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Reliability engineering based on operating data and monitoring systems within technical products: Challenges, requirements and approaches

S. Bracke & M. Hinz
Chair of Reliability Engineering and Risk Analytics, University of Wuppertal, Wuppertal, Germany

C. van Gulijk
Institute of Railway Research, University of Huddersfield, Huddersfield, England

F. Gronwald
Chair – Reliability of Technical Systems and Electrical Measurement, University of Siegen, Germany

M. Muenker
diondo GmbH, Hattingen, Germany

M. Inoue & S. Yamada
Department of Mechanical Engineering Informatics, Meiji University, Kanagawa, Japan

E. Patelli
Institute for Risk and Uncertainty, University of Liverpool, Liverpool, UK

B. Ulutas
Department of Industrial Engineering, Eskisehir Osmangazi University, Eskisehir, Turkey

M. Bonato
Valeo S.A., Paris, France

T. Yamada
Department of Informatics, University of Electro-Communications, Tokyo, Japan

ABSTRACT: The development process of complex technical products of the last years shows an increasing amount of sensors, electronic control units, data logging and monitoring systems within consumer goods (e.g. automobiles, washing machines) and industrial goods (e.g. machine tools, manufacturing systems). In many cases, the main goal of data logging is monitoring, controlling and optimisation of the product functionalities within the usage phase. A further aim is the fulfilment of the process capability of manufacturing processes. Therefore, the layout of the concept of operating data logging and monitoring systems—especially operating data (mainly type, volume, and format) as well as hardware (like sensors and storage)- is designed by the development engineer within the product concept development phase. This paper discusses challenges, requirements and approaches for future conceptual design of operating data logging concepts of technical products related to reliability engineering. Base of operations is the state of art. Based on that, the concept for operating data logging within a monitoring system is shown. The concept draft is subdivided in three parts which are divided as follows: part one deals with data analytics, part two contains data requirements, and part three focuses on hardware requirements. The presented research study was worked out on the international research platform "Computational Reliability Engineering in Product Development and Manufacturing (CRE) – 2017" and contains contributions of universities, institutes and original equipment manufacturers of industrial nations: Germany, United Kingdom, Japan, Turkey and France.

1 INTRODUCTION

The development process of complex technical products of the last years shows an increasing amount of sensors, electronic control units, data logging and monitoring systems within consumer goods (e.g. automobiles, washing machines) and industrial goods (e.g. machine tools, manufacturing systems). In many cases, the main goal of data logging is monitoring, controlling and optimisation of the product functionalities within the usage phase. A further aim is the fulfilment of the process capability of manufacturing processes.

Therefore, the layout of the concept of operating data logging and monitoring systems—especially operating data type, volume, format and storage—is up to this point of time in most cases designed by the development engineer within the product concept development phase. However, the design engineer is also responsible for the product functionality. Hence, the logged data is very often directly related to a technical discipline (e.g. automotive engineering: the rotation angle and cycle sensor is related to the antilock braking system which belongs to the division of chassis engineering). But this data can also serve as a foundation for the reliability analysis (e.g. automotive engineering: amount of steering turns, or frequency gathered from rotation angle sensor are live span variables, which can be used for statistical reliability models). Consequently, a comprehensive operating data logging (software) and monitoring system (hardware) for future technical complex product generations is needed with complementary functionality: Controlling product functionality and ensure product reliability of the actual and subsequently following generation.

2 GOAL OF RESEARCH ACTIVITIES

This paper discusses challenges, requirements and approaches for future conceptual design of operating data logging systems of technical products related to reliability engineering. In detail: (1) Requirements regarding operating data structure: e.g. data type, data volume, data format; (2) Requirements regarding data recording structure and hardware aspects: e.g. frequency, sensors and storage; (3) Aspects of data analytics based on gained operating data in the usage phase.

3 FUNDAMENTALS

3.1 *Design of the monitoring system within the product life cycle*

The product life cycle of technical products can be described in four main and eight subordinate phases, cf. (Bracke 2016):

1. Concept phase
   - 1a. Definition of the product characteristics
   - 1b. Development of the product concept
2. Development phase
   - 2a. Construction stages (different prototype levels and finalising the design)
   - 2b. Preparation of manufacturing
3. Production phase
   - 3a. Start of production (SOP)
   - 3b. Production
4. Sale/Usage phase
   - 4a. Sale of products to the markets
   - 4b. Usage phase and product observation

The concept of operating data logging and monitoring systems—especially operating data type, volume, format and storage – has to be designed by the reliability engineer of the Original Equipment Manufacturer (OEM) or Supplier within the product concept development phase (Phase 1b, cf. section 3.1).

