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Condition based maintenance optimization of multi-equipment manufacturing systems by combining discrete event simulation and multiobjective evolutionary algorithms

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Abstract

Modern industrial engineers are continually faced with the challenge of meeting increasing demands for high quality products while using a reduced amount of resources. Since systems used in the production of goods and deliveries of services constitute the vast portion of capital in most industries, maintenance of such systems is crucial (Oyarbide-Zubillaga, Goti, & Sánchez 2008). Several studies compiled by Mjema (2002) show that maintenance costs represent from 3 to 40 % out of the total product cost (with an average value of a 28%).

Within maintenance, the Condition-Based Maintenance (CBM) techniques are very important. Nevertheless, and comparing it to the Preventive Maintenance (PM) optimization problem, relatively few papers related to CBM have been developed: According to Aven (1996), one of the reasons to justify this fact is that CBM models are usually by its nature rather sophisticated compared to the more traditional replacement models. Within this maintenance strategy, Das & Sarkar (1999) distinguish two CBM subtypes, On-Condition Maintenance (OCM) and Condition Monitoring (CMT). OCM is based on periodic inspections, while CMT performs a continuous monitoring on the hardware through instrumentation.

Considering the described context, this paper focuses on the problem of CMT optimisation in a manufacturing environment, with the objective of determining the optimal CMT deterioration levels beyond which PM activities should be applied under cost and profit criteria in a multi-equipment system. The initiative considers the interaction of production, work in process material, quality and maintenance aspects. In this work the suitability of discrete event simulation to model or modify complex system models is combined with the aptitude that multiobjective evolutionary algorithms have shown to deal with multiobjective problems to develop a maintenance management and optimisation approach. An application case where the activities applied on a system that produces hubcaps for the car maker industry is performed, showing the quantitative benefits of adopting the detailed approach.

Keywords
Maintenance, Optimization, Discrete Event Simulation, Multi-objective Evolutionary Algorithm.

1. Introduction

Industrial plant management, especially maintenance optimization, is usually characterized by the need to consider multiple non-commensurable and often conflicting objectives (see i.e. (Bader & Guesneux 2007;Goti & Sánchez 2006)). Equipment can be over maintained increasing preventive maintenance (PM) expenditures or under maintained increasing catastrophic failures. In these situations, and considering that maintenance requirements depend on many facts (whether the maintained equipment is a productive bottleneck, if it has a crucial impact in manufactured products' quality, etc.), it is very difficult to determine the optimal maintenance strategy that maximizes the profitability of the studied equipment considering different criteria.
In the latest years, many works have been presented devoted to find an optimal maintenance policy focused on different points of view, mainly oriented to the optimization of single deteriorating equipment and without taking into account the configuration of the productive system which contains the equipments to be maintained. Single equipment optimization approaches may be especially interesting when productive bottlenecks or continuous processes (such as foundries, rolling mills, etc.) are analyzed. Nevertheless, these initiatives might be less useful in manufacturing machines which work in multi-equipment systems, as they usually do not take into account the influence that the whole system has in each of the studied machines. Maintenance requirements related to a single machine of a multi-equipment system depend strongly the amount of semi-elaborated products' stock related to the machine, whether it is a bottleneck or not, etc. For instance, if the studied machine is a bottleneck its availability will be crucial for the profitability of the company, whereas if not the impact of its failure will not be so important for the whole system (depending on stock levels and repair times (Li & Zuo 2007)). However, and although maintenance applied on equipment depends on the configuration of the system where the equipment is, little research can be found in the literature where a system composed by several equipments is optimized (Fiori de Castro & Lucchesi Cavalca 2006;Gharbi & Kenné 2005;Goyal & Kusy 1985;Grigoriev, van de Klunder, & Spieksma 2006;Kenne, Boukas, & Gharbi 2003;Yao 2005).
This paper provides a solution for the joint optimization of CBM strategies applied on several equipments. Precisely, the research is focused on the problem of CMT optimization in a manufacturing environment with the objective of determining the optimal age or deterioration levels when a Preventive Maintenance (PM) action should be performed for multi-equipment systems under cost and profit criteria. The approach developed takes into account the interaction of production, work in process material, quality and maintenance aspects. For this purpose, a model that considers maintenance, productive speed loss and non-quality costs along with productive profit has been developed.
The model has been implemented using Discrete Event Simulation (DES) and optimized using a Multiobjective Evolutionary Algorithm (MOEA). Thus, the suitability of DES to model or modify complex system models is combined with the aptitude that MOEAs have shown to deal with multiobjective problems.

This paper is organized as follows: the problem to be optimized is shown in section 2 whereas the age or deterioration model and the developed DES model are presented in section 3 and 4, respectively. The optimization MOEA is detailed in section 5 while problem formulation is shown in section 6. Finally, optimization results and concluding remarks are stated in section 7.

