Hindawi
Complexity
Volume 2018, Article ID 4084917, 8 pages
https://doi.org/10.1155/2018/4084917

Research Article

Reliability Assessment Methodology for Massive Manufacturing Using Multi-Function Equipment

M. López-Campos ,[1] F. Kristjanpoller,[1] P. Viveros,[1] and R. Pascual[2]

[1]*Department of Industrial Engineering, Universidad Técnica Federico Santa María, Av. España 1680, 2340000 Valparaiso, Chile*
[2]*Department of Mining Engineering, Pontificia Universidad Católica de Chile, Av. Vicuña Mackenna 4860, Santiago, Chile*

Correspondence should be addressed to M. López-Campos; monica.lopezc@usm.cl

Received 28 September 2017; Accepted 7 December 2017; Published 20 February 2018

Academic Editor: Jorge Luis García-Alcaraz

Experience reveals that reliability varies depending on the characteristics of operation. The manufacturing process based on multifunction equipment gives a usual case of variation in operating conditions. This work presents a methodology for the reliability analysis of multifunction processes, using the RCM approach, and a modification of the Universal Generating Function (UGF) under a massive manufacturing context. The result is a characterization of reliability, for each piece of equipment and for the production system. The methodology is applied in a workshop of a textile industry, where there is prior evidence that the failure behavior varies according to the type of function executed by multifunction machines.

1. Introduction

The theory of reliability is especially important under the competitive global scenario, since it is essential to determine the real productive capacity and economic benefit of a plant in the short and long term [1]. The failure behavior of plants and equipment is not totally explained by accurate causes assigned to preset conditions, but it varies depending on the characteristics of the use of each element within the system [2]. Time is the most common variable to determine the behavior and remaining life of components and equipment; however, empirical studies have shown that the behavior of the failure rate depends largely on the type of job, workload, and the characteristics of the products (or raw material) which are produced or processed [3–7]. On the other hand, within the environment of the Industry (4) 0 concept, manufacturing has experienced a growth on operations and data volume [8]. Flexibility and customization have made common manufacturing lines constituted by automatized multifunction equipment, which are able to run a variety of works in little time. Regarding advanced multifunction equipment, the different operating conditions demanded by each particular type of work suppose that the reliability of the multifunction system depends on the mixture scheduled to be produced [9]. Nevertheless, to the best of our knowledge, there are no previous works that consider, in the calculation of the systemic reliability, the differences originated by the operation of multifunctional systems. What is usually done is not to differentiate the effect on the reliability granted by the operation of each function, but the calculations are made in an aggregated form, which causes loss of information that can be valuable for the maintenance management of the system. Therefore, it is interesting to model this behavior, using for this the support of the existing reliability theory, taking into account the difference in the intrinsic properties of the multifunction equipment. To this aim, this proposal is based on addressing studies related to the analysis of Multistate Systems (MSS) [10, 11] and by suitable adaptation achieving a common and widespread valid approach for a multifunction production process [7].

One of the classic tools for the analysis of systemic reliability is the RCM approach (Reliability Centered Maintenance), which describes the operation of equipment arranged in a logical configuration and that allows its modeling and understanding, enabling formulation of suitable maintenance policies [12]. Given that the multifunction problem includes an important size of data of multiple states and transitions, it is necessary to have a structured methodology for its reliability study, which is based on the typical process for data analysis [13–15] composed of four phases: (1) data acquisition, (2) data preprocessing, (3) data analysis, and (4) prediction and application. In particular, the RCM approach and the Universal Generating Function (UGF) will be used during the second and third stages to deal with the complexity of the data dimension [16] and to obtain the reliability performance of the entire Multistate System (MSS) based on the performance of its elements, using algebraic procedures [17]. In this article, the proposed methodology is applied to a case study in the textile sector.

2. Problem Statement

Automatized multifunction machines, used in the last generation production systems, often work under very changing operation modes, characterized by varying loads and working speeds, using different raw materials, and being frequently under different environmental conditions. These operational modes result in different failure rates and life distributions. However, in terms of reliability analysis, this is a problem that to the best of our knowledge has not been fully addressed, with any formal proposals that quantify the effect of the multifunctionality in the systemic reliability. For this reason, it is interesting to propose a methodology for reliability analysis in multifunction processes. This methodology is structured as a sequence of analysis of data and as theoretical basis it has the existing previous studies in reliability for Multistate Systems (MSS), adapting them conveniently. A binary logic of operation of equipment is considered, either when functioning properly (UP) or with total failure (DOWN), and the type of function to be executed by the system is characterized defining multiple operating states. $J = \{1, 2, \ldots, n\}$ is the set of elements that compose the whole production system, and $H = \{1, 2, \ldots, k\}$ is the set of functions to be manufactured or states. A MSS composed of n different repairable elements (or equipment), where each element j has k_j different levels of performance, has a model with $K = \prod_{j=1}^{n} kj$ states. This number can be quite large even for a relatively small MSS, so the methodology proposed here uses tools like the UGF to simplify the problem.