3.2 *Design of operating data type*

In general, the operating data types can be subdivided in following different categories:

a. Secretly compiled data (OEM / Supplier):
   - Definition logging logic OEM,
   - Data encryption through OEM,
   - Storage strategy: “fleeting”, “semi-permanent”, “permanent”

b. Officially compiled data:
   Example automobile: eCall emergency system (since 31-03-2018), which gives an emergency call after an accident (“sleeping system”) and transfers basic automobile operating data.

c. Voluntarily compiled data:
   Example: Vehicle insurance, Policy with scoring option, logging function is always on.

The reliability engineer has to define the essential life span variables and operating data types in the concept development phase (cf. section 3.1). To ensure a long-term availability of the operating data regarding reliability analysis within the entire product life cycle, the storage strategy “permanent” (cf. numeration (a) above) is to be pursued. The strategy “fleeting” is only interesting for direct operating decisions, the strategy “semi-permanent” does not allow the data analysis after the end of product life. Officially compiled data is also interesting, if the storage strategy is “permanent”. Voluntarily compiled data is not in focus of this study.

4 OPERATING DATA AND MONITORING SYSTEM: DATA ANALYTICS, DATA AND HARDWARE REQUIREMENTS

Within this section, the data and hardware requirements, based on data analysis strategies, for an operating data and monitoring system are shown. The concept draft is subdivided in three following parts: Part one deals with data analytics e.g. uncertainty, second life and lessons learned aspects (cf. section 4.1). Based on the goal of data analysis, part two and three contains data requirements (cf. section 4.2; e.g. structure and format) and hardware requirements (cf. section 4.3, e.g. sensors and storage availability within monitoring systems in products and facilities).

4.1 *Data analytics*

4.1.1 *Aspects of data uncertainty regarding a reliability model*

Operating data logging and monitoring systems are largely used to improve the knowledge of a specific system or component. However, data are always associated with some noise or measurement error, e.g. due to different environmental conditions. In turn, the model used to, e.g. predict the useful reaming life of a component, or schedule maintenance is also affected by uncertainty. If such uncertainties are neglected, some wrong and costly decision can be made (for instance, recall a product). Such uncertainty can also nullify the benefits of using machine learning frameworks for analysing the continuously increasing available data.

One of the current challenges in the capability is to discriminate when such machines and tools are providing reliable estimate or their prediction has been fooled by noise. One possible solution is to use past experience and predictions to determine precise levels of confidence for the new predictions (Shafer and Voyk 2008). Another popular approach is based on the Bayesian paradigm for inference. In such framework, Bayes' rule is used to update our believe on validity of the model prediction with information from empirical observations (data) taking into account the associate uncertainty in such observations. The reader is referred to (Aki Vehtari and Janne Ojanen 2012) for detailed description of Bayesian methods.

4.1.2 *Aspects of the use of product operating data for a second life cycle*

In order to avoid environmental issues, it is necessary to minimize the material and energy consumption during the whole product lifecycle (Yamada 2012). One of the potentials for material circulation environmentally and economically is to reuse the End-of-Life (EOL) assembly products by remanufacturing in the second life cycle. Remanufacturing is the process of bringing an assembly to like-new condition through replacing and rebuilding its components at least to current specification (Ilgin and Gupta, 2012). There are two essential processes in the remanufacturing: disassembly and re-assembly of the EOL products (Lambert and Gupta 2005).

To conduct the data analytics for the disassembling process in an environmental friendly and economical way, a parts selection method (Igarashi, et al., 2016; Kinoshita et al., 2016) including reuse (Hasegawa et al., 2017a, 2017b) shows which parts should be reused, recycled and disposed in terms of environmental impacts and costs. The operating data of a part in the usage stage of the first life cycle helps on the parts selection that can be disassembled. Here, one of the challenges is that the data affects the decision of the part selection itself by the recovery costs with different sales revenues for the parts.

