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# EVALUATION OF THE EQUIPMENTS OPERATIONAL RELIABILITY IN XPS-MANUFACTURING COMPLEXES

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**Abstract.** The present paper describes the creation of reliability data trends, used as a basis for the further development of some advanced reliability models and techniques. The developed methods, models and techniques are then applied for an enhanced reliability analysis and determination of equipments operational reliability in fully functional XPS-manufacturing complexes, i.e., under real operational conditions.

**Keywords:** reliability analysis, operational reliability, failure data, modeling techniques

## 1. Introduction

For many years, the assessment of the *reliability growth rate*, as well as the *current MTBF* in *reparable* industrial equipment remains the main target of engineers and scientists, who develop methods and systems for reliability analysis and Fault Diagnosis – [1, 4, 5, 6, 9]. Such types of reliability studies are focused mainly on the *operational phase of the equipment*, i.e., once the development phase (the training period) of the equipment is accomplished [4, 8, 9].

One of the most important challenges for the reliability engineers and scientists, is to discover whether the *failure data's*, (characterizing the systems faults and failures), which are obtained during the *development phase* of the industrial equipment, ***have different nature*** compared to those, obtained during the *operational phase* of the equipment [1, 4].

In general, during the development phase of the equipment, faults and failures in the technologic and the logistic processes *do occur*. Since the major achievement of the reliability engineers has always been to provide a fault-free *operational phase* of the system, (of course, up to a certain point), then – some enhanced methods must be developed and used for *reducing the intensity* (and even for providing almost complete lack) of the systems/processes faults and failures during the *equipments operational phase*.

The most applied models for systems reliability assessment (mainly in the operational, but also in the development phase), respectively are: *the Weibull model (the Duane model as an alternative)*, the *Design for Reliability (DFR) approach*, the *Design to Life Cycle Cost (DLCC) model* [4, 7, 8, 9, 10].

All these types of models and methods provide opportunities for *enhanced analysis of extensive failure data*, which are *related to the operational reliability of reparable industrial equipment* [5, 9, 11, 12]. Thus, the emphasis of the reliability strategies (always during the equipments operational phase) *shifts from meeting the projects targets into maintaining them* [1, 4, 9].

In fact, this means, that, the maintenance philosophy should be changed from *"Test-Analyze-Repair(TAR)"*- strategy, developed mainly during the training phase, to *"Maintenance-by-Exchange-and/or Repair (MEXR)*-strategy, developed during the operational phase [1]. But, in order to proceed with such a change, some really important analysis must be performed over *the nature* of all failure data's, obtained, during the equipments development phase, but also, once the equipment goes operational [10, 12].

The core of such an analysis should be to reveal, whether the nature of the failure data is different during the development phase and the operational phase, i.e., that, the change from *TAR* to *MEXR* strategy should be adequate and successful [1, 9]. Such an enhanced reliability analysis, shall be based of course on the studies, performed over the data's, collected during the reliability tests and respectively during the FD procedures, developed over the equipment.

The present paper describes the development of reliability data trends that are used as a basis for the further creation of some advanced reliability models and techniques. The so-developed methods, models and techniques are then applied for an enhanced reliability analysis and determination of an operational reliability in fully functional XPS-manufacturing complexes, i.e., under real operational conditions.

## 2. Elaboration of reliability models and data trends – methods and models for analysis and assessment of operational reliability in an XPS industrial equipment

The elaboration of the specific reliability data trends (containing the failure patterns for the industrial equipment under investigation) must provide a complete and precise analysis of all *failure events*, but of course with a preservation of the genuine failure patterns (i.e., failure nature) for all data. Thus, all incidents (i.e., faults and failures) should be included in the analysis, whether or not a failure was diagnosed, or spare parts were consumed. So, all failures appeared during the detection and the development phases of the equipment should be processed and/or modeled and respectively considered as *"relevant failures"*, i.e., any types of failures and faults, that is likely to arise during the exploitation (i.e., under the "field service") of the equipment. Since all operational data's are derived from the field service (i.e., under real exploitation), then considering all failures as "relevant" is justified.

