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Editorial

Reliability Techniques in Engineering Projects

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In engineering projects, reliability is conceived as physical equipment's ability to function without failure. Thus, reliability can be described as a system's ability to operate under the design conditions for a determined period of time [1]. From the perspective of safety, reliability analyses aim to quantify the probability of system failure and its protective barriers [2].

Reliability planning [3] is required for high-quality engineering projects from the early stages of system design [4,5]. Probabilistic design for reliability allows for a comparison of the strength of a component with the stress it will be subjected to in different environments [6]. Failures are hierarchically linked according to the system architecture, and a failure mode, in turn, may cause failures in a higher-level subsystem or be the result of a failure of a lower-level component [7].

Reliability is associated with all project lifecycle stages. Starting with the customer's requirements and specifications, installation, operation, and maintenance are critical aspects that affect the reliability of systems. Thus, no matter how well a system has been installed, maintained and operated, if it was designed with inherently low reliability, it will remain unstable until redesigned.

Quality typically focuses on preventing defects during the warranty phase, while reliability is concerned with preventing failures during the lifespan of the product or system, from commissioning through operation to decommissioning [8]. Condition-based maintenance (CBM), also known as predictive maintenance, focuses on monitoring relevant parameters to empirically determine the percentage of service life that is consumed [9].

Operational reliability in engineering projects can be substantially increased by improvements in system design and the selection of more suitable parts and materials based on different reliability techniques and tools. Furthermore, some practices can improve reliability concerning manufacturing, assembly, shipping and handling, operation, maintenance and repair [10].

Before undertaking any design work, it is essential to specify the reliability and maintainability objectives of the product, i.e., a design trade-off between reliability and maintainability is necessary, since the more reliable the product, the less maintenance it needs [11,12].

Various tools can be used to analyze the reliability of an engineering project: Markov chains [13], machine learning [14], and Cox [15], etc. [16–18].

This Special Issue of *Applied Science* features new research and cutting-edge technologies related to reliability techniques in engineering projects. It includes research focused on: maintenance, reliability techniques, reliability prediction, design for reliability, failure modes, design for maintainability, facility and building design, the reliability-centred maintenance and improvement statistics-based approach, reliability testing, reliability modelling, maintenance 4.0, accelerated testing fail-safe design, detectability and common causes of failure, and built-in redundancy.

A total of eight contributions have been published in this Special Issue of *Applied Science*.

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In the first contribution, Li et al. identified the performance degradation characterization parameters by analyzing the storage degradation mechanism of the aerospace electromagnetic relay (AEMR) to build a storage degradation model and analyze the AEMR failure criterion conditions and degradation characterization parameters. The margin equation is then combined with the storage degradation model, and the uncertainties of the model parameters are quantified to complete the AEMR belief reliability model. From the analysis of the model parameter uncertainty, they found that aerospace batch relay storage reliability is mainly affected by the initial release time [19].

In the second contribution, Iovanas and Dumitrascu explored the main reliability indices of two milling tooth types: manufactured by conventional cutting processes (type I), and milling teeth manufactured by high-productivity laser weld cladding (type II). In comparison to the type II milling teeth, lower reliability function values were estimated for the type I milling teeth. The type II milling teeth displayed higher values for the statistical parameters, with a mean of 6 h, while the mean of the failure of type I milling teeth was 5.2 h. In addition, a more pronounced hazard rate was observed for the type I milling teeth compared to the type II milling teeth [20].

Grundler et al. presented a procedure that facilitates the integration of statistical power analysis into reliability demonstration test planning. To place statistical power in the context of the lifetime test planning of technical products, the Test Success Probability was introduced as a metric. Among the main results obtained from this study, four methods of calculating the Probability of Test Success for various test scenarios stand out: a general method that can deal with all possible scenarios, a calculation method that emulates the actual test process, and two analytical approaches for failure-free and failure-based testing that use the central limit theorem and the asymptotic properties of various statistics, and thus simulate the effort involved in lifetime test planning. In addition, the authors compared the calculation methods, analyzing their main advantages and drawbacks [21].

Bepary et al. investigated, using real-time silicon measurements, the retention behaviour of commercial dynamic random-access memory (DRAM) chips and how cell reliability degrades with accelerated ageing. To observe design-induced variations, analyze pattern dependence and explore the effects of accelerated ageing on multiple DRAM vendors, the authors analyzed retention-based errors at three different ageing points. They also investigated the statistical distribution of DRAM chips to determine the vital wear-out effects present in DRAM. Thus, they observed a continuous increase in retention error as DRAM chips age, inferring that aged retention signatures can be used to differentiate recycled DRAM chips in the supply chain [22].

Shu et al. introduced the inverse analysis strategy to analyze the calcium leaching effect using an orthogonal design and the finite element method. Time series data of the hydraulic head and leakage volume were applied to construct the objective function. The extreme learning machine (ELM) was proposed for the construction of the reflection sets. The genetic algorithm (GA), simulated annealing (SA), sparrow search algorithm (SSA) and particle swarm optimization (PSO) were employed to accelerate the iterative search for the objective parameters. Finally, the target parameters of the calcium leaching model were used for finite element verification by comparing monitored and simulated values [23].

Carretero-Ayuso et al. identified, catalogued and quantified, based on homeowner complaints and using the philosophy of "learning from failures", the failures in electrical and telecommunications installations in different dwellings. They analyzed and protocolized 154 complaints concerning these installations in Spain. Moreover, they defined and quantified all functional deterioration processes as well as the type of dwelling in which each of these parameters occurred the most. Finally, they determined a probability factor, which numerically quantifies the probable existence of complaints according to four ranges [24].

Ma and Zhang defined a comprehensive classification framework for multi-mode process tracking methods, which encompasses stationary modes and transition processes.

They observed that the dilemma for tje pattern recognition of offline data lies in the means of distinguishing modelling data for steady-state modes and transition modes, while the dilemma of online data is how to identify the mode category corresponding to online data in time.

Although many research studies have been conducted focusing on multi-mode process monitoring technology, there are few studies related to failure prediction and effective residual life prediction techniques [25].

Finally, Liu and Ananda conducted a literature review of a wide variety of studies from the engineering and medical fields and observed that hazard rates increase to a high peak at the beginning and then rapidly decrease to a low level. They investigated the properties of a model named exponentiated exponential-Pareto distribution and showed that the model has inverted bathtub hazard rates with specific parameter choices.

They also applied the model to a specific set of time-event data and compared the results with those of previous models. The exponential-Pareto model demonstrated a good performance when fitted to such datasets [26].

With this Special Issue, we have tried to contribute to the improvement of overall efficiency and help to minimize design failures in engineering projects.

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