2. Optimization problem

2.1 System definition

The approach shown in this paper is applied to the optimization problem of PM activities of a simplified hub cap production system installed in a company of the Mondragón Corporación Cooperativa (MCC) Corporation (the third largest company in Spain). The system consists of three identical plastic injection machines and a painting station, as it is described in Fig. 1:

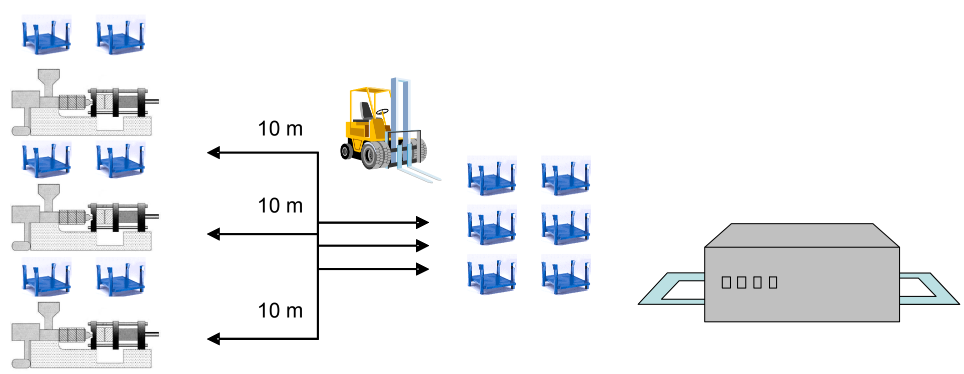

Fig. 1. Configuration of the simplified plastic injection system

The studied production system produces plastic made hub caps for car-maker companies. The production starts in the injection machine, where the plastic is injected, compressed concurrently, dwelled and cooled, to finally open the mould and extract the product. Then, the injected product is located next to the injection machine buffer (composed by two pallets of 100 hubcaps each). Once a pallet is filled with hub caps, a lift truck transports the pallet from the injection machine buffer to the painting station buffer (which has an area for storing up to 10 pallets). Then the products are loaded onto a conveyor that feeds the painting station. In the painting station the products are painted to be sent to a warehouse afterwards.

Each machine of the model consists of three subsystems (which are modelled as components) organized in serial configuration, and one maintenance activity is executed over each subsystem in order to control its aging: M1, M2 and M3 are respectively applied over sub-systems S1, S2 and S3 of the injection machines while M4, M5 and M6 are respectively executed on sub-systems S4, S5 and S6 of the painting station. The influence of each subsystem on the performance of each machine is defined in Table 1: for the injection machine, S1's deterioration influences only unavailability, S2's deterioration affects unavailability and productive speed loss and, S3's deterioration has an effect on unavailability and quality. Similarly, considering the painting station, S4's deterioration influences only unavailability, S5's deterioration affects unavailability and productive speed loss and, S6's deterioration has an effect on unavailability and quality.

Maintained equipment	Name of the PM activity executed when the age of its corresponding subsystem achieves an age	Subsystem	Influences on
Injection machines	M1	S1	Unavailability
	M2	S2	Unavailability and Productive speed loss
	M3	S3	Unavailability and Quality
Painting station	M4	S4	Unavailability
	M5	S5	Unavailability and Productive speed loss
	M6	S6	Unavailability and Quality

Table 1. System components, PM activities and their influences on productive parameters

The equipments failure process is modeled by using a two-parameter (λ_1, γ_1) Weibull failure rate. Additionally, it is considered that the production process can be subject to a process deterioration that shifts the system from an under-control state to an out-of-control state. This process deterioration follows also a Weibull distribution of parameters λ_2, γ_2. Table 2 shows the Weibull reliability data for the studied problem.

Group	$\lambda_1(10^{-2}hrs^{-1})$	γ_1	$\lambda_2(10^{-2}hrs^{-1})$	γ_2
S1	5	2		
S2	2	2.9		
S3	4	2	4	2
S4	6.6	2		
S5	7.7	3		
S6	10	3	10	3

Table 2. Weibull data of the studied subsystems

3. Deterioration or reliability model

3.1 Deterioration model

Traditionally, the effect of the maintenance activities on the state of a equipment is based on three situations: a) perfect maintenance activity which assumes that the state of the component after the maintenance is "As Good as New" (GAN), b) minimal maintenance which supposes that activity leaves the equipment in "As Bad as Old" (BAO) situation, and c) imperfect maintenance which assumes that the activity improves the state of the equipment by some degree depending on its effectiveness. Last situation is closer to many real situations.

