Abstract

Advanced technology requires to use products in a range of conditions what may lead to their unintended performance in practical situations. In order to achieve reliability and safety different sources of uncertainties and variations in design, manufacturing and operation of products should be considered. Moreover, in the paper concepts of novel approaches to quality control of products robust against to uncertainties are proposed which enable to increase product reliability and safety operations.

Keywords: Product; Quality control; Reliability; Uncertainty; Variation; Optimization

1. Introduction

Customer satisfaction determines the success of a new product and only products at high value meet needs of clients who expect them to perform correctly in their whole life cycle. In order to fulfill such requirements the minimum of variation of parameters should be assured within the manufacturing processes and the product itself. From an elementary part to compound parts, they must be designed and manufactured on high quality level and be reliable and safe in use.

In the literature the notions: quality, reliability and safety are often used interchangeably. However, they do not have the same meaning as quality is conformance to specifications, whereas reliability concerns functioning under...
defined conditioned for a specified time. So, it can be said that reliability is the extension of the term quality over time and can be defined as “the time period over which a product meets the standards of quality for the period of expected use” [1]. Moreover, it is a fundamental attribute for safety operations [2] as common methods are used for their analysis and it happens that they require input from each other [3]. In reliability analysis the subject matter is the uncertainty in the failure occurrences, noises and disturbances during product operation and consequences, whereas the objective of safety is to protect the product against the uncertainties of its accidental scenarios [2]. Both reliability and safety engineering aim at study, characterization, measurement, analysis of failure, its repair and consequences to be able to improve operational system use. They result from product complexity, development of technology, customer requirements, public awareness, market competition, safety and liability legal requirements, former system failures and their consequences [4].

Following the classical methods such as worst-case performance in order to protect a product from the uncertainty of its failure, the behavior of a product is viewed upon as a direct assessment of the manufactured attributes [5,6]. So, the quality of the final product depends on the quality of its component and therefore, the worst scenario is assumed. On the basis of it, the consequences are predicted and barriers for preventing and protecting from such scenario are designed. This approach is still undertaken in practice in spite of the fact that it is based on the consideration of huge catastrophes, sometimes even highly unlikely. It may lead to unnecessary, sometimes even excessive regulatory barriers, in the design and operation of the product [2]. Thus, in the last two decades of the previous century more and more attention has been paid to approaches which rely on statistical assessment of probability of manufacturing faulty product [7,8]. The effectiveness of these methods depends on the number and representativeness of data used for statistical analysis. Moreover, these approaches are not always able to detect all defective items, thus in order to overcome these problems it is advisable to apply control methods in which the manufactured attribute is compared with nominal product. These methods are originally based on expensive hardware redundancy but currently instead of the nominal product an analytical model is used and it reflects the behavior of the product [9].

In the paper some considerations of quality, reliability and safety are shared as a number of problems and challenges must be faced in manufacturing and operation of products which are becoming more and more complex. Different approaches to quality control of products are presented and widely discussed. Their pros and cons are shown in order to indicate the direction of further research in this scope.

2. Variations and uncertainties as the sources of product failures

In order to tackle the development of advanced technologies, the reliability of products has become a significant matter of concern. It regards with respect to failure avoidance rather than probability of failure [10]. Product failure occurs when the product is not able to perform its objective functions and does not meet its requirements. Thus, reliability is a product capability to fulfill intended tasks for a specified performance period. Performance period can be a function of cycles, distance or time [11]. Its rapid growth results from the introduction of the idea of safety and risk as nowadays it is expected to produce and sell high reliability products and purchase and operate them safely without any risk [12,13,14].

Failures are usually attributable to one or a group of failure modes which can result from a chain of causes and effects such as: a symptom, trouble or operational complaint [15]. They can be categorized into different types and sources. Considering all product failures two types can emerge: random (or physical) and systematic (or functional). Random failures result in casual lack of achieving its objectives what may lead to one or more degradation mechanisms in the hardware, whereas if the product does not perform its intended tasks but no components have already failed is the example of systematic failure [16]. Failures can be categorized due to intrinsic and extrinsic causes which result from weakness and/or wear-out or errors, misuse or mishandling [17]. Among them the following can be distinguished: design faults, material defects, processing and manufacturing deficiencies, lack or improper quality control, inadequate testing, human errors, improper assembly or installation, off-design or unintended service conditions, improper operation, lack of protection against over stress and maintenance deficiencies [4,15,18]. Failures lead to losses in repair cost, warranty claims, customer disappointment, product recalls, loss of sale, and finally loss of life [19]. To reduce them, variations can be decreased or a product can be
designed robust against these variations. Moreover, other uncertainties such as incomplete information regarding the phenomena, data, model errors, human mistakes and parameter uncertainties have to be taken into account.

