The use of product information along its entire lifecycle: a practical framework for continuous development

O. Borgia*, N. Fanciullacci*, S. Franchi*, M. Tucci*

**Department of Industrial Engineering, University of Florence, Viale Morgagni 40-44, 50134, Firenze, Italy in collaboration with Ferrari S.p.a., Via Abetone Inferiore, 19, 41053 Maranello (MO), Italy (orlando.borgia@unifi.it, nelson.fanciullacci@unifi.it, serena.franchi@stud.unifi.it, mario.tucci@unifi.it)*

Abstract: With the development of IT technologies a lot of information can be collected during the product lifecycle. These pieces of information can be useful and can drive inspiration to redesign a product in order to increase its performance and reliability. Nevertheless most of the companies trace their products only during the design and the production phases without putting any effort to collect data during the middle and the end of life (e.g. use, maintenance, service, disposal etc.). The aim of this study is to develop an analytic framework to integrate and analyze data collected along all phases of a product lifecycle; this is done to give continuous feedback to the designers in order to enhance the product performance and reliability. A common database format was set to collect data from different departments. A systematic graphical and statistical procedure to analyze data was implemented; the use of well known statistical inference methodologies as individual value plot, scatterplot, boxplot, distribution fitting, analysis of variance, regressions, control charts made up a framework able to give important feedback information to designers. All of these techniques have been integrated into a software that allows a well defined and systematic exchange of information in compliance with a product lifecycle management approach. This tool is currently used by the manufacturer and allows to find correlations between various experimental measurements, product criticalities, anomalous behavior and processes out of control. The transformation of the proposed framework in a software tool led to time saving and higher quality and standardized reports.

Keywords: Reliability, PLM, closed loop PLM, single item PLM

1.Introduction

The constant demand for efficiency from production and commercialization phases has led companies to invest on methodologies and frameworks aimed at a continuous development along the whole product lifecycle.

The process of unceasing upgrading and redesigning of a product is fundamental, especially for companies that: (i) operate in high competitive sectors where the product must be superior than that of competitors, (ii) produce goods that need to evolve constantly in order to bridge the technology gap and increase performance and (iii) follow the philosophy of reliability growth (O'Connor et al., 2012).

For these types of companies it is fundamental to collect data relative to the product not only during design and production phases (e.g. BOM, CAD and CAM, SPC reports etc.) but also during the remaining of its lifecycle. According to Jun et al., 2007 design and production belong to the product beginning of life (BOL), logistics, distribution, use, service and maintenance belong to product middle of life (MOL), while reverse logistics, disassembly, failure diagnosis, remanufacturing and disposal make up the product end of life (EOL).

The aim of the product lifecycle management (PLM) is to connect "various product stakeholders over the entire lifecycle of the product from concept to retirement". Moreover, PLM "establishes a set of tools and technologies that provide a shared platform for collaboration among product stakeholders and streamlines the flow of information along all the stages of product life cycle", (Ameri and Dutta, 2005). In recent years, PLM becomes established also thanks to the development and the decreasing price of IT resources, such as embedded systems, wireless connections, remote control etc.. These technologies allow to collect, elaborate and broadcast information during the whole product lifecycle (Saaksvuori and Immonen, 2008; Stark, 2011).

PLM has been widely discussed in literature and there are many case studies in the industrial field. The majority of these papers, however, refers to mass products where information is mainly concentrated in the BOL. In most cases, in fact, companies are not able to collect data from MOL and EOL (Niemann et al., 2008) or they cannot find the right methodology to efficiently analyze and extract useful information from them (Ameri and Dutta, 2005).

Scarce are the case studies published where data relative to the final stages of product life (maintenance and disposal) are also used (Yang et al., 2007). These pieces of information are relevant and very important especially to determine the in-field product reliability performance (Yang, 2007). In fact, the difference between the in-house and in-field reliability can be significant; faults data collected directly in field are fundamental to grasp the real