There exist several models developed to simulate imperfect maintenance (Chan & Shaw 1993;Malik 1979;Shin, Lim, & Lie 1996). In this paper, an age reduction preventive maintenance model, named Proportional Age-Set Back (PAS), proposed by Martorell et al. (1999) is used to model the effect of the maintenance activities on the equipment.
In the PAS approach, each maintenance activity is assumed to shift the origin of time from which the age of the component is evaluated. PAS model in Ref. (Martorell, Sánchez, & Serradell 1998) considers that the maintenance activity reduces proportionally, in a factor of ε, the age that the component has immediately before it enters maintenance, where ε ranges in the interval [0,1]. If $\varepsilon = 0$, the PAS model simply reduces to a BAO situation, while if $\varepsilon = 1$ it is reduced to a GAN situation. Thus, this model is a natural generalization of both GAN and BAO models in order to account for imperfect maintenance. Based on Ref (Martorell et al. 1999), the age of the component immediately after the (m-1)-maintenance activity (w^{+}_{m-1}) is given by:

$$w^{+}_{m-1} = (t_{m-1} - \sum_{k=0}^{m-2} (1-\varepsilon)^{k} \cdot \varepsilon \cdot t_{m-k-1}) \tag{1}$$

where t_{m-1} is the time in which the component undertakes the m-1 maintenance activity

As Sherif & Smith (1981) state, if it is assumed that a probability distribution of the time to failure is available, risk can be measured. Risks associated to degradation in monitoring equipment consider poor quality and performance, productive breakdowns related to Corrective Maintenance (CM), etc. The following paragraphs go deep into the modelling of such risks.
Considering a CMT strategy, PM is performed when the component gets a determined critical age or deterioration level (w_c). It is worth to remember that PAS model considers that the maintenance reduces proportionally, in a ε factor, the age that the component has immediately before it enters maintenance. Considering these conditions, maintenance always will be applied to a component when it has the same age, and as effectiveness is assumed to be constant the age of the component will always be the same after performing a PM action. This means that w^{-}_{m} and w^{+}_{m}, which represent respectively the age of the component just before and after the mth PM intervention, will always get the same values:

$$w^{-}_{m} = w_c \tag{2}$$

$$w^{+}_{m} = (1-\varepsilon) \cdot w_c \tag{3}$$

As a consequence, the time interval M between two PM activities will have this value:

$$M = w_c \cdot \varepsilon \tag{4}$$

3.2 Reliability model

Using Equations 2-4, it is possible to obtain an age-dependent reliability model in which the induced or conditional failure rate, in the period m, after the maintenance number m, given by:

$$h_m(w_m(t,\varepsilon)) = h(w_m(t,\varepsilon)) + h_0 \tag{5}$$

where h_0 represents the initial failure rate of the component, that is, the one that equipment has when it installed. Considering the age of the component after maintenance m given by Equation 1, and adopting a Weibull model for the failure rate, the expression for the induced failure rate after the maintenance number m can be written as:

$$h_m(w_m(t,\varepsilon)) = \left\{\lambda^\gamma \cdot \gamma \cdot \left[w_m(t,\varepsilon)\right]^{\gamma-1}\right\} + h_0 \tag{6}$$

where λ is the scale parameter, γ is known as the shape parameter. The behaviour of $h_m(w_m(t,\varepsilon))$ function fluctuates between two values as was observed for the age of the component and its maximum and minimum values are given by:

$$h_m^- = \lambda^\gamma \cdot \gamma \cdot \left(w_m^-\right)^{\gamma-1} + h_0 \tag{7}$$

$$h_m^+ = \lambda^\gamma \cdot \gamma \cdot \left(w_m^+\right)^{\gamma-1} + h_0 \tag{8}$$

Then, in order to introduce the effect of maintenance activities into the cost and profit models, to be presented in the following section, it is derived an averaged standby failure rate over the component's life based on a double averaging process. First, it is formulated h_m^* the average failure rate over the period between two consecutive maintenance activities, m and m+1. Next, it is formulated the average failure rate, h^*, over the analysis period, L, which is practically equal to h_m^*. Thus is:

$$\begin{aligned} h^* \approx h_m^* &= \frac{1}{t_{m+1}^- - t_m^+} \int_{t_m^+}^{t_{m+1}^-} h_m(t).dt \\ &= (M)^{\gamma-1} \cdot \left(\frac{\lambda}{\varepsilon}\right)^\gamma \cdot \left[1-(1-\varepsilon)^\gamma\right] + h_0 \end{aligned} \tag{9}$$

3.3 Availability model

As a consequence of what it is explained in the previous subsection, and based on Ref. (Martorell, Serradell, & Samanta 1995), $u_r(\mathbf{x})$, the time-dependent unreliability for discontinuous equipment can be calculated as:

$$u_r(\mathbf{x}) = \rho + (1-\rho).\left(1 - e^{-h^*.M}\right) \tag{10}$$

where ρ is the probability of failure on demand, and h* is evaluated using Equation 10. Then $U(\mathbf{x})$ is the total unavailability of the studied system evaluated using the system fault tree and the single component unavailability contributions. These contributions are $u_{cm}(\mathbf{x})$ which is the unavailability due to CM given by:

$$u_{cm}(\mathbf{x}) = \frac{1}{M} \cdot u_r(x, M) \cdot d_{cm} \tag{11}$$

Where d_{cm} is the mean time for CM; and $u_{pm}(\mathbf{x})$ that represents the unavailability associated to the PM interventions launched due to CMT monitoring in the L period. Considering the periodicity of the PM activities explained in Equation 4, $u_{pm}(\mathbf{x})$ is given by:

$$u_{pm}(\mathbf{x}) = \frac{1}{M} \cdot d_{pm} \tag{12}$$

Where d_{pm} the mean time for PM; Finally, the total availability of the studied system $A(\mathbf{x})$ is evaluated as:

$$A(\mathbf{x}) = 1 - U(\mathbf{x}) \tag{13}$$

being U(**x**) the system unavailability to be evaluated using the system fault tree and the single component corrective and preventive maintenance unavailability contributions.

