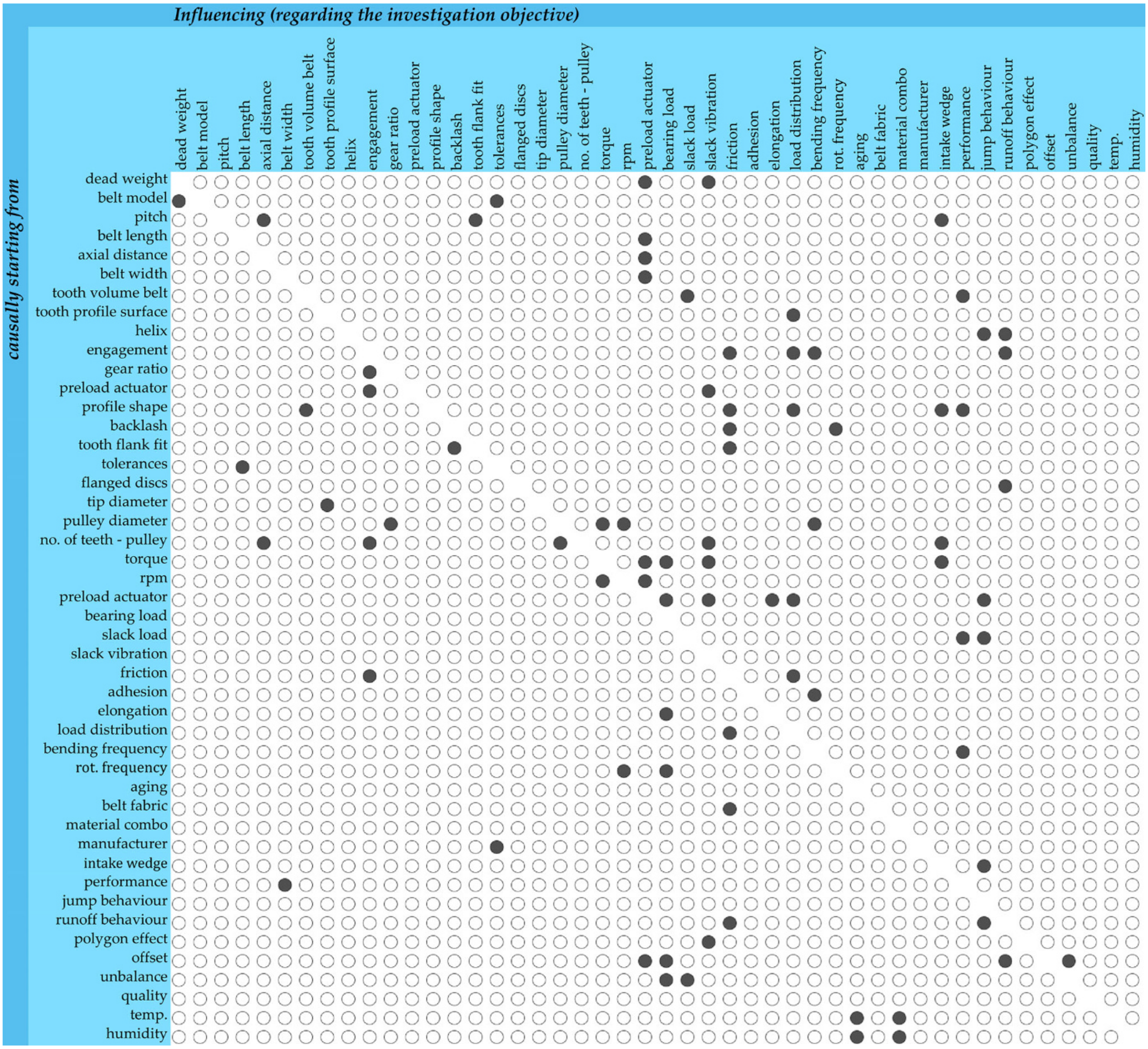

Fig. 17 Binary DSM for a timing belt, based on findings from [34, 35]

were also discussed and considered in the structuring process. As a result, the identified parameters were first ranked according to their assumed relevance in terms of *failure mechanisms* and *lifetime*. Comparing these findings with a binary DSM (see Fig. 17 and Sect. 3.3.1) and an extended Ishikawa-Diagram (compare Fig. 18 and Sect. 3.2.3), this ranking was abstracted to a network of interactions and potential effects on various stages of timing belt lifetime. With the Ishikawa, in particular, it was thus possible to simultaneously represent all lifetime factors as well as interactions and main effects in a differentiated manner. Although the clarity and simplicity in the presentation suffered from the holistic representation of these interrelationships, it promoted the basis for solid discussion within DM. Even presumed cross-domain interactions, whose development, for instance, should only be noticeable after certain logistical storage or run-in times, could be outlined in this way. Since this research on lifetime-influencing parameters for a timing belt resulted in a large number of factors, but not in a ranking order of relevance, the evaluation of DSM and Ishikawa was further utilized.