3. Proposition for Methodology

The analysis of data coming from heterogeneous sources, as machines operating at different conditions, is a challenge. In general, there is an elemental algorithm used by several authors [13, 15], to deal with maintenance data. This algorithm is taken as the structure for this methodological proposal and it is composed of the following stages or phases: (1) data acquisition (to define the object of study and to collect data), (2) data preprocessing (to extract, transform, and prepare data), (3) data analysis (to obtain a diagnosis about the reliability of the system), and (4) prediction and application (to generate a prognosis analysis for decision making). According to Wang and Zang [13] the prediction accuracy improves when data is increased in size.

The proposed methodology has as an innovative characteristic of its application for the reliability analysis of a multifunction manufacturing system. As it is known, the reliability analysis is a key element of decision making by analyzing the technical and economic performance of a manufacturing system. To this aim, data such as product demand, manufacturing quantities, and probabilities associated with the execution of each function shall be considered as given, for example, by the production planning. It should be emphasized that this proposal is a methodology and not an algorithm, so its application is not one hundred percent accurate and tight end to stringent rules. The phases of the proposed methodology are represented in Figure 1. The methodology includes four phases and each phase is made by several steps.

Phase I (data acquisition). This involves the use of physical inspection and/or wireless sensors about the health condition of equipment and its main control variables. Besides, historical information from a Computer Maintenance Management System (CMMS) is another valuable source of data to be used throughout the methodology. The interoperability of devices is an important issue, solved by ISA-95, MIMOSA, ISO 15745/13374 standards. Proactive maintenance techniques as CBM+ and PHM are based on adequate interoperability and data acquisition. At this point, the proposed methodology emphasizes the previous identification of the system, production system, or equipment, object of analysis in a multifunction context. Having multifunction machines is a necessary condition, but not sufficient to satisfy this point, since it is essential that the equipment have the tendency to react differently (or to support different loads, e.g.) depending on the function it is performing. Then, it is necessary to focus the methodology on a production system that processes a common set of functions. In the case of several sets, the methodology should be applied separately on each form. The focus of the reliability analysis is on the parts of the production system which satisfy the multifunction condition. However, the parts that do not meet this condition should also be considered since they still make an impact on the reliability of the system.

Phase II (data preprocessing). The general objective of this phase is to extract, transform, and prepare data. Here the collected data is synchronized and segmented; the control features are extracted and combined into a matrix. There is a myriad of explicit techniques to do this, nevertheless, specifically for reliability proposals, the preprocessing focuses on treating data to characterize the different states of equipment. This phase is done through the following steps.

Step 2.1. To determine the normal operational conditions of the n elements of the system when they are performing each function h and to determine a measure of performance of each j element, depending on the nature of the process executed, this can be represented by a workload g_{jh} given by the production planning and assuming that each function generates a different workload for the equipment performance. The set $g_j = \{g_{j1}, g_{j2}, \ldots, g_{jk}\}$ represents the standard load or performance of the element j in the state h. G_j is a random variable of each item j and it represents the load