Uncertainty encompasses the occurrence of events which are beyond human management capabilities. Any uncertain variable has a random characteristic which yields a level of error. In the literature there are various classifications of uncertainties [20,21], however, they are generally categorized as either aleatory and epistemic uncertainties. The first one concerns the underlying, inherent uncertainties such as randomness of a phenomenon, scattered in life and the load variation within a population when the modeler is not able to foresee the possibility of their reduction. The latter one refers to the uncertainties due to lack of knowledge, which can be decreased by the application of additional data or information, better modeling, and parameter estimation methods. It should be emphasized that in the reliability modeling, it is possible to divide the second kind of uncertainty into statistical uncertainty and model uncertainty, whereas the first type of uncertainty is called random variation (or physical uncertainty, noise factor). Statistical uncertainty refers to estimation of model parameters based on the available data where the observations of the variable may not represent the real situation perfectly, and thus, the recorded data may be biased. Additionally, different sample data sets usually provide diverse statistical estimates. Model uncertainty results from the use of one (or more) simplified relationship which is supposed to represent the “real” relationship or phenomenon of interest. Such an approach results from lack of knowledge or increased availability of data. Another important kind of uncertainty is related to the uncertainties due to human factors. Such uncertainties result from human errors and interventions undertaken in the design, manufacturing and operation. For example, they can be caused by misuse, gross errors and human mistakes [22,23,24]. They can be considered by creating robustness through product changes or using an extra safety, however, in practice they are primarily subjects to quality management [10].

3. Product reliability

The behavior of the product depicted in Fig. 1 can be described by the following relation:

$$y_k = F(p, u_k) + \varepsilon_k$$

(1)

where $u_k$ and $y_k$ are product inputs and outputs, respectively. $p$ are parameters representing physical features of a manufactured product such as dimension or physical characteristics of product components. All these values, manufactured in the production process, are influenced by control factors $s$. Moreover, $F(\cdot)$ is the relation between inputs, output and parameters describing the behavior or properties of the product and $\varepsilon_k$ represents the noise.

![Diagram](image)

Fig. 1. The general scheme of the product.

The problem of product reliability and safety has to be considered during product design, its manufacturing and operation stages (c.f. Figs. 2-4). In order to ensure the product reliability it is necessary to ensure its robustness against different sources of uncertainty. Robustness is defined in Taguchi et al. [25] as ‘the state where the technology, product, or process performance is minimally sensitive to factors causing variability (either in manufacturing or user’s environment) and aging at the lowest manufacturing cost’. Thus, its aim is not to eliminate noise but to create insensitivity to it [26]. The general scheme of the reliable product design is depicted in Fig. 2.
As it can be seen it includes conception design, identification of product uncertainty sources and robust product design. The most important tasks concern product parameters and its tolerance design. In the literature several method to solve them can be found (i.e. QFD, Taguchi, Worst Case, Six Sigma, Monte Carlo, optimization-based methods) [5,6,25,26,27,28,29,30]. The optimization-based methods seem to be especially attractive as they are based on the choice of parametric structure of the model during conception product development stage and parameter estimation with the application of optimization techniques [30]. This mathematical model can be used to elaborate a control method of product quality in the manufacturing process and operation. Moreover, such an approach allows to choose the optimal values of parameters of the model which accurately reflect clients’ expectations. To improve the model, design of experiments, which is based on fractional factorial designs or orthogonal arrays, can be applied. Control factors, which include the design parameters in product or process design, are set at fixed levels, whereas the settings of noise factors (variables), which have a potential influence on the product outputs, are varied systematically to show their changeability in normal conditions. The appropriate choice of the setting of control factors allows to make them less sensitive to noise variations what reduces the performance variation of the product.
The problem of ensuring the product reliability at the stage of its manufacturing is presented in Fig. 2. Besides development of the conception of the manufacturing process and identification of the uncertainty sources the task of manufacturing process design and its quality control is one of the most important. To ensure process quality control the well-developed control charts techniques can be applied [31]. Such methods allow to stop the manufacturing process in order to avoid production of faulty products.

The reliable product operation is usually ensured by the application of different failure avoidance techniques. They are generally effective when a whole potential operation uncertainty sources are known but it is often impossible. The product quality control (supervision of quality), which takes place during product operation, is directed to detection of deterioration of product quality (or its parameters). In this case it is vital to detect it early enough not to accept the situation where a damaged component can make a breakdown of other product elements.

![Identification of operation uncertainty sources diagram](image1)

![Product quality control](image2)

**4. Product quality control methods**

Robust product design on the basis of the optimization methods allows for the development of the robust quality control methods which can be applied during manufacturing process and product operation stages. Such methods enable increase the products reliability by the fault detection of the incipient or small faults before they cause serious damage of the whole product. In practice one of the most frequently applied quality control method is based on the comparison of the nominal parameters with the parameters of the controlled product. It is assumed that the product is not faulty when the parameters of the controlled product are similar to the nominal one obtained during robust parameters design stage. The concept of the above quality control method is depicted in Fig 5.