### 2.1. Elaboration of the reliability reparable models

Since the generalization properties of the *Weibull reparable model* are extremely enhanced, it should be applied in the present study as an initial reliability model. It is of common knowledge, that, when applied in a "log-log" graph, the observed cumulative incidents (i.e., faults and failures) in the studied system, versus the cumulative operating hours (time) are presented via straight line [1, 9, 10, 11]. It also known, that, if, the rate of all *cumulative faults and failures*, versus the studied time, is *linear* on "log-log" graph, then, s*ystems failures times could be presented via non-homogeneous Poisson law, but with a Weibull failure rate* [1, 9, 10, 11], i.e.

$$\overline{M}(t) = \alpha \cdot T^{\beta} \tag{1}$$

where, $\overline{M}(t)$ is the expected number of incidents (faults and failures) in the studied systems at time "$t$"; $T$, is the cumulative time to the occurrence of an incident (fault and/or failure); $\alpha$ - the scale coefficient in a Weibull reparable model; $\beta$ - is the power coefficient in the Weibull reparable model.

Since the application of the Weibull reparable model was accepted only *as an initial variant*, its practical application should be verified via some specific criteria, i.e., via a development of a "Goodness-Of-Fit (GOFT)" test. Of course, many different tests could be used for the purpose.

One of the most enhanced statistics tests for significance (especially for this purpose) is the $C_n^2$ test [10], [11], which is presented by the expression

$$C_n^2 = \frac{1}{12(n-1)} + \sum_{i=1}^{n-1}\left[\left(\frac{T_i}{T_n}\right)^{\beta} - \frac{2i-1}{2(n-1)}\right]^2 \tag{2}$$

where, "$i$" is any kind of incident (fault and/or failure), occurring in any studied data set; $n$ – the number of incidents, occurring in any studied data set; $T_i$ and $T_n$ – the cumulative time to the occurrence of the ***i-th*** incident and *n-th* incident respectively.

The critical values of the $C_n^2$ - test (statistics) are determined via Monte Carlo simulation, and respectively are rounded to the nearest integer. The sense of the statistics $C_n^2$ is as follows:

- If the value $C_n^2$, calculated from each studied data set is greater than the critical value at the designed level of significance, then the conclusion, that the data set follows non-homogeneous Poisson process with Weibull failure rate ***is rejected;***
- If the value $C_n^2$ is less than the critical value, then the conclusion is accepted.

The GOFT test was performed over 120 data sets, simulated on an experimental laboratory platform - please see [2]. The results from the GOFT test indicated, that of 120 tested data sets, 68 % were accepted at 5% level of significance and 74 at 1% level of significance. The so-obtained results were used as a base for the generation of criteria for acceptance, and only those data sets that accepted the Weibull reparable model at 1% of significance were selected for further analysis.

Almost identical results were obtained via an application of Genetic type Algorithm (GA). The data sets were grouped in pools and submitted to significance test via the Genetic operators "Reproduction" and "Recombination".

### 2.2. Development and comparison of the regression methods for estimation of modeling parameters

Once the data, accepting the Weibull reparable model are selected, there remains only to develop the estimation of the modeling parameters via the following relation:

$$\overline{M}(t) = E_\alpha \cdot T^{E_\beta} \quad (3)$$

where, $E_\alpha$ and $E_\beta$ are the best estimates of the Weibull modeling parameters $\alpha$ and $\beta$.

The estimation of the modeling parameters shall be performed via the Least Squares techniques (LST) and the Maximum Likelihood Method (MLM). The LST uses dependent variables, that are submitted to fluctuation and independent variables that are not subjected to fluctuation. Thus, the obtained LST best estimates $E_\alpha$ and $E_\beta$ should then be those that converged to the minimum sum of the squares for all differences, generated between the observed values of the independent variables, and respectively the corresponding "Best Fit" values of the dependent variables. The data sets that are used in the LST must be reconfigured into sequential zones (clusters) of equal width (for the independent variables) versus the numbers of simulated incidents, contained in the zones (i.e., the dependent variables).

A specialized LST computer algorithm is therefore applied, for determination of the best estimates $E_\alpha$ and $E_\beta$ for the model parameters $\alpha$ and $\beta$ (regressed for each one of the simulated data sets). The best estimates $E_\alpha$ and $E_\beta$ obtained via MLM are those, that correspond to the maximal probability for the occurrence of all events, which really took place (i.e., the occurrence of the incidents in each data set, reflecting the studied equipment) at the observed times.

A specialized MLM computer algorithm is therefore applied and the best estimates $E_\alpha$ and $E_\beta$ for the model parameters $\alpha$ and $\beta$ are determined (also for the simulated data sets). Some representative results, obtained by the regressing of the Weibull reparable model parameters $\alpha$ and $\beta$ (for a typical data set), are presented at Figure 1.