4. Discrete event simulation model

DES concerns the modeling of a system as it evolves over time by a representation in which variable states change suddenly at separate points in time, as it is detailed in the other chapter of this book authored by the same author. These changes happened in the system are considered events. Systems do not change between events, so DES considers that it is not necessary to analyze what happens in a system in periods taken place between two events.

The main advantages of DES are two: i) standard DES-based tools provide capabilities of modeling or modifying complex system models easily, and ii) DES is closely related to stochastic systems so they are appropriate when simulating real-world phenomena, since there are few situations where the actions of the entities within the system under study can be completely predicted in advance. In order to generate stochastic events, simulation packages generate pseudo-random numbers to select a particular value for a given distribution. Similarly, equations related to analytical models (i.e. breakdown models) can also be implemented due to the generation of these pseudo-random numbers. Thus, using pseudo-random numbers it is possible to implement the stochastic nature of real models in DES models.

The DES model simulates the injection machines, the painting station, the lift, the product buffers and its pallets. The implementation of each of these components is detailed in the following subsections.

4.1 Equipment modeling

The behavior pattern of the machines represented in the DES model bases on an analytical model. This model is presented in (2006). In that work a single equipment model is detailed. The paper models maintenance, quality and production speed loss costs jointly with the benefit related to the production of non-defective products. All of these terms depend on the PM activities performed, which act as decision variables (**x**) and are optimized under cost and profit criteria.

That equipment model was developed considering the following assumptions: 1) the effect of the maintenance activities is modeled by using an imperfect maintenance model. In this case a Proportional Age Set-Back (Martorell, Sánchez, & Serradell 1999) is assumed, 2) the failure process and deterioration process are independent, 3) the system only produces non-conforming items, with a rate constant (α), while the process is out-of-control, 4) Preventive maintenance and process inspection are performed simultaneously, 5) inspections are error free and 6) the process is restored to under control state when the preventive maintenance is realized, 7) productive speed is assumed to fall from its initial speed (V_0) to another speed value ($V^*(\mathbf{x})$) which depends on the PM frequency, 8) as in (Li & Pham 2005), we assume that all the deterioration processes of the three studied components are independent, and 9) it is assumed that the process produces a single product type, so setup times of reference changes are not simulated.

The relevant productive parameters of the described equipment model include: i) direct maintenance parameters, ii) quality parameters and iii) productive speed loss parameters. These parameters can be evaluated as:

$$V^*(\mathbf{x}) = V_0 - \left[\tau \cdot M \cdot \left(\frac{2-\varepsilon}{2\varepsilon}\right)\right] \tag{14}$$

$$\kappa^*(x) = \frac{1}{M}\int_0^M t \cdot f_m(w(t,\varepsilon))dw \approx \frac{1}{2} \cdot h^* \cdot e^{-h^*(x)\cdot M} \tag{15}$$

Where; $V^*(\mathbf{x})$ the mean production speed of the equipment during the L period; and $\kappa^*(\mathbf{x})$ the mean fraction of time where the process is under control. In addition, the following notation is used: V_0 the initial (e.g. as per design) production speed; τ the speed loss coefficient; ρ the cyclic or per-demand failure probability; and $f_m(w(t,\varepsilon))$ the density function obtained using the conditional hazard function.

In this research, analytical formulation corresponding to each machine of the productive system is implemented within the equipment to generate stochastic events that make equipment work as it is defined in the analytical model. This integration is performed in two steps: first the components of the decision vector related to the studied machines are evaluated analytically, obtaining the working parameters $U_{cm}(\mathbf{x})$, $U_{pm}(\mathbf{x})$, $V^*(\mathbf{x})$ and $\kappa^*(\mathbf{x})$ of the corresponding PM frequencies (where $U_{cm}(\mathbf{x})$ and $U_{pm}(\mathbf{x})$ are respectively the unavailability of a machine due to CM and PM, evaluated using the system fault tree and the single component $u_{cm}(\mathbf{x})$ and $u_{pm}(\mathbf{x})$ contributions). In a second step, the generated working parameters are introduced as inputs in the DES modelled machines to execute then a simulation where the results to be optimised are obtained.