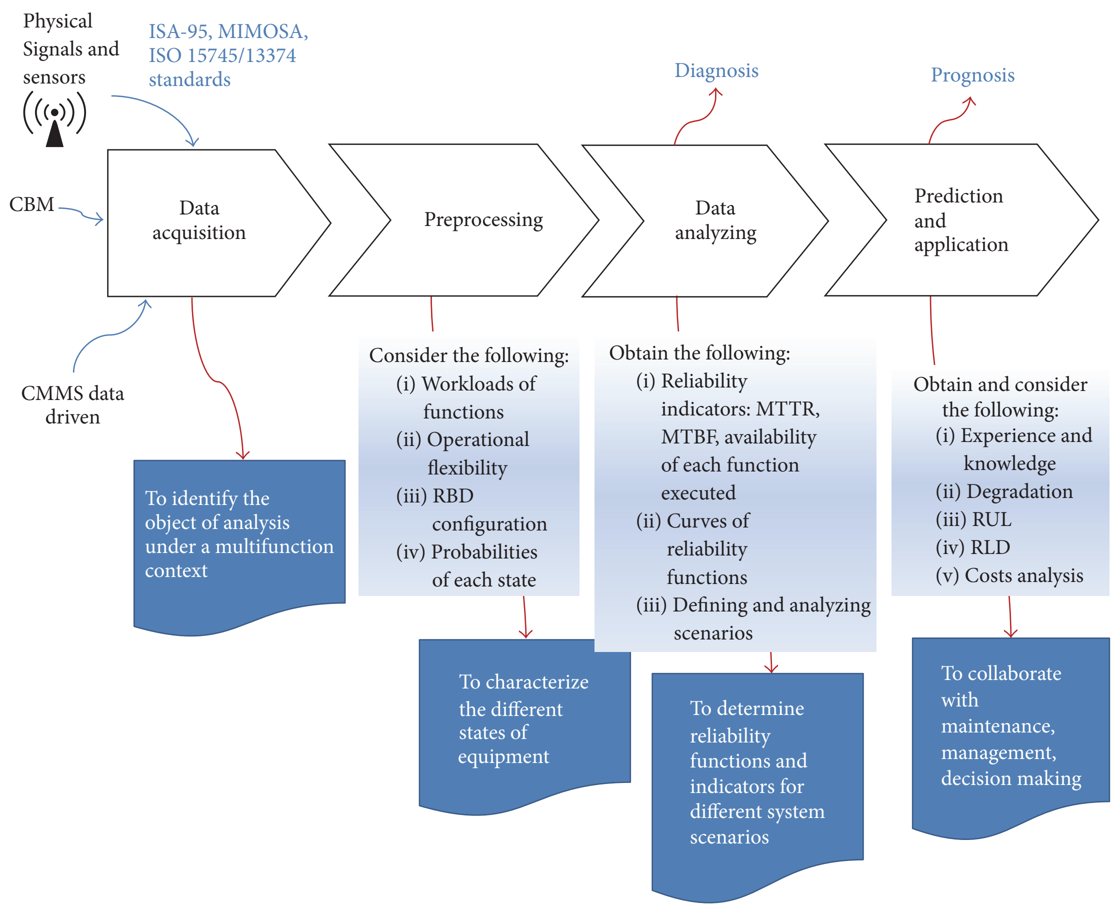

FIGURE 1: Phases for the proposed methodology for the reliability analysis of multifunction manufacturing systems.

(type of function) that the equipment is executing. This also involves knowing the respective probabilities of the process according to each element or knowing them according to each function to execute. The probabilities associated with the different states of the element j can be represented by the set: $p_j = \{p_{j1}, p_{j2}, \ldots, p_{jk}\}$, where $p_{jh} = \Pr\{G_j = g_{jh}\}$ and $\sum_{h=1}^{k} pjh = 1$.

Step 2.2. It includes making an analysis of operational flexibility, describing the results of the production scheduling of the equipment, regarding their working standard time intervals (minimum time during which only one type of function is executed).

Step 2.3. It includes illustrating the logical configuration of the system using the Reliability Blocks Diagram (RBD) and understanding the size and behavior of product flows circulating in the system and the dimension of each executed function.

Step 2.4. It includes obtaining the possible output values of each function and the probability of occurrence of each one of these states, by the modified UGF tool, the equation of the u-function (see (1)), and the polynomial $U(z)$ of the entire system (see (2)), taking into consideration the polynomial $U_{\text{disp}}(z)$ that includes the availability (A) (see (3)).

$$u_j(z) = \sum_{h=1}^{k} p_{jh} z_h^{g_{jh}} \tag{1}$$

$$\begin{aligned} U(z) &= \underset{\varphi}{\otimes}(u_1(z), \ldots, u_n(z)) \\ &= \underset{\varphi}{\otimes}\left(\sum_{h=1}^{k} p_{1h} z_h^{g_{1h}}, \ldots, \sum_{h=1}^{k} p_{nh} z_h^{g_{nh}}\right) \\ &= \sum_{h=1}^{k}\left(\prod_{j=1}^{n} p_{jh} z_h^{\varphi(g_{1h},\ldots,g_{nh})}\right) \end{aligned} \tag{2}$$

$$U_{\text{disp}}(z) = \sum_{h=1}^{k}\left(\prod_{j=1}^{n} p_{jh} z_h^{\varphi(g_{1h},\ldots,g_{nh}) * A_h}\right). \tag{3}$$

Phase III (data analysis). The main objective of this phase is determining the reliability functions and the main indicators for different systemic scenarios. The steps involved in this phase are the following.