4.1.3 *Transforming operating data in Lessons-Learned-Data-Structure for subsequently following product generations*

Application of data analytics to improve manufacturing operations and transferring critical information to following product generations are an integral part of data-driven decision making. When processes are better defined and more standardized, lessons can be combined into standards and guidelines. It is rather hard to share lessons in areas of complex or context-specific need, for topics that are rapidly changing, and where new problems are frequently being identified. Therefore, lessons should be written down and stored in a database in such a way that other related people can find and access the required knowledge. It is important to sort the individual lessons and store them under themes or topics in the lessons learned database. By this means, data can be filtered and previous actions of any problem can be considered during product's engineering design process. Updating the database (i.e., guidance documents, best practices and standards for the process) is also a crucial issue to sustain the garbage in, garbage out philosophy. The quality of lessons knowledge may change from extremely useful to completely unhelpful. Therefore, the ease and accuracy of transforming data for product generations depend on how data is collected, stored, and updated.

Commonly used data mining applications in manufacturing include failure evaluation, quality control, safety analysis, and capacity planning. Statistical Process Control (SPC) is one of the techniques suggested for real-time monitoring of operational performance of manufacturing systems. There is an ongoing research on better ways of collecting data and developing big data infrastructure technologies. Besides sensor technologies, Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES) are also used for data collection technology the development of cloud service platforms.

4.1.4 *Aspects of reliability analytics: Probabilistic uncertainty based on input data/operating data*

The quality of the data can have a significant influence on the analysis results and their interpretation which could cause a wrong conclusion of the product reliability. In fact, the amount, quality, format and processing of the data are only few of many other factors which have to be considered during the statistical analysis of operating data. It is still uncertain, whereupon and in which order it is necessary to pay attention by the examination of particular properties during the statistical analysis. A comprehensive list of factors which can influence the data analysis, or much more the results, is shown in (Hinz 2015). The proposed factors are divided into four groups:

- Data quality – demonstrates the requirements with respect to the compound of diverse inputs and properties of a data set (e.g. diverse load profiles or the unit on life span variables)
- Empiricism – knowledge based on experience regarding the application of the product fleet as well as market specific boundary conditions (e.g. product derivatives or user profiles)
- Aim of analysis – various purposes of the statistical analysis will result in the application of different methods which may cause further uncertainties (e.g. the kind of a damage case)
- Mathematical models – this group describes statistical models, equations and algorithms which can be used with regard to the reliability analysis (e.g. various methods for the estimation of the distribution parameters).

In plenty of cases, even the application of methods that can be expected to provide always reliable results may lead to high uncertainties. For example, the estimation of the shape parameters of Weibull distribution based on different estimators (here: Maximum Likelihood, Gumbel, Least Squares, Method of Moments, Nelson, and DIN 55303) and various sample sizes (varying between 10 and 1000) shall be considered. The results are shown in

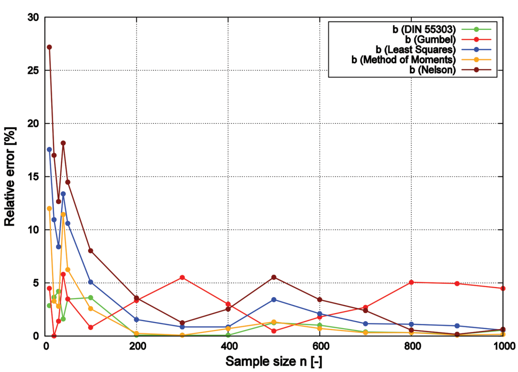

Figure 1. Relative error of the estimated shape parameters of Weibull distribution using various estimation models.

Figure 1. The mentioned methods are compared to the maximum likelihood (MLE) and the relative error is plotted as a function of the sample size.

It can be easily observed, that especially for the small sample sizes, the application of different parameter estimators can cause big differences in the gathered results. For a sample consisting of 10 entries, the difference between MLE and Nelson equals to 28%.

In many cases combinations of multiple factors play a major role during the data analysis. This can cause a high uncertainty of the results which can differ exponentially from the reality.