reliability performance (De Carlo et al., 2013; Persona et al., 2009; Pham, 2005). In addition, with products that involve mechanical systems it is useful to get information concerning wear, operating hours, state of the machine etc. while the product is in use in order to implement operations such as diagnostics, prognostics and condition based maintenance (Gulledge et al., 2010; Venkatasubramanian, 2005). From the disposal phase several pieces of information are useful as well (failure time, failure modes, number of faults etc.), but scarcely used by the manufacturer (Yang et al., 2007). These are needed not only for reliability estimation but also to extract wear indicators, to elaborate and validate damage models. Other parameters that can give information about the state of health of the product at the end of its life can be extracted too (Parlikad and McFarlane, 2007). All these information about system health and failures are used to better organize maintenance operations (Kiritsis et al., 2003; Lee et al., 2008).
Igba et al., 2013; Jun et al., 2007; Kiritsis et al., 2003 show how a closed loop PLM can help to create a systematic data flow to redirect information from MOL and EOL in order to provide knowledge to redesign or upgrade a product. In literature little attention has been given to analyze case studies where feedback information from MOL and EOL is systematically acquired and converted to knowledge useful to design for a new product release.
The aim of this study was to create a set of analytic procedures (framework) that could be able to analyze MOL and EOL data and to give feedback results supporting the redesign phase. A case study of a continuously evolving small-series product where redesign is intended to improve its reliability, will be introduced.
To implement the systematic analysis of data from MOL and EOL, a software was developed in order to integrate data collected during the whole product lifecycle.

2.Case study

In this paper we analyze the case study of a company that produce complex mechanical systems in small series. The manufacturer belongs to the type identified at point (ii) in chapter 1, whose products need to be continuously upgraded and redesigned in order to increase their reliability and performance. The product is composed by electrical and thermal subsystems and it includes: an high power battery, control units, hot and cold fluids (water, air, oil) and their cooling systems, under pressure circuits, rotating parts and bearings. The peculiarity of this case study is that each product has its signature and therefore can be considered different from previous releases (an individual or a single item).
In the context where the manufacturer operates, fault occurrence has disastrous effects (similarly to aerospace industry). Once a new component is introduced into the project, it is fundamental to test its behavior with bench tests in order to obtain the approval for the in-field use. If a certain number of tests with the new product release are successful it becomes the new product referential. If tests give negative results (failure occurs, or performance is not satisfactory) the new component is redesigned and tested again until it passes the approval test.
Therefore there is the need to exchange experimental data between the testing and validation phase and the design phase through a continuous, systematic and bidirectional data flow. The information coming from the field is, in this case study, abundant and high quality because of the high number of sensors employed (temperature, pressure, flow, vibration, etc.). In addition, the manufacturer has already a well-structured measurement procedure applied during the BOL where quality is checked before and after the assembly of the final product. Many measures are also performed at the end of life (whether the product has stopped due to failure or retirement) in order to monitor the wear of the components, their mechanical and electrical properties after use.
Faults are monitored and diagnostic analysis such as geometric measurements, penetration tests, analysis of materials etc. are performed.
Each single component of the bill of materials is tracked from the beginning to the end of its life.
All these experimental data are collected by separate company's departments and placed in different databases with different formats.
With such data abundance and quality it is necessary to create a well-structured and systematic framework that integrates analytic tools in order to extract information and transform it to knowledge useful to increase performance and reliability of the product. The framework proposed in the next chapter integrates statistical analysis and an automated procedure to analyze data from all the company's departments.

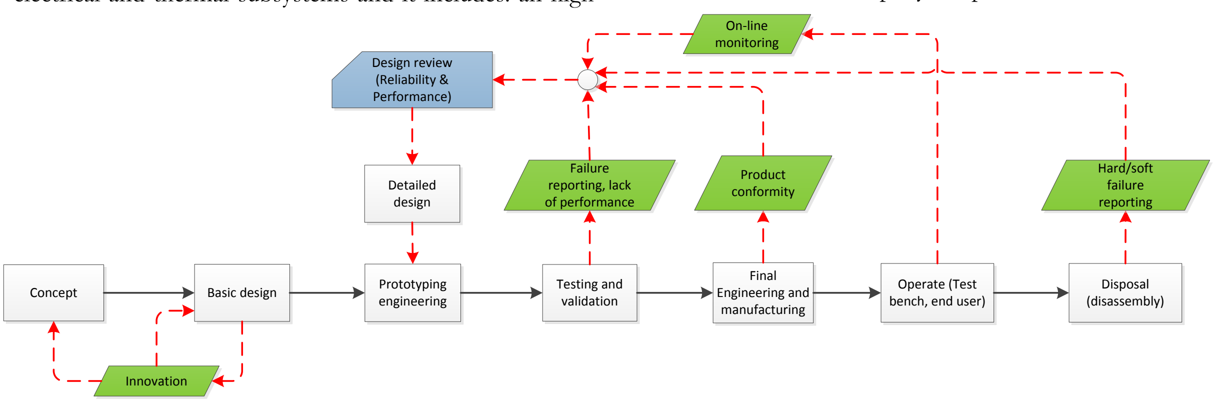

Figure 1: the information flow along the whole product lifecycle. In red the information loop that lead to redesign the new prototype