Step 3.1. Once the polynomial $U(z)$ of the production system is known, it is possible to obtain indicators for the analysis of reliability of the system from an acceptability function $f(V,\theta)$, which represents the desired relation between the performance of the system V and some limit value θ called system demand ($f(V,\theta) = 1$, if the performance of the system is acceptable, and $f(V,\theta) = 0$ if it is not). The MSS reliability is defined as its expected acceptability. Given the probability mass function of the q_i system, v_i, $1 \leq i \leq K$, where $q_i = \Pr\{V = v_i\}$, it is possible to obtain its reliability as shown in

$$R(\theta) = E[f(V,\theta)] = \sum_{i=1}^{K} q_i f(v_i,\theta) \quad (4)$$

Step 3.2. Get output data useful for reliability analysis of each function executed, such as mean time between failures (MTBF) and mean time to repair (MTTR). These data can be found in the CMMS.

Step 3.3. It includes estimating the different availabilities of the system according to the functions executed and by polynomial $U_{\text{disp}}(z)$ (see (3)), to determine the output quantities of each function h, depending on the availability and the probabilities associated with each state.

Step 3.4. It includes performing an appropriate parameterization of the failure data according to the executed function, adjusting the data to the probability density curves of representative failures of the case under study, and showing the reliability model of the equipment.

Step 3.5. Through a mathematical tool, a probabilistic reliability assessment scenario is defined, which depends on the odds of developing each function and on the operational flexibility of the production system.

Step 3.6. A simulation with multiple iterations that change the executed functions at each minimum time interval of processing, whose transition probabilities depend on the function executed in the previous time interval, is performed. This is with the aim of determining expected values of reliability for the equipment, in other words, getting the reliability values that together consider all the executed functions and, thus, building an expected reliability curve for each equipment.

Step 3.7. The reliability analysis at the level of the entire production system is added, by performing mathematical operations required to reach the global values from those thrown by the equipment.

Phase IV (prediction and application). This phase consolidates the information obtained to facilitate the decision making. This is made into a prognosis context. The main idea is to develop an analysis of the future condition of each machine and of the production system, to decide the best strategy. Several elements have to be considered. First of all, the experience and knowledge of expert personnel are considered. As Kreinovich and Ouncharoen [18] set, the expert knowledge is still valuable in an automated analysis environment. In fact, they propose several techniques to best handle this knowledge. Other important methods for prediction and decision making are the analysis of the Degradation Function, Remaining Useful Life (RUL) function, Remaining Life Distribution (RLD), and the Total Cost evaluation during the entire life cycle of the asset. If desirable, with the results already obtained, complementary analysis tools are applied. Latest trends point out that the results of an analysis of Big Data should be delivered not as a noneditable document, but as an interface where the final user can experiment with different scenarios, trying to find correlations and useful data for everyday use.

4. Case Study

Consider a production process in a textile and embroidery factory. This factory works with massive volumes of sewing, embroidery, and quilting. The main workshop machines are multifunctional. Each machine is capable of performing the three functions: sewing (function A), embroidering (function B), and quilting (function C). These machines are remotely programmable in terms of the type of stitch and the function to be carried out. They also can be controlled by touch screen. The machine reminds sequences and changes performed in the stitches with each production batch.

Each machine is integrated into a system equipped with a processor, memory to keep the scheduled works and stitches, and devices to send and receive information. There is a set of sensors that control variables of performance and condition of the equipment, mainly vibration, speed, term of materials, and position of the needle and the thread. They also are able to generate data about their operational time, number of detentions, and duration of detentions and the causes of it. There is information of failure data of a period of five years. Then, this case study is developed according to the four-phase methodology proposed in this article.

4.1. Stage I: Data Acquisition

4.1.1. Process Description. The system under study is a production process of the textile industry, comprised of 25 work stations of multifunction equipment, specifically, machines to sew, embroider, and make quilts. The production configuration is typical of this kind of processes and it consists of numerous machines arranged as a workshop. Due to the characteristics of the process, quality and velocity of the sewing, embroidering, and quilting affect the entire flow process and the productive capacity of the entire plant.

Each work station contains one multifunction machine and each machine may present various failure modes. The movement of material between work stations is carried out by mechanical means.