![Product quality control method diagram](image3)
In the first stage the identification of the parameters of the diagnosed product is performed. Usually, this task boils down to measurement of the controlled product parameters $p$. However, when such measurements are not available the estimate of their values can be obtained by the application of appropriate estimation methods [32]. Such procedure can be performed when the measurements of controlled product inputs $u_k$ and outputs $y_k$ are available and when the relation $\tilde{F}(\cdot)$ describing the model of the product is known. The knowledge about the values of parameter estimate $\hat{p}$ and nominal parameters $p$ allows to calculate their difference. When the absolute value of such difference is smaller than threshold value $\delta_p$, it is assumed that the product is fault-free.

$$|p_u - \hat{p}| \leq \delta_p$$  \hspace{1cm} (1)

Unfortunately, the disadvantage of the above presented method is that the $\delta_p$ is usually assumed in the arbitrary way. It should be underlined that the above method has one fundamental weakness. It can be easily applied for the simple linear products when the parametrical structure of the product is known. In the case of complex products, when the relation $\tilde{F}(\cdot)$ between parameters, inputs and output is unknown, it cannot be applied. Furthermore, the described method is not robust against uncertainty following from the measurements noise.

In order to overcome the last mentioned problem the so-called robust parameter estimation methods can be applied e.g. Bounded-Error Approach or Outer Bounding Ellipsoid algorithm [31]. The concept of such methods relies on the calculation of the parameter estimate $\hat{p}$ and its uncertainty (c.f. Fig. 6).

![Fig. 6. Product robust quality control method based on the parameter and its uncertainty estimation.](image)

If the parameters estimate of the controlled product and its uncertainty are not included in the parameters tolerance region of nominal product its means that the controlled product is faulty.

Unfortunately the presented method cannot be applied for fault detection of the complex non-linear products when the relation $\tilde{F}(\cdot)$ is unknown. In order to solve such a challenging problem the development of a new robust product quality control method independent on the measurement or estimation of parameters has to be performed. Such an approach relies on the identification/modeling of the controlled product on the basis of the nominal product inputs and outputs [33]. As a result, the mathematical model of the product is obtained which just reflect the nominal product behavior. It should be underlined that the certain model of the product obtained during identification procedure is a crucial for appropriate working of the proposed quality control method. It results from the application of the nominal model to the generation of the nominal product response estimate $\hat{y}$ and it comparison with response of the controlled product $y$. The calculated difference of such outputs, which is called as a residual signal, contains the symptoms of the faults. The most often applied fault detection method based on the residual generation [33] assumes that the controlled product is faulty when the absolute value of the residual signal is larger than an arbitrarily assumed threshold value $\delta_y$ (cf. Fig. 7).

$$|y - \hat{y}| \leq \delta_y$$  \hspace{1cm} (2)
Unfortunately, such a simple fault detection method can suffer in the practice because it is not robust against uncertainty. The changes of the residual signal caused for example by the noise or model uncertainty make impossible to perform the correct fault detection. As a result the undetected faults or false alarms can occur. In order to omit such a problem, it is necessary to assign wider threshold $\delta_y$ in order to avoid false alarms what reduce the fault detection sensitivity.

To solve such a challenging problem, a framework of a novel fault detection method robust against uncertainty has to be developed. In the proposed method the model of the nominal product can be obtained with the application of the non-linear product identification method e.g. the Extended Kalman Filter, Artificial Neural Networks (ANNs) or Fuzzy model [33]. It should be underlined that for such kind of models the uncertainty description can be obtained, however, it is not a trivial task. For example, in the case of application of the ANNs the parameters of neural model obtained during training procedure are not uniquely obtained but they are approximated by a so-called feasible parameter set which represent the neural model uncertainty. The size of such parameters set depends on the inaccuracy of parameters estimates resulting from the values of noise contained in the training data and neural architecture inaccuracy. The mathematical description of the model uncertainty enables to calculate the output adaptive thresholds [33] which allow performing the robust fault detection according to the scheme presented in Fig. 8. The adaptive threshold, contrary to the constant one, bounds the residual at a level that is dependent on the model uncertainty, and hence it provides a more reliable fault detection.

The output adaptive threshold containing the diagnosed product response $y_k$ in the fault-free can be defined as:

$$\hat{y}_k^m - \varepsilon_t \leq \hat{y}_k \leq \hat{y}_k^u + \varepsilon_t$$

where $\hat{y}_k^m$ and $\hat{y}_k^u$ are the lower and upper bounds of the adaptive threshold calculated on the basis of the model uncertainty and $\varepsilon_t$ represents the noise. The values of the output adaptive threshold change along with the changes of the values of the product input $u_k$. The faulty product is detected when the controlled product response crosses the bound of the output adaptive threshold.
5. Conclusions

In engineering approach to new product design, manufacturing and operation it must be ensured that all variations and uncertainties affecting its performance are considered as far as practicably possible. In order to achieve it, it is advisable to apply robust design methods. These methods allow for further development of quality control of products in the manufacturing and operation. Quality control methods based on the parameters estimation can be applied for simple products in which the linear relation between parameters and outputs can be found. In the case of more complex nonlinear products the above approach cannot be applied and the application of output adaptive threshold technique presented in the paper seems to be a promising solution.

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