3.Framework

In order to support data analysis and monitoring requested by designers a framework is introduced. The aim of the framework is to collect and streamlines a series of graphical and statistical tools for data analysis, which can be used in series or in parallel according to the analyst's needs.
The described process allows to feed with the right data the loops between BOL, MOL and EOL in order to support the redesign of the product. From another perspective, the conversion into knowledge of feedback data, lead the EOL phase of a prototype to coincide with BOL of its new release as show in Figure 1.
The proposed framework consists of several steps that will be explained below.
The first phase consists in doing an automatic standardization of the file format shared by all the stakeholders; an interchangeable and easy to share format was designed using Visual Basic® and MSSQL®.
In the second phase the analyst can plot data using several types of graphs. The aim is to highlight any possible abnormal behaviour, deviation from baselines, processes out of control, outlier etc.. Graphical tools are an easy but effective way to identify non-standard state of the system, of the production line, of the measurement procedure, sensor malfunction, causal relation among variables, etc.. by each type of operator (designers, workers, engineers, managers etc.).
The third phase allows to statistically quantify any anomaly detected in the precedent phase, and look for correlation models among variables (e.g. the relationship between the material of a component and its state of wear at the end of its life). The tools used in this phase are both graphical and analytical. The latter are techniques of statistical inference by which hypothesis on average, standard deviation, median etc. are tested with the chosen confidence interval (in this case 95%). Dependency and causal relations can be investigated through the afore mentioned methodologies and the outcomes can be used to identify design directions to improve the product.
These types of analysis can be time consuming because of the sample size and the number of variables involved. Moreover it can be very hard to find the optimal model in a limited time. To solve this problem an heuristic algorithm was also implemented into the framework and the operator can choose which methodology to use for correlation analysis. In these cases, methodologies typical of optimization problems are preferred; in fact, they don't always converge to the best result but allow to obtain the best solution among those analysed till the moment the algorithm is stopped.
The final step consists in the organization of a clear, standardized and intelligible output that can be easily used to produce a report of the analysis performed. This document is ready to be forwarded to other product stakeholders to disseminate the knowledge and the emerged results.

4.Results

To get the necessary feedback to implement a closed loop strategy it is necessary to create a framework designed and shared with all the actors that may look at analysis reports and results (H.-B. Jun et al., 2007; Hong-Bae Jun et al., 2007).
For this purpose a data analysis software that includes and organizes the various stages of the framework described in the previous chapter, was implemented (figure 2). The software was developed using MatLab® and was divided into different sections. In main window on the left area there is the definition of the variables while on the right area the user can choose which type of analysis to perform.

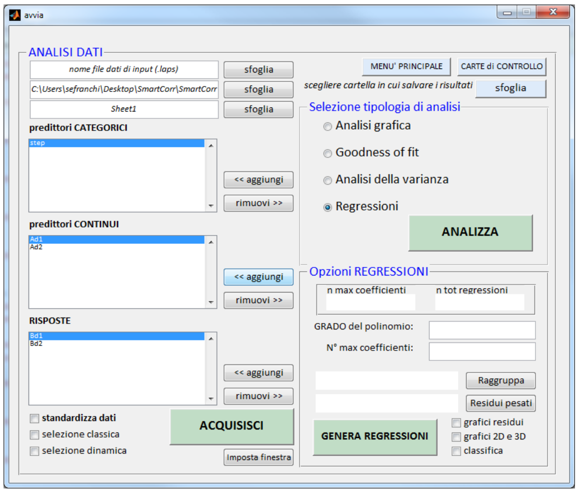

Figure 2: interface of the software that include the proposed framework.

The acquisition process implemented in a section of the software generates a sheet file that contains discrete and continuous numerical data (sample size, geometrical measures, product layouts, ID, etc ...). The sheet file is stored in a local database created to standardize data.
To perform the graphical analysis described in phase two, control charts (figure 3), individual value plot (figure 4) and box plot (figure 5) were implemented. They can be used to monitor the temporal trend of variables highlighting possible deviations or out of control processes. When using control charts lower control limit and upper control limit can be determined by default by MatLab® rules or defined by the user. An example of Control Chart is shown in figure 3. In this chart on the horizontal axis there is the subgroup temporal sequence while on the vertical axis there is the value of the measure for each subgroup. Points are connected by a blue line representing the analysed data while the red lines represent the upper and lower control limit.
Individual Value Plot with Box Plot (Figure 4) are also used to monitor trends of measurements. In this case red dots represent individual values of the elements of the subgroups. Tolerance limits relating to the analysed measures are shown in green.