4.1.2. Identification of Multifunction Components in the Production System. In the experience of the staff, the failure behavior of some machines of the workshop depends more on the operation constitution than on the operating time. In this case, the three functions executed (sewing, embroidery, and quilting) present processing conditions that cause different failure rate conditions (this is especially because of differences in speed of the needle, length of the stitch, and hardness of the yarn used).

The machines to be analyzed are identified, as well as their associated data repositories. The main variables to control are related to their operational condition according to reliability requirements: type of function executed, operational time, number, cause, and duration of interruptions.

4.2. Stage II: Data Preprocessing

4.2.1. Analysis of Normal Operation Conditions. The machines have a different processing capacity in units per hour for each function. The production planning determines the type of product to be manufactured per shift and the type of function to execute. The probability of switching between functions and the proportion of each function relative to the total executed are stationary at the long term. Modeling reliability will depend on the specific long-term behavior.

4.2.2. RBD System Configuration. The system is composed of 25 machines. Considering that the machines are characterized by their flexibility and dynamism, it is possible to determine that the plant is under a load sharing configuration. The particularity of a load sharing configuration is that it allows obtaining a required capacity based on the sum of available pieces of equipment that can even operate at a lower load than the required.

4.2.3. Universal Generating Function (UGF) in the Production System. By using the (1) and (2), it is possible to know the polynomial $U(z)$ of the production system performance, according to its RBD configuration. This polynomial shows the stationary probabilities that are associated with the execution rate, per hour, of each function. For elements in load sharing configuration, the minimum production rate in each composition is considered.

4.2.4. Failure Data Collection. Besides the information given by the signal repository, there has been access to records of failure that the technicians maintained during each shift, for a total of 1810 days, that is, considering almost five years of operations. This data is cleaned and treated before being used. During the analyzed period, the line operated for 16 [h/day]. The repository contains the failure modes for this period, classified for each shift, including the time between failures (TBF) and the time to repair (TTR). It is important to highlight that each failure mode was classified with the respective function (sewing, embroidery, and quilting). The total amount of intervention was 3.287 records.

4.3. Stage III: Data Analysis

4.3.1. Parameter Calculation. Knowing the values of time between failures (TBF) and time to repair (TTR), a curve fitting process was developed with the objective of finding the one that best explains the behavior of failures. This was done separately for each function in the case of the stations with a multifunction nature and through a commercial software. In the case of TBF the adjustment chosen was Weibull, from which scale (α) and shape (β) parameters were obtained. Meanwhile the TTF are better fit to a lognormal distribution, whose parameters are the mean (μ) and the standard deviation (σ). For TTR, besides, there is no evidence that shows a variation depending on the function executed whose process has led to the failure, so its modeling is the same for all functions.

4.3.2. Availability in Static State. Considering the individual information about reliability and maintainability, it is possible to make the estimation of availability (A) level for each executed function. For the system, the availability level is calculated based on the RBD configuration.

4.3.3. Polynomial $U(z)$ according to the Availability. By using (3) it is possible to calculate the amount produced per hour, depending on the availability of the workshop at steady state, by adding the system availability to the already known execution probabilities of each function. This represents a performance indicator to the expected output per hour in an undefined instant; however, it does not consider that this influences a short-term scenario, in which there is a probability of transition between the execution of a function and another and where the elaborate proportions are not the ones from the static scenario.

4.3.4. Reliability Analysis

(1) Failure Density and Failure Rate Functions. $f_{jh}(t)$ is defined as the probability density function of failure time of station j when executing function h, and $\lambda_{jh}(t)$ is defined as the failure rate of station j when executing function h. By plotting both $f_{jh}(t)$ and $\lambda_{jh}(t)$ for each function, the failure behavior that each function causes in each station can be appreciated. In addition, the parameters calculated in Section 4.3.1 report differences in times of good performance for each case. It is important to analyze the specific results for the parameter β, showing the different function effects. The function A obtains β of 1.87 (increasing failure rate), the function B obtains β of 1.0 (constant failure rate), and the function C obtains a value of 1.22 (increasing failure rate).

(2) Reliability Curves per Equipment When Executing a Type of Function. By using the classical formula of reliability function from Weibull it is possible to derive the equations of the reliability curves per equipment and function executed, where $R_{jh}(t)$ is the reliability function of machine j when executing function h. In static state it is possible to obtain a reliability curve of the system, which is different for each function executed.