4.2 *Data requirements: Operating data structure: e.g. data type, data volume, data format*

To some extent, the requirements for data are relatively flexible as long as that data supports the data-scheme for monitoring systems. The requirements therefore focus on data scheme and depend less on the actual data itself. The objective is to enable communication between the data-sender and the data-receiver. The data sender, say a logging system, has a data scheme to store relevant information in its own local database (which may be small if there are detectors only). The data may be system state messages, error messages or alarms that may contain a timestamp, serial numbers, identification codes, numeric values and meta-data. The date receiver, say a Matlab application for reliability engineering, has its own data scheme. Only part of the data from the data logger is useful for the Matlab application; some kind of data transformation is required. Such transformations can be made in many different ways; the key, however, is that the meta-data about the data-scheme is correct, informative and up-to-date. In many industries data standards have been developed to harmonize efforts of different industry partners; this tends to be efficient for many industries. For instance, the Oil and Gas industry uses ISO 15926 as an International Standard for the representation of process plant life-cycle information. This standard specifies a generic, conceptual data model that is suitable as the basis for implementation in a shared database or data warehouse. Many industries have developed similar standards; aligning with them in own field is well-worth the effort; IT solutions that do not follow the standards may not be accepted in the industry. Summarizing, data requirements focus on correct data scheme descriptions. For engineers, such descriptions are captured in technical reports. For the computer it is captured in the format of database.

4.3 *Hardware requirements*

4.3.1 *Aspects/requirements of hardware (sensor and storage technologies) within certain products*

The hardware components of data recording and monitoring systems typically represent a measurement chain that consists of four blocks for sensing, signal conditioning, signal processing, as well as data presentation and storage (Bentley 2005). Depending on the field of application, each hardware component has to fulfil certain requirements that are typically provided by established standards. An example of a general high-level standard is the RTCA-DO-160 standard for the environmental testing of hardware in an aerospace context (RTCA-DO160). The related tests are, for example, of a mechanical, chemical, or electromagnetic nature and, as a whole, rather involved and time-consuming. Depending on the field of application of a data recording and monitoring system, it might be neither feasible nor economical to perform the whole variety of desirable tests for each component. This leads to the challenge of determining, on a component level, meaningful hardware requirements that avoid excessive testing while keeping necessary standards. There is no general solution to this problem, which highly depends on the actual case. Existing standards, however, can provide valuable guidelines.

Moving from component to system level, the proper integration of a data recording and monitoring system into a complex technical product is required. Due to the general increase of complexity and electromagnetic sensitivity within technical systems, this task becomes increasingly challenging as well. The traditional approach for a proper integration involves the analytical and numerical modelling of possible unwanted electromagnetic couplings between different components (Tesche 1997). This is caused by the signal propagation between sensor and data unit along the aforementioned four blocks which is mainly of an electromagnetic nature. However, it has recently become apparent that increasing complexity requires, besides deterministic methods, also statistical methods that are adapted from reliability engineering to electrical engineering (Mao 2016). As a result and new development, both hardware requirements and aspects of uncertainty have to be considered as a whole during the system integration.

4.3.2 *Hardware requirements: Aspects of monitoring systems in complex technical facilities*

In an industrial environment a monitoring system will be developed, installed and operated only if a commercial benefit, either direct or on multi-level basis, can be expected.

The basic kind of monitoring is meant to prevent from system damage under use, offering upfront indications (e.g. life span variables like temperature, vibrations, etc.) for imperative service, usually combined with routine maintenance. It is applied for cheap and simple mass products. Second order monitoring is used to acquire data about the product quality during production (etc. weight, shape, homogeneity); it is recommended for mass products of some value and complexity. Ideally, this information is used to control the production process inline.

On the next level, sensor data combined with the operating parameter log can be used to continuously diagnose the present system status and so the product quality. It is combined with preferably non-destructive sample inspection of the product to verify the process' stability. Such kind of monitoring may also allow to adapt the maintenance frequency to the actual strain of the system. It is used for complex processes where reliability is the most important aspect (low-volume, costly or safety-related products).

Finally, these vast amount of information and data has to be merged with a system behaviour model to approve, recommend or tune warily operation modes and to venture a prediction for remaining lifetime, while the maintenance schedule is aligned with production requirements. On this level, the product is not necessarily a touchable item but could also mean energy (battery), information (data storage), or movement (aircraft engine).