The implementation of values obtained in the analytical evaluation executed in the DES model derives in the generation of planned PM, unplanned CM, speed reduction and defective product actions and events during the simulation. As a consequence, at the end of the simulation machines generate the same values of $U_{cm}(\mathbf{x})$, $U_{pm}(\mathbf{x})$ and $\kappa^*(\mathbf{x})$ defined by the analytical model to produce items in a $V^*(\mathbf{x})$ productive speed. Fig. 2 shows the generation of unavailability, speed loss and quality events for an equipment during a simulation:

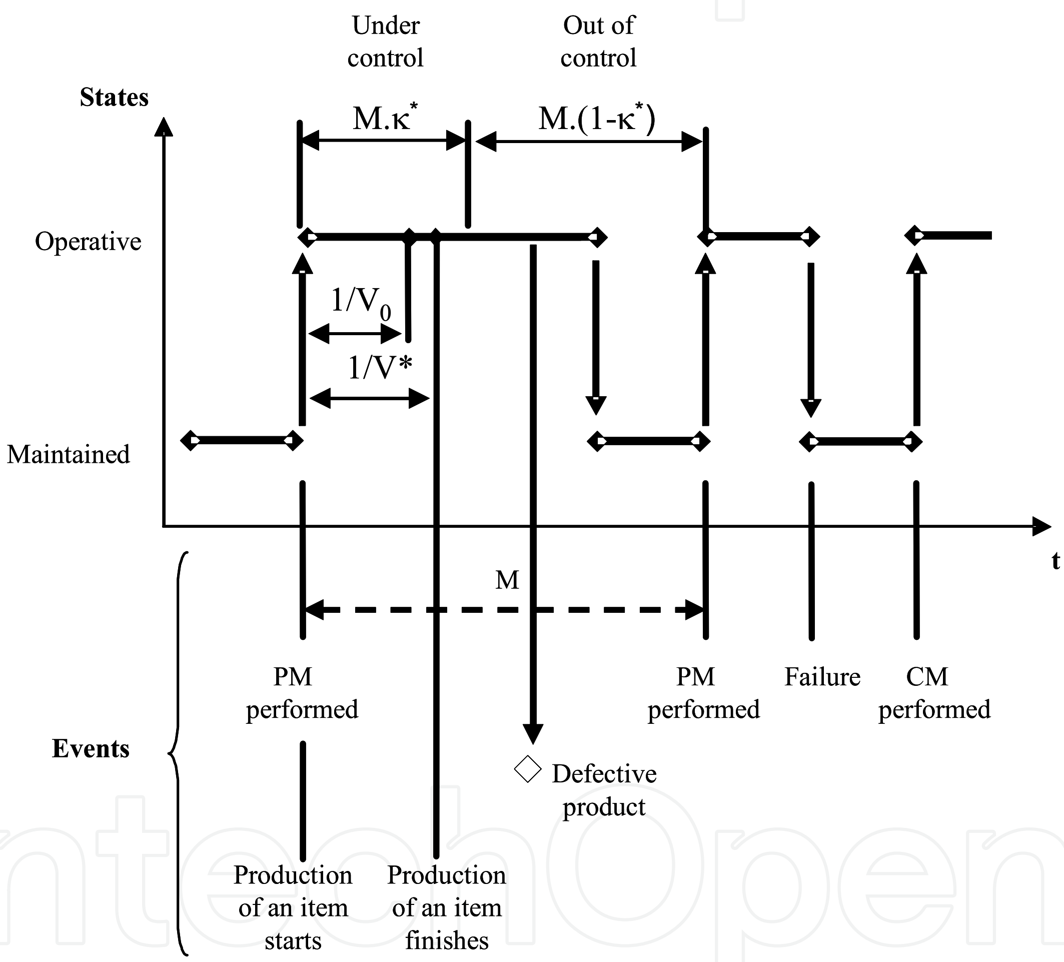

Fig. 2. Generation of events related to maintenance, productive speed and quality

As it can be seen in Fig. 2 events related to PM are generated with a determined periodicity (M) and each product needs a $1/V^*$ cycle time to be produced. Failures are generated randomly to obtain an unavailability related to CM which is equal to $U_{cm}(\mathbf{x})$. Referred to quality, there are no defective products during the first $\kappa^*(\mathbf{x})$ fraction between two PM activities, while there is a α defective fraction during the following $(1-\kappa^*(\mathbf{x}))$ fraction. Thus, thanks to the interaction between analytical evaluation and DES modelling simulation equipments work as it is defined in analytical models shown in Eqns. (14 – 15). Additionally,

and thanks to the capability of combining different machines in a system, the DES model not only models the features of a single machine, but the interaction among several machines.
The generation of each one of the above mentioned events is related to a specific inefficiency so their costs have to be taken into account. Costs are quantified considering CM, PM, speed loss, quality and CMT terms. In order to do that, individual cost counters related each one of these terms ($c_{cm}(\mathbf{x})$, $c_{pm}(\mathbf{x})$, $c_{sl}(\mathbf{x})$, $c_q(\mathbf{x})$ and $c_{cmt}(\mathbf{x})$, respectively) are defined; these counters are initialized to zero at the beginning of the simulation and increased every time an event related to them is generated by the simulation using Eqns. (16 – 20):