(3) Calculation of the Expected Reliability with Multifunction. Based on the analysis of Sections 4.3.4(1) and 4.3.4(2), it is possible to model the reliability curves for each executed function and in consequence to analyze the complete multifunction scenario. The reliability of the equipment will then be variable depending on the type of executed function in

a determined time horizon and on the order these are executed. The first step then is to define a stochastic model that shows the possible scenarios of the workshop over time. These scenarios can be generated by simulation, considering a horizon of working days and shifts. For this case it is defined as follows: for each shift it is possible to execute either function A, function B, or function C, depending on the transition probabilities between the manufacturing of products which were previously calculated. Taking into account the fact that during one shift a single type of function is executed, the reliability function of each equipment is built depending on which function has been executed during all the shifts on the horizon of analysis. For this, the parameters in the reliability function change depending on their last condition. Therefore, the reliability when executing function j and during a shift m decreases in the proper proportion to the length of time to process that function, but since the case is integrated with the other functions, the "initial" availability of that shift depends on the function configuration adopted during the $m-1$ previous shifts. Hence, the curves are formed section by section, and they take countless forms through the iterations.

(4) Reliability Curves per Equipment and for the Production System with Multifunction. A simulation was performed with 1.000.000 iterations that make the executed function change shift by shift, producing changes in the reliability values of each equipment. The expected reliability value was obtained in every single instant of time t, between 0 [h] and 1.000 [h], and from that information the expected failure density curves, the expected failure rate, and the expected reliability per equipment were built, all of them under the multifunction conditions. The expected reliability curve of the machine j is denoted as $R\exp_j(t)$. From this curve the reliability parameters of the 25 machines were estimated, iterating with Weibull parameters according to the situation and looking for a coefficient of determination value (R^2) as high as possible. $f\exp_j(t)$ was also calculated and plotted as an expected failure density function of the machine j and $\lambda\exp_j(t)$ as an expected failure rate of the equipment j, both considering multifunction. Subsequently, the expected values of reliability of the entire system are calculated, as the product of the stochastic reliability of all the machines. The expected reliability curve of the entire system is denoted as $R\exp(t)$. As an example, Figure 2 shows the expected reliability curve of the entire workshop in the case under study, besides the reliability curve for the iterations performed. Each iteration generates a different curve according to the production planning.

Furthermore, just as in the analysis done for each equipment, from the expected values of reliability of the system, the Weibull parameters are estimated and $f\exp(t)$ is obtained as an expected failure density function for the entire system (Figure 3). Then, $\lambda\exp(t)$ is calculated as an expected failure rate function for the workshop (Figure 4).

(5) Calculation of MTTF, MTTR, and Expected Availability with Multifunction. With the Weibull parameters for reliability, it is possible to obtain the mean time to failures (MTTF) values, the mean time to repair (MTTR) values (this is the called "maintainability"), and the availability (A), the latter being both at a disaggregated level and as a total for the workshop. By using the equations of the reliability curves obtained for each station and expression (5), it is possible to obtain the MTTF of the stations for multifunction stochastic scenario.

$$\mathrm{MTTF} = \int_0^\infty R(t)\,dt. \tag{5}$$

For the maintainability analysis, the values of MTTR are obtained from the CMMS database, remembering that it is

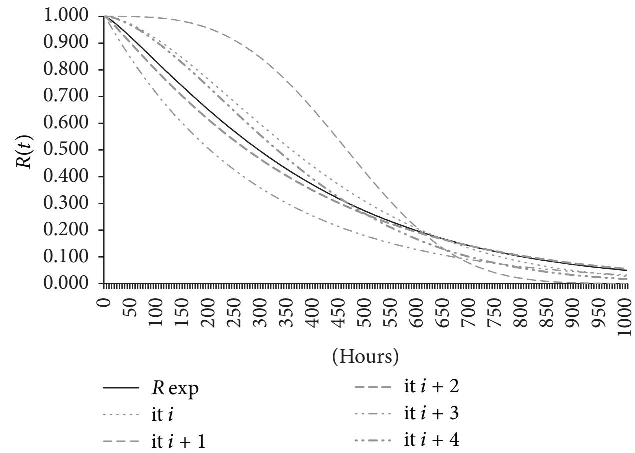

Figure 2: System expected reliability curve and reliability curves in iterations.