Some of the economic effects of such monitoring efforts are obvious: increased lifetime, less downtime, higher throughput, less spares on stock and sufficient time to plan inevitable replacements. But there are also savings due to less failure in general, and less risk caused by unknown defective parts distributed into the market (product liability: documented monitoring is mandatory to defend claims). Wherever potential savings outbalance the costs an appropriate level of monitoring will be established.

4.3.3 *Conceptional aspects of standardisation of operating data recording within technical products*

The purposes of the operation data logging system regarding reliability engineering are detection of the cause of a failure or observation as well as prediction of failure and providence of maintenance action to user or producer. To formulate failure and its cause, monitoring system, and necessary and sufficient kind and number of sensors need to be allocated to product system. Hence, failure mode needs to be deployed into basic events by using FTA: Fault Tree Analysis (Lee et al.

1985) where designer selects appropriate sensor by reference to these events. On the other hand, many existing products such as automobiles and machine tools are already equipped with a monitoring system for attainment of its functionality. This monitoring system consists of sensors, ECU: Electronic Control Unit, and actuators and these components are modularized from the perspective of functionality usually by using DSM: Design Structure Matrix (Eppinger et al. 1994). Therefore, in the case of developing reliability monitoring system additionally, this system is desired not to change the structure of the existing functionality-it has monitoring structure which includes existing system modules. In addition, the occurrence of product failure depends on various elements such as the usage time, client usage, and other external factors. The sensors which are components of functionality-based system might not detect external factors such as temperature, humidity, and electromagnetic wave. Hence, for attainment of building failure-based monitoring system, designer needs to integrate undermentioned three steps: (1) deploying target failure mode to basic event by using FTA, (2) identifying necessary functionality-based monitoring systems and additional sensors for detecting external factors, and (3) modularizing these functionality-based sub-systems, additional sensors, and administration unit for transmitted signals. Figure 2 illustrates the concept structure of the failure-based monitoring system.

This failure-based monitoring system does not affect the structure of the existing functionality-based monitoring system. Therefore, this system has possibility to be optionally added to operating product system by upgrading without major design or structure changes.

4.3.4 *Hardware in use: Impacts on reliability of data recording safety within the product use phase*

The first impact of data recording systems within the product usage phase is related to scenarios in which the measurements are performed:

1. Field test: the goal is to measure the transient and steady state inputs of a vehicle as it operates over the real environment, in order to anticipate market region of use
2. Proving ground measurement: the goal is to replicate the most significant drive profiles from the field test, but in a more controlled environment (e.g. test track or climatic wind tunnel).

Field test are designed to capture all the environmental loadings that might affect the reliability of the vehicle or single components during its in-use phase. This type of measurements takes usually days or weeks. Data are recorded by the mean of a mobile data logger, which allows the simultaneous recording of a wide variety of sensor measurements. This type of device can be small and with integrated sensors, making them ideal for final customers' survey (Figure 3 left).

Proving ground measurements are based on the results from field test and focused on precise driving events during the development phase of a new vehicle. They are performed by an acquisition system, which guarantees more refined measurements, but it is less robust towards environmental stresses, and need to be interfaced to a laptop for data saving and storage.

Be either a road field test or a wind tunnel test, vehicle measurements are expensive. To perform such tests, one must first built a prototype (for Original Equipment Manufacturer - OEM) respectively buy or rent the selected car (for component suppliers). The required sensors need to be mounted, connected, and cabled. There must be enough room for all sensors, the cables, and a comfortable environment for both the driver and the acquisition system. Additional care must be taken when measuring the response of a component, which needs to be equipped with sensors (e.g. strain gages and thermocouples) by a reliable supplier, and then assembled in the vehicle.

Because of so many time and money consuming aspect, the key role of the test engineer is to make sure that measurement sessions are not jeopardize because of 1) improper sensor mounting 2) inadequate data acquisition/storage.

Once the suitable acquisition system has been considered for the measurements, the key aspect of a successful measurement lies on the type of sensors.

Sensors need to be tailored to the physical value of interest. It is therefore fundamental a prior

Figure 2. Structure of failure-based monitoring system.