Simultaneously, time and capacity constraints combined with the selection of a suitable test design defined the organizational maximum number of factors to be possibly investigated, as compared to Sect. 4. Findings from the DSM and Ishikawa were also compared with expert knowledge and literature findings in terms of the observed strengths of interaction and presumed influences on lifetime iden-

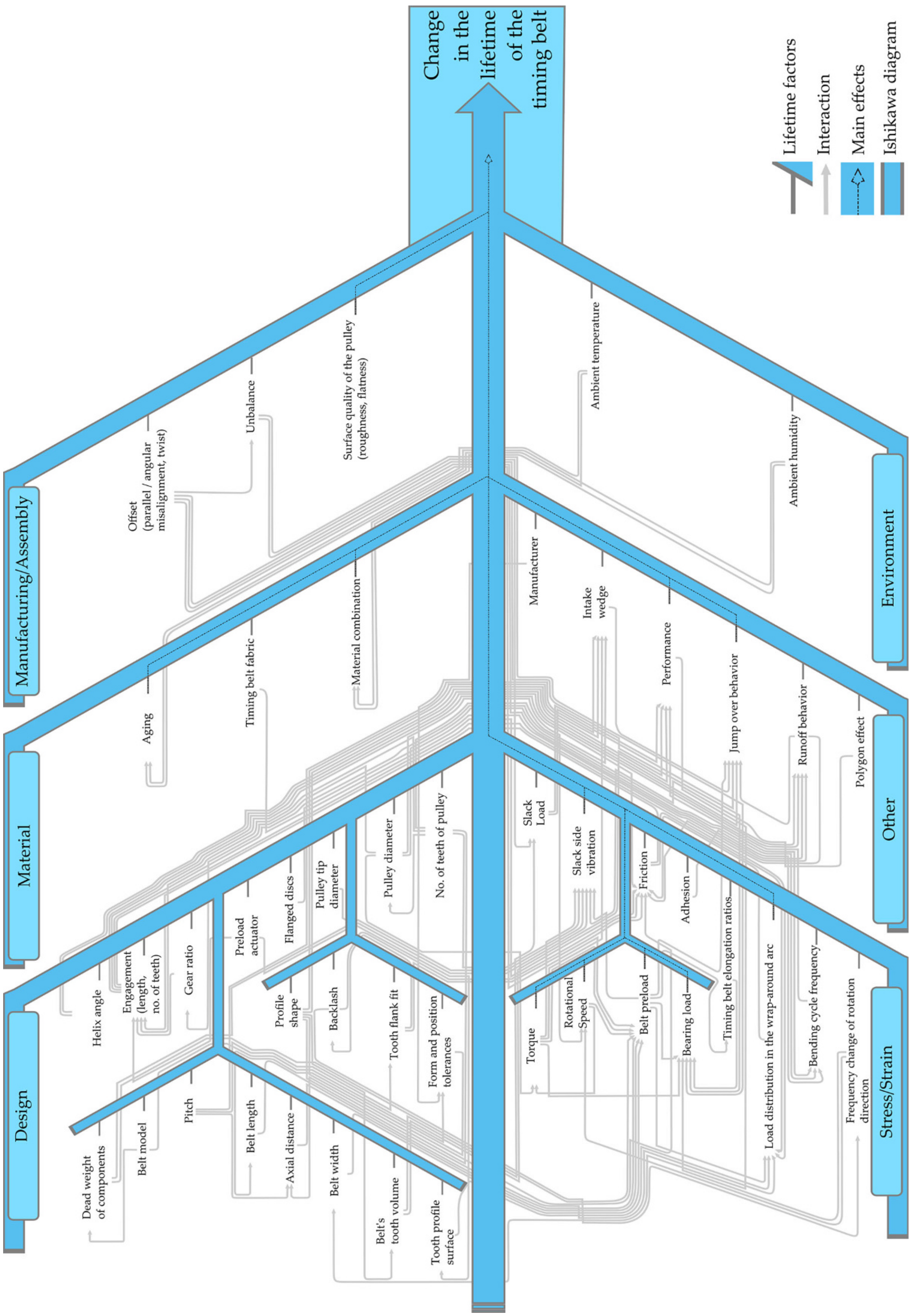

Fig. 18 Ishikawa-Diagram of influencing system parameters with interactions affecting the lifetime of a timing belt, based on findings from [34, 35]

tified therein. The total amount of identified parameters influencing the lifetime was first balanced therewith and reduced from 46 to six putative relevant factors. Qualitative attention was paid to non-correlating parameters and factors whose influence and interaction with other factors should accelerate a degradation process towards end-of-life, cf. Fig. 5. Here, it was also elementary to heuristically evaluate possible damage mechanisms and to estimate, based on experience, whether those could cause other failure modes.