$$c_{cm}(\mathbf{x}) = c_{cm}(\mathbf{x}) + d_{cm} \cdot c_{hcm} \tag{16}$$

$$c_{pm}(\mathbf{x}) = c_{pm}(\mathbf{x}) + d_{pm} \cdot c_{hpm} \tag{17}$$

$$c_{sl}(\mathbf{x}) = c_{sl}(\mathbf{x}) + \left[\left(1/V^*(\mathbf{x})\right) - \left(1/V_0\right)\right] \cdot c_{hsl} \tag{18}$$

$$c_q(\mathbf{x}) = c_q(\mathbf{x}) + c_\alpha \tag{19}$$

$$c_{cmt}(x) = c_{hcmt} \cdot L \tag{20}$$

where c_{hcm}, c_{hpm}, c_{hsl} and c_{hcmt} represent respectively the hourly cost related to the CM, the PM, the reduced speed and the CMT, while c_α represents the cost of manufacturing a defective product. Finally, $P(\mathbf{x})$ characterizes the profit function obtained as a result of selling non-defective products, which can be evaluated as:

$$P(\mathbf{x}) = n(\mathbf{x}) \cdot \psi \tag{21}$$

where $n(\mathbf{x})$ represents the amount of non-defective products obtained during the analysis period (L), and ψ is the estimated margin of a single product.

4.2 Buffer and transportation modeling

System buffers have a determined maximum capacity. The model assumes that if a buffer is full it will not receive any products until it has free pallets to store them (so the transportation events will not be executed). This means also that a machine will stop producing products in case it does not have any place to leave them. The painting station is fed by a buffer of ten pallets, being each one capable of storing 100 products, whereas each injection machine feeds a buffer of two pallets of 100 each.
Referred to transportation modeling, only semi-elaborated product movements have been modeled, considering movements between: i) a machine and a buffer location, ii) two machines, iii) a buffer location and a machine, and iv) two buffer locations. It is worth to note that for transportation types i), ii) and iii) products are moved one by one, whereas for movements between two buffer locations products are transported in pallets. All of these movements are modeled by introducing a delay in the system. Thus, in instant t the element is at the initial point, to be at the destination point in instant t+delay. For sake of simplicity transportation types i), ii) and iii) are not modeled (delay=0), whereas injection machines are fed with empty pallets and empty pallets of the painting station are removed from the

system automatically and instantaneously. The lift truck transport is modeled using a delay which has a uniform distribution range between 14.4 and 28.8 s.

4.3 Simulation values of the productive system

Data collected for the simulation model is shown in the next 4 tables. Tables 3 and 4 show parameters related to PM and CM, whereas Tables 5 and 6 detail respectively information about inputs related to CM, unavailability, speed, quality and cost for the injection machines and the painting station.

Preventive maintenance activity	ε	d_{pm} (hrs)
M1	0.9	0.5
M2	0.9	1
M3	0.9	1
M4	0.9	2
M5	0.9	1
M6	0.9	3

Table 3. PM data related to the productive system

Corrective breakdown of sub-system	d_{cm} (hrs)
S1	0.5
S2	1
S3	2
S4	0.5
S5	1
S6	2

Table 4. CM data related to the productive system

C_{α} (€/u[1])	τ (u/h^2)	C_{hsl} (€/hr)	ρ (10^{-3})	α	h_0 (fail/hr)	V_0 (u/hr)	c_{hcm} (€/hr)	c_{hpm} (€/hr)	c_{hcmt} (€/hr)
6	0.0017	25	1	0.03	0	180	45	30	1

Table 5. Productive and cost parameters for the injection machines

C_{α} (€/u)	τ (u/h^2)	C_{hsl} (€/hr)	ρ (10^{-3})	α	h_0 (fail/hr)	V_0 (u/hr)	c_{hcm} (€/hr)	c_{hpm} (€/hr)	c_{hcmt} (€/hr)
6	0.02	150	1	0.04	0	900	175	160	1

Table 6. Productive and cost parameters for the painting station

[1] Where u represents a product unit

Additionally, the net profit value of a non-defective product (ψ) is 0.2 €/unit and the simulation time L is 62400 working hours, which corresponds to 10 years of production working 5 days a week and 24 hours a day.

Finally, the time required to execute a simulation in DES increases in an exponential way compared to the complexity of the studied model (Oyarbide-Zubillaga, Baines, & Kay 2003). For this reason and in order to reduce the time which the simulation is being executed products are elaborated in batches of 100 units.