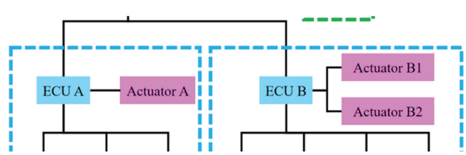

Figure 3. Small data logger with integrated sensors (left). PC interfaced Data acquisition system (right) (cf. (MSRDatenlogger)).

knowledge of the value range (maximum and minimum value, the frequency etc.).

Sensors must also be accurate, enough sensitive to properly measured small variations, but robust toward the inevitable environmental stress resulting from driving ground: shock, heat, humidity, and contamination associated to the potential adverse conditions of the road profile (dust, mud, water etc). In general, sensors must be operative under all ambient temperature conditions.

Similarly, the acquisition system must be tailored to the measurement type. There must be a trade-off between system performance and robustness and in some case its dimensions. As a typical example, integrated circuit piezoelectric (ICP) accelerometers are less intrusive (smaller and lighter) and more accurate than capacitive ones, but less resistant to high temperature and shock. ICP sensors would perfectly fit for vibration measurements on the chassis or cabin component, but be unreliable for engine vibrations, due to the high temperature reached during combustion.

High care should be taken when mounting the sensors: external factors that might interfere with the measurements are electrical leakage and shorts. Moreover, the electromagnetic compatibility of the acquisition systems and logger should be verified to avoid the presence of electromagnetic parasitic noise.

Some additional consideration and precaution should be used when planning long field measurements.

The settings of the data logger (usually mounted inside the cabin) require a trade-off between frequency of acquisition and storage memory. Particular care must be taken for acceleration measurements, since their high frequency and long acquisition time might be computationally demanding during data post-processing.

Solid State Drive (SSD) memory devices are preferred to Hard Disk Drives (HDD) because they are less affected by dust contamination and vibration loading. Moreover, SDDs do not require rotating component such as the platter or the fan system.

Planning of field measurements also need to consider the available memory and how it works, to avoid data loss. The most commonly used memory storage methods are i) erasable data storage systems (once the memory is full, after a certain time the system is erased) and ii) circular or buffer memory (oldest data gets overwritten when the memory is full).

During field or proving ground measurements, both data loggers and acquisition systems can be used to record data coming from the on Board Diagnostics (ODB) or the control area network (CAN) bus. It is obvious that when recording both data from sensor and form the vehicle on-board computer, the measurements needs to be synchronized.

A check-list to avoid potential problems encountered during field measurements could include the following topics:

– Sensors: must be robust, accurate and properly calibrated.
– Acquisition system: suitable to the type of measurements (portable PC interfaced vs. data logger).
– Memory storage: chosen with respect to the amount of expected data, limitation of the memory capability and post-processing computational effort.
– Post processing: properly labelling of measurements channels; data saved in an exploitable format.
– Privacy issue: field tests on final customers (e.g. users' fleet) must be compliant to privacy policy, which varies from one country to another.

5 SUMMARY

The development process of complex technical products of the last years shows an increasing amount of sensors, electronic control units, data logging and monitoring systems within consumer goods (e.g. automobiles, washing machines) and industrial goods (e.g. machine tools, manufacturing systems). This operating data can be a foundation for statistical analysis regarding the reliability of the product. The goals of data analytics (focus: data uncertainty, reliability analytics, second-life-cycle aspects, Lessons-Learned issues) are the base of operations for the data and hardware requirements.

Main requirements regarding the monitored data are as follows:

- Clear data Scheme regarding the local data storage system,
- Data content (storage): Messages, error, alarms, timestamp, serial number, identification codes, numeric values, meta data,
- Data receiver: Possibility of data transformation
- Consideration of industrial data standards, depending on product category,
- Possibility of technical report,

Main requirements regarding the monitoring system hardware are as follows:

- Considering standards for sensing, signal conditioning, signal processing, data presentation and storage,
- Considering possible electromagnetic sensitivity regarding signal propagation between sensor and data unit,
- Modularisation of monitoring system components,

- Considering upgrade possibility during product life cycle,
- Considering load profile regarding expected product life cycle within monitoring prototype testing (field test versus proving ground measurement).

The shown requirements can be used as a guideline for the reliability engineer for the design of operating data logging and monitoring systems within the product concept development phase of a new product generation.

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