In a second step, this number was further reduced to three factors depending on a preferred experimental design, a desired knowledge gain, the predicted total experimental duration as well as the presumed descriptive function between influencing variables and output, cf. Sect. 4.2. Eventually, the heuristic analysis of the interactions and reduction of the influencing parameters, which was plausibilized in this way, was successful on the basis of precisely the proposed methodical procedure and on the basis of a predictable trade-off.

Summarizing the case study, a minimum amount of selected parameters was obtained for the application of L-DOE by this way for the presented use case. In conclusion, the decision chain is thus based on idealized and rational decisions, which can only be strengthened by compensation in the model quality or experimental proofs.

7 Discussion and conclusion

(L-)DOE offers the highest degree of efficiency in relation to gain of holistic system understanding for the experimental investigation of product, process and system lifetime besides competing methods. In this respect, some research is available complementary to basics according to *Fisher*, *Taguchi* and *Shainin* with meaningful, efficiency-increasing options. As versatile as the investigation objectives and boundary conditions for DOE are, the methodical implementation can be standardized and abstracted according to the steps shown in Fig. 2. Recent findings and extensions in the application of DOE in both lifetime investigation and reliability modeling towards L-DOE have additionally expanded the field of application, cf. [12]. An equally efficient preparation phase for these investigations, however, is only roughly defined and available so far just for e.g. process and target variance investigations or robustness optimization, but not linked to the specific characteristics of (L-)DOE—and furthermore not explicitly targeted to *reliability*.

This work thus gives a manageable overview of available methods for information acquisition, structuring of influencing parameters and decision making (Sects. 3 and 4) with the aim to heuristically reduce the total number of lifetime-influencing parameters to a manageable size of the most relevant ones. Cogently, properties of L-DOE experimental designs and advantages for the workflow are taken up and linked with heuristic screening tools already in the early planning phase of DOE preparations. On this way, relevant thoughts and features are made present that would arise anyway in the later course of a dedicated application of L-DOE for reliability. Since both disciplines, DOE methods and heuristic assessment tools, are only partially linked so far, this now leads to a capital efficiency advantage. Eventually, here correlations are identified and classified just on a rational, qualitative-analytical level, without having to initially proceed to cost-intensive experimental investigations for lifetime. Thus, most likely, only those factors are within the experimental (L-)DOE process whose direct influences *and* interactions cannot actually be explained in a physically trivial way. Experimental investigations, on the other hand, are then only recommended and placed in a procedural step as rational DM is already performed. An incorrect selection of influencing factors for the experimental investigation of their effects on a target variable lifetime can therefore become highly improbable by means of this plausibilization. This procedure is therefore very advantageous especially for planned knowledge gain in the field of basic research or in case of completely unknown system behavior. This is done decisively focusing on factor interactions and evaluating the manifold influence of the same on degradation of a system performance over the time line up to the end-of-life. Finally, a successful application of this method is briefly outlined using the example of heuristic factor screening to perform an L-DOE for reliability modeling of a timing belt drive.

In perspective, the approach presented here can of course be empirically substantiated. For this purpose, a heuristic factor assessment can be carried out for a large number of cases and then confirmed experimentally with end-of-life tests. However, this would involve an enormous monetary and temporal effort. Thus, for the moment, this procedure is recommended on the basis of experience with the best conscience and from a reliability point of view.

If, in addition, extensions are to be taken into account, the automation of the procedure subsequently becomes highly relevant. Here a fully digitalized as well as automated execution of the entire procedure is desirable. Almost all of the processing creative techniques from Sect. 3 are suitable for the application of algorithms that assign ratings and evaluate correlations on an attribute-by-attribute or line-by-line basis. The extent to which automation with the use of machine learning is suitable here remains to be worked out in future projects.

Funding This research was funded in cooperation with thyssenkrupp AG as part of a joined research project.

Funding Open Access funding enabled and organized by Projekt DEAL.

Conflict of interest The authors declare no conflict of interest.