The analysis, performed over the generated representative results shows, that, there exists a tendency in LST regression model to follow the recent (i.e., the latest) incidents much closely, than the earlier incidents.

This is due mainly to the phenomena that the results of the LST model depend on the duration of the sub-intervals, into which the entire studied period was divided.

But in fact, this phenomena is of little significance since there should always be a reasonable (an adequate) amount of data available, since the observed incident patterns (faults and/or failures) in the various intervals reflect the overall expected pattern.

For illustration and analysis of this phenomena a "representative" data sets (i.e., sets, containing the necessary amount of data, reflecting the typical incidents) were submitted for processing to both LST and MLM algorithms, in order to regress the best estimates of the model parameters $\alpha$ and $\beta$. The representative data bases came from the simulated relationship of the type.

$$\overline{M}(t) = 0.01 \cdot T^{1.0} \quad (4)$$

During the regression procedures, an interesting fact became obvious – that, all proportions of data sets, which contained fewer than twenty incidents, generated some difficulties in the developed LST and MLM models, and more specifically in their capability to provide "perfect" best estimates of the model parameters.

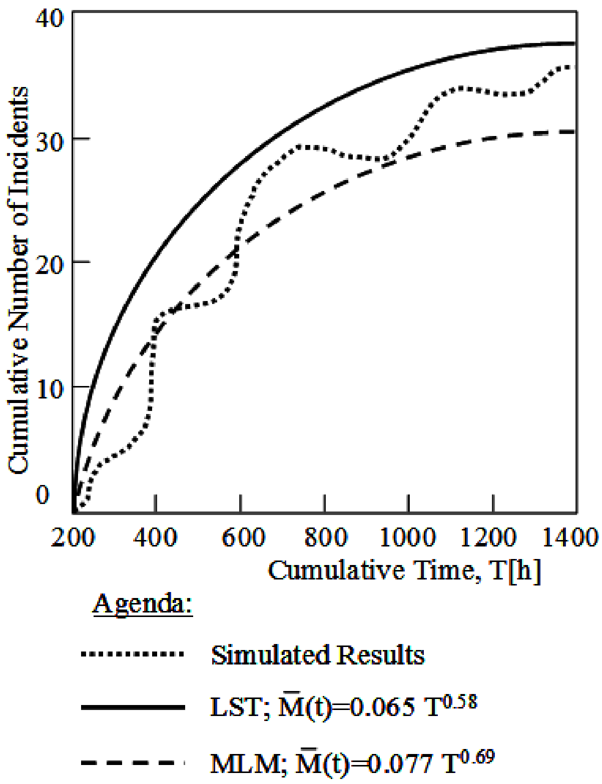


Figure1. Representative results for the model parameters, obtained via LST and MLM algorithms

The results, obtained via specialized LST and MLM computer algorithms, on a "log-log" scale, for 20 and for 40 incidents respectively are shown at Figure 2.

The analysis, performed over the results (presented at Figure 2) reveals, that, if the number of incidents (fault and failures) in the processed data set is greater (up to 20 and more), then the applied regression method is able to provide much better estimates of the model parameters $\alpha$ and $\beta$.

### 2.3. Application of the developed models and regression procedures for analysis of operational reliability in an industrial XPS-manufacturing extrusion system (i.e., under real operational conditions)

The specific industrial equipment, that was studied and respectively submitted to analysis aiming the assessment of the operational reliability represented a rather complex extrusion system (composed by three pairs of tandem extruders), designated to manufacture extruded polystyrene foam sheets (XPS foam sheets), from raw polystyrene granules.

The so-manufactured XPS foam sheets are then used for manufacturing of many types and kinds of multi-layer XPS foam boards for construction thermal insulation, as well as for producing many types of food containers (as an alternative to the insulation boards).