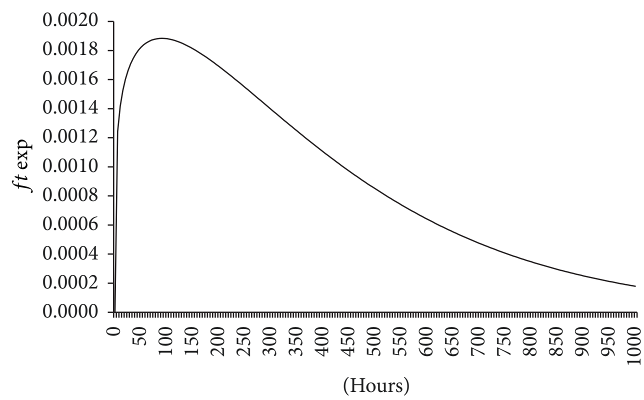

Figure 3: System expected failure density function.

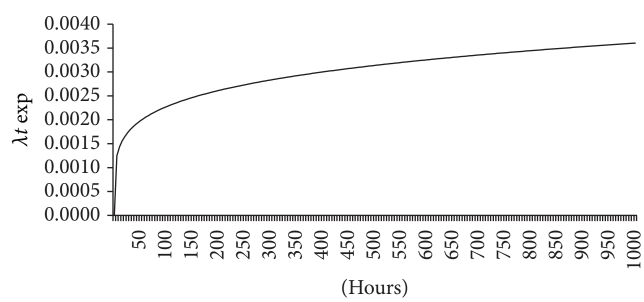

Figure 4: System expected failure rate function.

assumed that these values do not vary depending on the function being executed, the availability both for each piece of equipment and for the workshop as a whole is calculated, throwing a value for this case study of A exp = 0.9320.

4.4. Stage IV: Results Analysis. Considering the results of Stage III it is possible to elaborate an analysis that facilitates the understanding of the failure behavior and the decision making related to the production process, as follows.

After modeling each machine and the system under a load sharing configuration, the reliability analysis confirms the presence of a multifunction failure behavior, considering increasing failure rates for sewing (function A) and quilting (function C). The embroidering (function B) has a constant failure rate behavior. So, it is necessary to incorporate an analysis of the accumulated time per function for each machine, because the wear-out degree of the elements will be driven by this indicator, transforming the maintenance policies from an operation time criterion to an accumulated function operation time criterion.

To provide to the user with a way of easy access, this phase should be supplemented designing a Web platform. This should allow referring to both information and reports, so as to see the state of the system in real-time, as well as making new simulations bounded to scenarios determined by the user.

5. Conclusions

It is common in manufacturing industries of a varied nature that the same equipment participates in a mixture of functions. The reliability analysis of this multifunction manufacturing has not been fully explored, and a general solution for this problem has not been raised, at least to the best of our knowledge. To try to fill this gap, this work has developed a methodology based on the general procedure of data analysis, the Universal Generating Function, and the classical RCM reliability approach for the analysis of a multifunction manufacturing system. It is important to mention that this methodology is recommended primarily to be applied to very standardized processes, working as a continuous production system. Typical workshop configurations are not subject of the application of this methodology. Also, as expected, the more different the nature of each function, the more potent the application of this proposal.

Through a case study, consisting of the analysis and evaluation of reliability in a plant of automated textile production, the use of the methodology proposed was shown. The analysis was able to show that the nature of the machines of the workshop is multifunction, since the failure behavior varies depending on the function they are executing. Through the analysis of the operating conditions of the machines and the analysis of the operational flexibility, the stochastic scenario of production was defined. By using the methodology, it was possible to determine the failure behavior of the entire workshop according to the scheduled jobs. This is useful for the decision making in a static scenario, but it also shows the reliability effects of making certain products and executes each function on a long-term horizon.

Numerous iterations were executed that show possible scenarios of shifts programming in the production. Through them and through the expected values of reliability for each instant of time, the expected reliability of each machine was modeled, and an aggregated analysis of the system was performed. The analysis is completed using the graphic display of the probability density functions of failures and the failure rate functions. Through the joint analysis of results and studying the impact that each workstation has on the failure behavior of the workshop, it was possible to generate some conclusions about the reliability of the whole process and about the criticality of the elements that compose it.

Some recommendations for possible future studies are as follows: it would be helpful to develop approaches that beyond analyzing reliability also consider other areas of interest in the industry, like the costs analysis, maintenance strategies, equipment sizing, and problems of demand satisfaction, among others. All of these focused on any case of multifunction manufacturing and even beyond on any other multistate condition. It is also possible to recommend a posteriori some complementary analysis as a support to the study performed with additional points of view, such as those that the Markov chains can provide for the evaluation of reliability in Multistate Systems, and to formulate an optimization model of global costs that integrates load distribution decisions and tactical production planning, considering the costs of switching the equipment capacity and the idle capacity costs.