5. The NSGA-II multiobjective evolutionary algorithm

In this approach the Non-dominated Sorting Genetic Algorithm (NSGA-II) proposed by Deb et al. (2002) has been implemented. The NSGA-II is the most recent and improved version of the NSGA which incorporates: a) a faster non-dominated sorting approach, b) an elitist strategy i.e. the best non-dominated individuals are preserved from one generation to another by using a crowding measurement, and c) no niching parameter. This algorithm is capable of performing a joint optimization under several criteria offering non-dominated solutions. The non-dominated results are situated in a Pareto optimal front, where each of the solutions is better than any other solution of the front at least in one of the studied optimization criterion.
The working procedure of the NSGA-II is shown in Fig. 3 and detailed in the following steps:

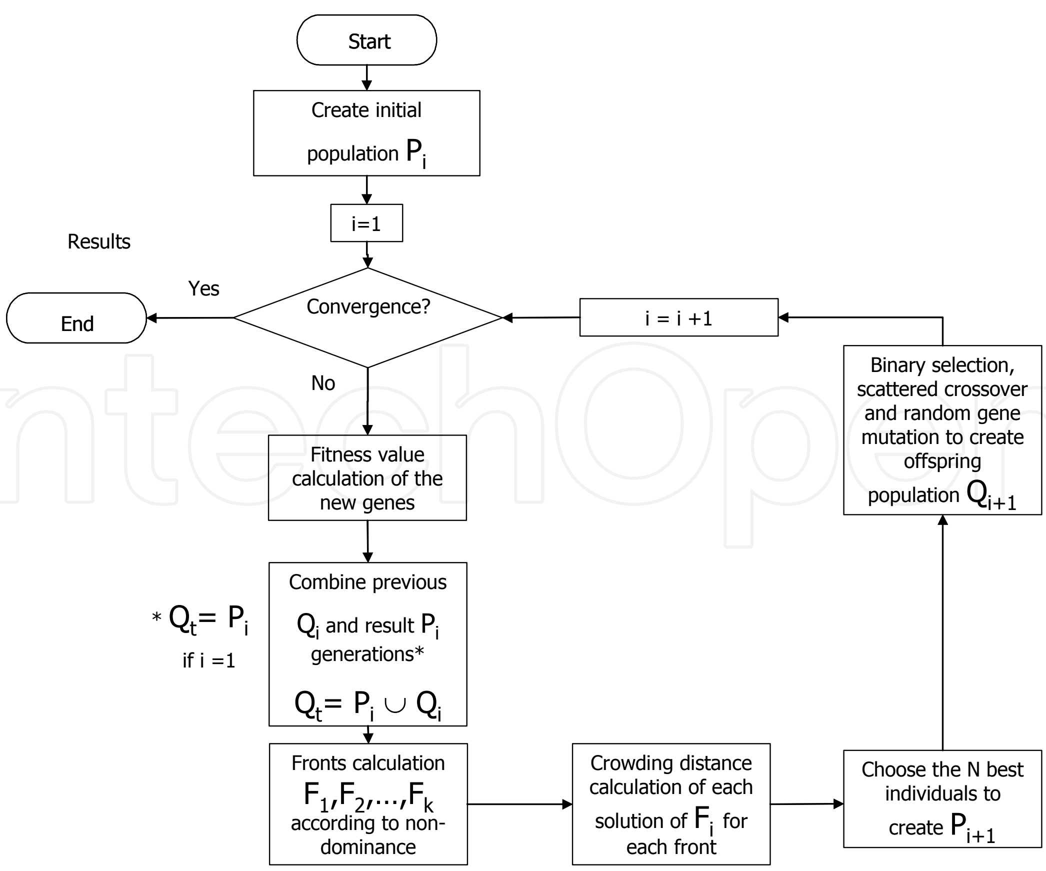

Fig. 3. Working procedure of the NSGA-II

Step 1. Fix N, i=1, and i_{max}.

- N = population size
- i = number of generations
- i_{max} = maximum number of interactions of the genetic algorithm

Step 2. Create and evaluate a random parent population P_i of size N.

Step 3. If $i=i_{maxGA}$ return P_i else:

Step 4. Form a combined population of size 2N as $T_i= P_i \cup Q_i$.

- Q_i = offspring population
- T_i size N and equal to P_i in the first interaction

Step 5. Ranking (according to restriction violations).

Step 6. Identify non dominated fronts F_1, F_2, …., F_k. Thus an each solution is assigned a fitness equal to its non-domination level.

Step 7. Create P_{i+1} as the N best individuals from P_i.

Step 8. Select randomly N couples from P_{i+1} using a binary tournament selection.

Step 9. Create offspring population Q_{i+1} applying crossover and mutation (size N).

Step 10. Evaluate the offspring population.

Step 11. Do i=i+1.

Step 12. Go to step 4.

Following the procedure detailed above the algorithm evaluates the $\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_N}$ genes of each generation. In this case, to obtain the respective $f(\mathbf{x_1}), f(\mathbf{x_2}), \ldots, f(\mathbf{x_N})$ fitness values of the evaluation, the DES model performs a simulation where PM frequencies act as decision variables to obtain economic parameters.