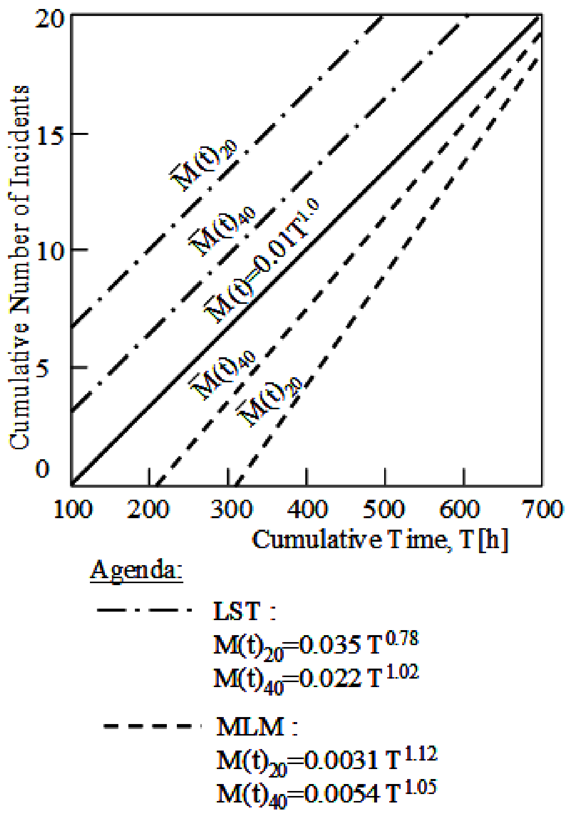


Figure 2. Results for 20 and for 40 incidents, obtained via LST and MLM algorithms.

The extrusion system, designated for an XPS-manufacturing represents an essential part of the already built and operated “Technologic and Logistical facility for Manufacturing of Extruded Polystyrene (XPS) products”.

The general logistical structures, the main and the supplementary equipment, as well as all technologic and logistics processes are developed in details in [3]. The XPS industrial complex was created under the financing of the US Export Import Bank (Ex-Im bank) programme in 2005, and is located near the town of Varna.

In total, three (similar) XPS extrusion systems were submitted to this specific reliability study. An extract of some typical sets of results from the study are presented in Table 1. The pairs of extruders are marked as: Ex A; Ex B; Ex C; Ex D; Ex E and Ex F. The tested groups of specific equipment are marked as EQ “G” and EQ ”T”, and represent respectively the Iso-Butane Gas dosing device and the Temperature Controller – these are one of the most sensible parts, which possess a great impact (effect) over the capabilities of the final product (i.e., the XPS foam sheets), manufactured by the extrusion systems.

In fact, this means, that, providing an adequate operational reliability of the EQ “G” and EQ “T” devices is one of the major tasks for the reliability and control engineers, who control and supervise the entire XPS-manufacturing facility.

The data, listed in Table 1, follow a Weibull reparable reliability model, which means, that, the developed LST and MLM techniques and algorithms, could be applied successfully under real operational conditions.

The application of these models and techniques provides not only a real time assessment and control of the operational reliability, but also are a powerful tool for further deduction of a method for prognosis, i.e., for prediction of the operational reliability of these devices under real operational conditions.

Table 1. Sets of results, obtained via reliability study of an XPS-extrusion system (3 pairs of tandem extruders).

| **Type Equip.** | **Type Tech.** | **EQ “G”** $E_\alpha$ | **EQ ”G”** $E_\beta$ | **EQ “T”** $E_\alpha$ | **EQ ”T”** $E_\beta$ |
|---|---|---|---|---|---|
| **EX A** | **LST** | 0.039 | 0.79 | 0.031 | 0.81 |
| **EX B** | **MLM** | 0.0041 | 0.68 | 0.0036 | 0.92 |
| **EX A** | **LST** | 0.032 | 0.89 | 0.029 | 0.87 |
| **EX B** | **MLM** | 0.0039 | 0.97 | 0.0044 | 0.67 |
| **EX C** | **LST** | 0.029 | 1.09 | 0.057 | 0.79 |
| **EX D** | **MLM** | 0.0045 | 1.00 | 0.0063 | 1.02 |
| **EX C** | **LST** | 0.033 | 1.11 | 0.074 | 1.08 |
| **EX D** | **MLM** | 0.0056 | 0.99 | 0.0066 | 0.99 |
| **EX E** | **LST** | 0.021 | 0.91 | 0.059 | 0.91 |
| **EX F** | **MLM** | 0.0047 | 0.89 | 0.0049 | 0.86 |
| **EX E** | **LST** | 0.025 | 0.78 | 0.035 | 1.11 |
| **EX F** | **MLM** | 0.005 | 0.74 | 0.0029 | 1.05 |

## 3. Conclusions

A Weibull reparable reliability model was developed and applied for assessment of operational reliability over simulated data trends, reflecting incidents in industrial equipment. An LST and MLM techniques were developed and applied for the purpose.

The developed models and techniques are applied then for reliability analysis of operational reliability in a real industrial systems for XPS-manufacturing, i.e., under real operational conditions.

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