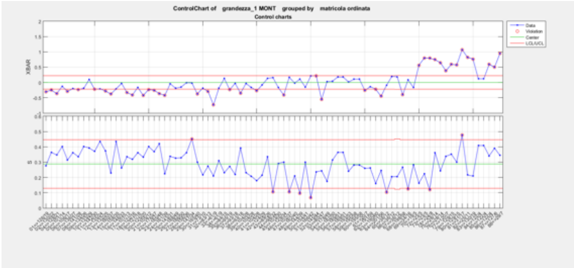

Figure 3: Example of a control chart.

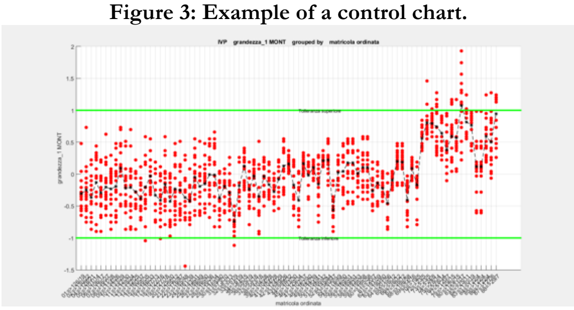

Figure 4: Example of Individual Value Plot used to monitor the trend of measurement of subgroups.

If there are values that show an abnormal behaviour compared to the rest of the population is necessary to investigate the source of the deviation using statistical methodologies. To analyse elements or subgroups that have distinctive characteristics compared to the rest of the population, graphical tools such as Box Plot (figure 5), individual value plot (figure 4 and 6), 2D or 3D histograms and statistical tests such as one-way or n-way ANOVA were implemented. Figure 4, 5 and 6 horizontal and vertical axis represents factors/treatments and the value of the variable monitored, respectively.

IVP values are drawn in red and the size of the dot depend of the frequency. The dashed line connects the average value of each factor. In particular, analysis of variance (ANOVA) with other test of hypothesis allows to check if there is a statistically significant difference between subgroup measures within a certain confidence interval, typically 95%. These tests are introduced and used to explore the nature of the data and explain the variance highlighted in each subgroup. ANOVA hypothesis statements and assumptions are tested and a concise and easy-to-interpret output is produced. Using this type of format each user is able to understand which model fits the data better.

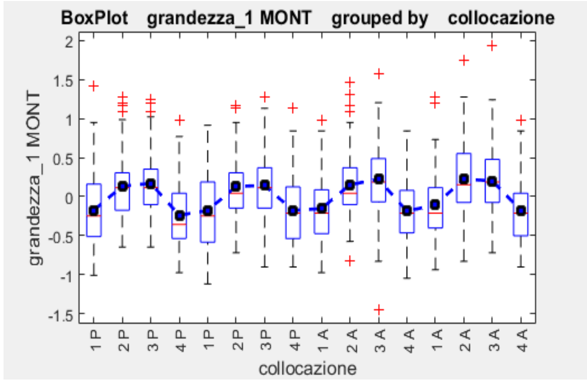

Figure 5: Example of Box Plot which can highlight the presence of sub-populations.

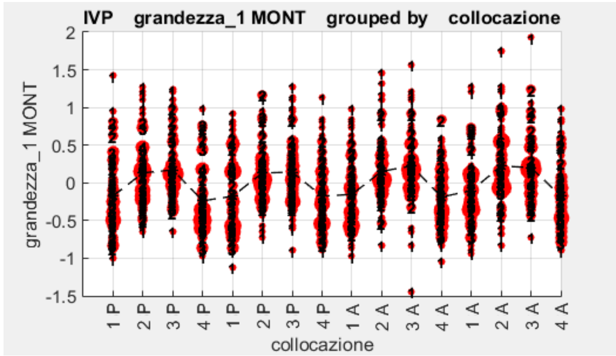

Figure 6: Example of Individual Value Plot which can highlights the presence of sub-populations.

Another software section performs the search of linear and nonlinear correlations. All possible regression models are generated and classified using the corrected AIC as the goodness of fit estimator. This parameter is considered better than R-square adjusted since it allows to overcome the overfitting problem (Akaike, 1974). The tool well satisfies the need to obtain clear results in extremely short times using graphical representation of the results through summary tables, 2D and 3D scatterplots (figure 7). This graphs help the user to identify the presence of a correlation between two analysed variables. The experimental data is displayed in red and the estimated regression line, calculated with the least squares method, is displayed in blue.