Authors' contributions Conceptualization, M.A. and M.D.; methodology, M.A.; software, M.A.; validation, M.A., W.R. and M.D.; formal analysis, M.A.; investigation, M.A.; resources, M.A.; data curation, M.A.; writing—original draft preparation, M.A.; writing—review and editing, M.A., W.R. and M.D.; visualization, M.A.; supervision, M.D.; project administration, M.A., W.R., M.D. and B.B.; funding acquisition, W.R., M.D. and B.B.; All authors have read and agreed to the published version of the manuscript.

References

1. Montgomery DC (2020) Design and Analysis of Experiments, 10. Aufl. Wiley, Hoboken, NJ, USA
2. Yang G (2007) Life Cycle Reliability Engineering. Wiley, Hoboken, NJ, USA https://doi.org/10.1002/9780470117880 (http://www.loc.gov/catdir/enhancements/fy0740/2006019150-b.html)
3. Kleppmann W (2020) Versuchsplanung: Produkte und Prozesse Optimieren, 10. Aufl. Hanser eLibrary. Hanser, München https://doi.org/10.3139/9783446463974 (https://www.hanser-elibrary.com/doi/book/10.3139/9783446463974)
4. Bertsche B (2008) Reliability in Automotive and Mechanical Engineering: Determination of Component and System Reliability, 1. Aufl. Springer, Berlin and Heidelberg https://doi.org/10.1007/978-3-540-34282-3
5. Coleman DE, Montgomery DC (1993) A systematic approach to planning for a designed industrial experiment. Technometrics 35(1):1–12. https://doi.org/10.2307/1269280
6. Fisher RA (Hrsg) (2003) Statistical Methods, Experimental Design, and Scientific Inference: A Re-issue of Statistical Methods for Research Workers, the Design of Experiments, and Statistical Methods and Scientific Inference, 9. Aufl. Oxford science publications. Oxford University Press, Oxford, UK
7. Siebertz K, van Bebber D, Hochkirchen T (2017) Statistische Versuchsplanung: Design of Experiments (DoE), 2. Aufl. VDI-Buch. Springer Vieweg, Berlin and Heidelberg https://doi.org/10.1007/978-3-662-55743-3
8. Mayers B (1997) Prozeß- und Produktoptimierung Mit Hilfe der Statistischen Versuchsmethodik: Dissertation. Berichte aus der Produktionstechnik. Shaker, Aachen
9. Gundlach C (2004) Entwicklung Eines Ganzheitlichen Vorgehensmodells zur Problemorientierten Anwendung des Statistischen Versuchsplanung: Dissertation. Kassel Univ. Press, Kassel (http://d-nb.info/971843546)
10. Meeker WQ, Escobar LA (1998) Statistical Methods for Reliability Data. Wiley, New York, NYC, USA (http://www.loc.gov/catdir/bios/wiley041/97039270.html)
11. Wu C-FJ, Hamada M (2000) Experiments: Planning, Analysis, and Parameter Design Optimization. Wiley series in probability and statistics Texts and references section. Wiley, New York, USA (http://www.loc.gov/catdir/description/wiley034/99052840.html)
12. Kremer A (2021) Statistische Versuchsplanung in der Lebensdauererprobung Mit Vertrauensintervallen: Dissertation. Berichte aus dem Institut für Maschinenelemente, Bd. 202. University of Stuttgart - Institute of Machine Components (IMA), Stuttgart https://doi.org/10.18419/opus-11728 (https://nbn-resolving.de/urn:nbn:de:bsz:93-opus-ds-117451)
13. Klein B (2011) Versuchsplanung - DoE: Einführung in die Taguchi/Shainin-Methodik, 3. Aufl. Oldenbourg, München https://doi.org/10.1524/9783486711363
14. Nelson WB (1990) Accelerated Testing: Statistical Models, Test Plans and Data Analysis. Wiley series in probability and mathematical statistics. Applied probability and statistics. Wiley, New York, USA https://doi.org/10.1002/qre.4680060214 (https://ebookcentral.proquest.com/lib/kxp/detail.action?docID=469757)
15. Daenzer WF (Hrsg) (2002) Systems Engineering: Methodik und Praxis, 11. Aufl. Industrielle Organisation, Zürich
16. Pahl G, Wallace K (Hrsg) (2007) Engineering Design: A Systematic Approach, 3. Aufl. Springer, London, UK https://doi.org/10.1007/978-1-84628-319-2 (http://site.ebrary.com/lib/librarytitles/docDetail.action?docID=10230457)
17. Hirtz J, Stone RB, McAdams DA, Szykman S, Wood KL (2002) A functional basis for engineering design: Reconciling and evolving previous efforts. Res Eng Des 13(2):65–82. https://doi.org/10.1007/s00163-001-0008-3
18. Krallmann H, Bobrik A, Levina O (2013) Systemanalyse Im Unternehmen: Prozessorientierte Methoden der Wirtschaftsinformatik, 6. Aufl. Oldenbourg, München https://doi.org/10.1524/9783486729825
19. Breiing A, Knosala R (1997) Bewerten Technischer Systeme: Theoretische und Methodische Grundlagen Bewertungstechnischer Entscheidungshilfen. Springer, Berlin and Heidelberg https://doi.org/10.1007/978-3-642-59229-4
20. Lindemann U, Maurer M, Braun T (2009) Structural Complexity Management: An Approach for the Field of Product Design. Springer, Berlin and Heidelberg https://doi.org/10.1007/978-3-540-87889-6 (http://digitale-objekte.hbz-nrw.de/webclient/DeliveryManager?pid=2842666&custom_att_2=simple_viewer)
21. Gharajedaghi J (2012) Systems Thinking: Managing Chaos and Complexity: A Platform for Designing Business Architecture, 3. Aufl. Elsevier, Burlington, VT https://doi.org/10.1016/C2010-0-66301-2 (http://gbv.eblib.com/patron/FullRecord.aspx?p=730205)
22. Theden P, Colsman H (2013) Qualitätstechniken: Werkzeuge zur Problemlösung und ständigen Verbesserung, 5. Aufl. Pocket-Power, Bd. 2. Hanser, München
23. Brückner C, Bopp R, Krauss F (Hrsg) (2019) Qualitätsmanagement: Das Praxishandbuch Für die Automobilindustrie, 2. Aufl. Hanser eLibrary. Hanser, München https://doi.org/10.3139/9783446459724
24. Montgomery DC (2009) Introduction to Statistical Quality Control, 6. Aufl. Wiley, Hoboken, NJ, USA
25. Thompson G (1999) Improving Maintainability and Reliability Through Design. Professional Engineering Publ, London, UK https://doi.org/10.1205/026387601528444
26. Albers S, Gassmann O (Hrsg) (2005) Handbuch Technologie- und Innovationsmanagement: Strategie - Umsetzung - Controlling, 1. Aufl. Gabler, Wiesbaden https://doi.org/10.1007/978-3-322-90786-8 (http://bvbr.bib-bvb.de:8991/F?func=service&doc_library=BVB01&doc_number=013335393&line_number=0001&func_code=DB_RECORDS&service_type=MEDIA)
27. Buzan T (Hrsg) (2010) The Mind Map Book: Unlock Your Creativity, Boost Your Memory, Change Your Life. Pearson/BBC Active, Harlow, UK