Finally, it is well known that if we have a forecast of the maintenance interventions with high levels of compliance and efficiency, the management of spare parts inventories can be favored. The demand for spare parts would be more accurately known. This could be another interesting future extension of this multifunction analysis work.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] C. Stenström, P. Norrbin, A. Parida, and U. Kumar, "Preventive and corrective maintenance cost comparison and costbenefit analysis," *Structure and Infrastructure Engineering*, vol. 12, no. 5, pp. 603–617, 2016.

[2] J. Yuan, C. Lin, S. J. Chang, and S. Lai, "Reliability modeling and evaluation for networks under multiple and fluctuating operational conditions," *IEEE Transactions on Reliability*, vol. 36, no. 5, 1987.

[3] M.-Y. You, H. Li, and G. Meng, "Control-limit preventive maintenance policies for components subject to imperfect preventive maintenance and variable operational conditions," *Reliability Engineering and System Safety*, vol. 96, no. 5, pp. 590–598, 2011.

[4] A. Decò, D. M. Frangopol, and B. Zhu, "Reliability and redundancy assessment of ships under different operational conditions," *Engineering Structures*, vol. 42, pp. 457–471, 2012.

[5] Z. Burciu and F. Grabski, "The experimental and theoretical study of life raft safety under strong wind," *Reliability Engineering & System Safety*, vol. 96, no. 11, pp. 1456–1461, 2011.

[6] L. Barberá, P. Viveros, V. González-Prida, R. Mena, L. Barberá, and V. González-Prida, “Influencia de la carga de alimentación en la fiabilidad de líneas de molienda. Caso de estudio,” *DYNA*, vol. 89, pp. 560–568, 2014.

[7] F. Kristjanpoller, A. Crespo, M. López-Campos, P. Viveros, and T. Grubbesich, “Reliability assessment methodology for multiproduct and flexible industrial process,” in *Realibility and Safety: Innovating Theory and Practice*, L. Walls, M. Revie, and T. Bedford, Eds., pp. 1101–1107, Taylor & Francis Group, London, UK, 2017.

[8] F. Xie, “A new surveillance method of machine status using big data,” *International Journal of Control and Automation*, vol. 8, no. 3, pp. 99–108, 2015.

[9] M. Nourelfath and F. Yalaoui, “Integrated load distribution and production planning in series-parallel multi-state systems with failure rate depending on load,” *Reliability Engineering & System Safety*, vol. 106, pp. 138–145, 2012.

[10] A. Lisnianski, “Extended block diagram method for a multi-state system reliability assessment,” *Reliability Engineering & System Safety*, vol. 92, no. 12, pp. 1601–1607, 2007.

[11] A. Lisnianski, I. Frenkel, and Y. Ding, *Multi-State System Reliability Analysis and Optimization for Engineers and Industrial Managers*, Springer, London, UK, 2010.

[12] J. Moubray, *Reliability Centered Maintenance*, Industrial Press, 1997.

[13] J. Wang and J. Zhang, “Big data analytics for forecasting cycle time in semiconductor wafer fabrication system,” *International Journal of Production Research*, vol. 54, pp. 7231–7244, 2016.

[14] S. Yang, B. Bagheri, and H. Kao, “A unified framework and platform for designing of cloud-based machine health monitoring and manufacturing systems. Journal of Manufacturing Science and Engineering,” *Transactions of the ASME*, vol. 137, no. 4, Article ID 4030669, pp. 10–1115, 2015.

[15] J. M. Tien, “Big Data: Unleashing information,” *Journal of Systems Science and Systems Engineering*, vol. 22, no. 2, pp. 127–151, 2013.

[16] G. Levitin, *The Universal Generating Function in Reliability Analysis and Optimization*, Springer, London, UK, 2005.

[17] A. M. A. Youssef, A. Mohib, and H. A. Elmaraghy, “Availability assessment of multi-state manufacturing systems using universal generating function,” *CIRP Annals - Manufacturing Technology*, vol. 55, no. 1, pp. 445–448, 2006.

[18] V. Kreinovich and R. Ouncharoen, “Fuzzy (and interval) techniques in the age of big data: An overview with applications to environmental science, geosciences, engineering, and medicine,” *International Journal of Uncertainty, Fuzziness and Knowlege-Based Systems*, vol. 23, pp. 75–89, 2015.