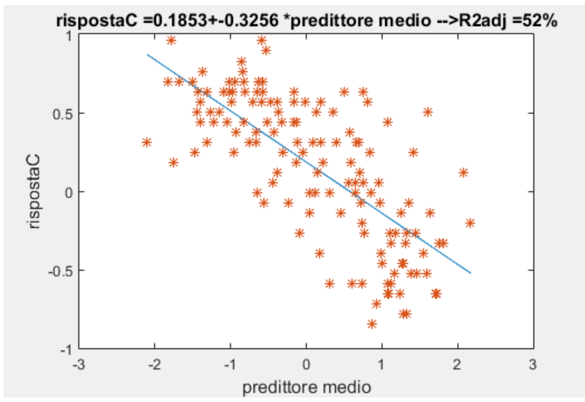

Figure 7: Regression plot with the linear interpolation line.

Also, to check the assumptions of ANOVA and regression plots relative to residuals distributions, histograms, homoscedasticity etc. are produced (figure 8). On the top left section of the figure there is the distribution of residuals while on the bottom left sector there is the Histogram of residuals. On the top right there is the trend of residuals in function of the estimated variable and on the bottom right there is the residual trend in function of the data sample.

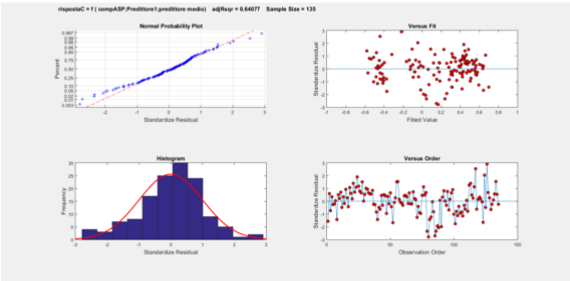

Figure 8: Example of Residual Plot.

As anticipated, two ways to seek the best regression model were implemented into the software. The first one enumerates all the possible linear and nonlinear combinations of each predictors including variable interaction. This procedure can be highly time consuming. To make the analysis effective and to obtain the results in a shorter time, genetic algorithms were also implemented.
In particular, each regression model can be easily represented with a chromosome composed by a string of binary numbers. Within the chromosome the true value indicates the presence of a coefficient in the regression model while false value represents the lack of it. Combining two chromosomes a feasible solution is always found and no constrain is needed. In this way both methodologies can be implemented into the software within a user friendly interface where just few parameters need to be set (regression order and number of coefficients).
In order to understand which methodology is more efficient in function of the number of variables considered and of the number of records a comparison of the elaboration times was performed. Results show (figure 9) how genetic algorithms (blue line) are faster (ordinate) than the enumerative solution (red line) independently by the complexity of the model (abscissa).

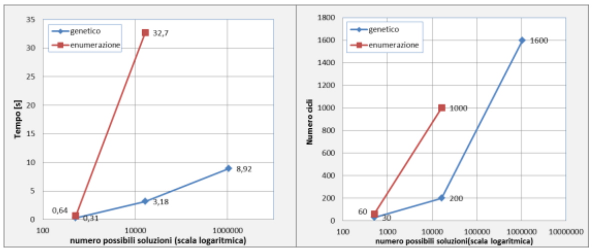

Figure 9: Comparison between processing time of genetic algorithms (blue) and the enumeration method (red).

5.Conclusions

The purpose of this paper was to analyse data from all the phases of the product lifecycle so that they can be used as knowledge to redesign the product in order to improve its performance and its reliability. The case study of a company that produces complex mechanical systems was considered. The manufacturer follows a rigorous measurement procedure before and after the assembly phase, during the use, and at the end of the single item life. Therefore data are high in number and quality and are stored in different databases with different formats.
For this purpose a framework was developed; its format was discussed with all operators involved during the product lifecycle. The framework establishes a series of standardized analytical procedures to be implemented in accordance with closed loop product lifecycle management (H.-B. Jun et al., 2007; Hong-Bae Jun et al., 2007; Kiritsis, 2011).
Furthermore, the data flow can be used to improve the product reliability performance, proactively (designing for reliability) or reactively (using field feedback as a baseline information to solve technical problems). The development of the proposed systematic approach is necessary to have the correct timing between design and test phase, and to have the proper reactivity to manage and implement corrective actions (for example after abnormal behaviour of a product).
To support the proposed framework a software that can automate and speed up all the analyses specified in the framework was developed.
With the proposed framework and the developed software it was possible to standardize data from various departments and use them effectively to monitor and redesign the product.
This methodology was successfully introduced along the product lifecycle in accordance with the requirements of the company and with the actors involved.
The tool brought benefits in terms of results quality because of the structured format of the output produced by the software.
The time spent to get the feedback from a different product stakeholder and the time needed to exchange information between them was reduced by about 60% with respect to the precedent procedure.

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