28. Tittmann P (2019) Graphentheorie: Eine Anwendungsorientierte Einführung, 3. Aufl. Hanser eLibrary. Hanser and Ciando, München https://doi.org/10.3139/9783446465039 (http://ebooks.ciando.com/book/index.cfm/bok_id/2643806)
29. Probst GJB, Gomez P (Hrsg) (1991) Vernetztes Denken: Ganzheitliches Führen in der Praxis, 2. Aufl. Gabler, Wiesbaden https://doi.org/10.1007/978-3-322-89072-6
30. Fülöp J (2005) Introduction to decision making methods. BDEI-3 Workshop, Washington, USA
31. Eppinger SD (2012) Design Structure Matrix Methods and Applications. Engineering systems. MIT Press, Cambridge, MA, USA (https://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=458479)
32. Antony J (2010) Design of Experiments for Engineers and Scientists, 2. Aufl. Butterworth-Heinemann, Amsterdam, NLD https://doi.org/10.1016/B978-0-7506-4709-0.X5000-5
33. Dazer M, Stohrer M, Kemmler S, Bertsche B (2016) Planning of reliability life tests within the accuracy, time and cost triangle. 2016 IEEE Accelerated Stress Testing & Reliability Conference (ASTR). IEEE, S 1–9 https://doi.org/10.1109/ASTR.2016.7762270
34. Nagel T (2008) Zahnriemengetriebe: Eigenschaften, Normung, Berechnung, Gestaltung. Hanser, München https://doi.org/10.3139/9783446416727 (http://www.hanser-elibrary.com/isbn/978-3-446-41380-1)
35. Perneder R (2009) Handbuch Zahnriementechnik: Grundlagen, Berechnung, Anwendungen. Springer, Berlin and Heidelberghttps://doi.org/10.1007/978-3-540-89322-6