6. Problem formulation

The optimization of preventive maintenance activities based on cost and benefit criteria can be formulated as a multi-objective optimization problem (MOP). A general MOP includes a set of parameters (decision variables), a set of objective functions, and a set of constraints. Objective functions and constraints are defined in terms of the decision variables using the models presented in the previous section. The optimization goal can be formulated to optimize a vector of functions of the form (Martorell et al. 2004):

$$\mathbf{y} = f(\mathbf{x}) = \left(f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_n(\mathbf{x})\right) \tag{22}$$

subject to the vector of constraints

$$g(\mathbf{x}) = (g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_n(\mathbf{x})) \tag{23}$$

where

$$\mathbf{x} = \{\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_n}\} \in \mathbf{X} \tag{24}$$

$$\mathbf{y} = \{\mathbf{y_1}, \mathbf{y_2}, \ldots, \mathbf{y_n}\} \in \mathbf{Y} \tag{25}$$

and **x** is the decision vector (vector of decision variables), **y** the objective vector, **X** the decision space and **Y** is the objective space, that is to say **Y**=f(**X**).
The optimization of PM activities proposed in this paper considers the productive costs and profit as optimization criteria. Both cost and profit models depend on maintenance intervals, which act as decision variables and are encoded in the decision vector, **x**. So, the vector of bi-objective function, f(**x**), is defined as:

$$f(\mathbf{x}) = \{C(\mathbf{x}), P(\mathbf{x})\} \tag{26}$$

where the objective is to minimize the function C(**x**) and maximize a profit function P(**x**). C(**x**) is the cost system which is evaluated as sum of the maintenance, production speed lost and quality costs for each of the m machines of the system which are evaluated using Eqns. (16 - 20).

$$C(\mathbf{x}) = \sum_{i=1}^{m} \left(c_{cm_i}(\mathbf{x}) + c_{pm_i}(\mathbf{x}) + c_{sl_i}(\mathbf{x}) + c_{q_i}(\mathbf{x}) \right) \tag{27}$$

and P(**x**) is the profit function obtained as a result of selling non-defective products, evaluated as it is detailed in Eq. (9).

In this case there are no constraints defined in terms of the vector of constraints. Nevertheless, constraints are imposed directly over the values the decision variables can take, which must get typified values, representing each one a day, two days, etc.
This maintenance optimization MOP can be solved using a MOEA. A MOEA is a multi-objective search method based on Darwin's evolutionary theory applied to a population of possible solutions which evolves and tends to converge to an optimal solution set.
The MOEA, in this case the NSGA-II, evolves the population which is evaluated executing simulations by using the developed model. The scheme of the optimization approach is shown in Fig. 4:

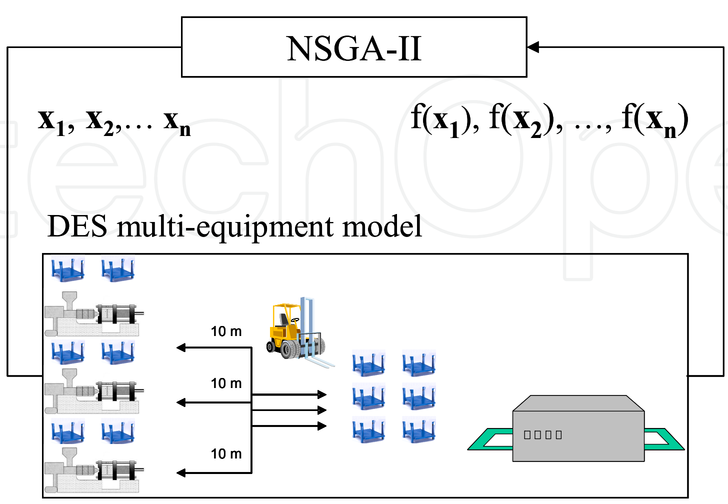

Fig. 4. Optimization approach

As it can be seen in Fig. 4, the NSGA-II creates a population of n decision vectors ($\mathbf{x}_1$, $\mathbf{x}_2$,… $\mathbf{x}_n$) which are evaluated executing simulations. The model returns the fitness values of each one of these vectors (f($\mathbf{x}_1$), f($\mathbf{x}_2$), …, f($\mathbf{x}_n$)) which are processed in the NSGA-II to generate new populations. These evolutions tend to achieve solutions which are located in a Pareto optimal front, where it cannot be determined that a solution obtained is better than another without considering additional information.

7. Results

Fig. 5 represents a cost plot of results found by the NSGA-II. The results shown were calculated using a Pentium 4 3.2 GHz 1 GB RAM running the MOEA evolving a population of size 50 individuals for 200 generations with a selection rate of 0.25, crossover rate of 0.5 and mutation rate of 0.75. The DES model was using Witness PwE 1.00 by Lanner while the NSGA-II was implemented in Matlab R2010a by The Mathworks 2010.

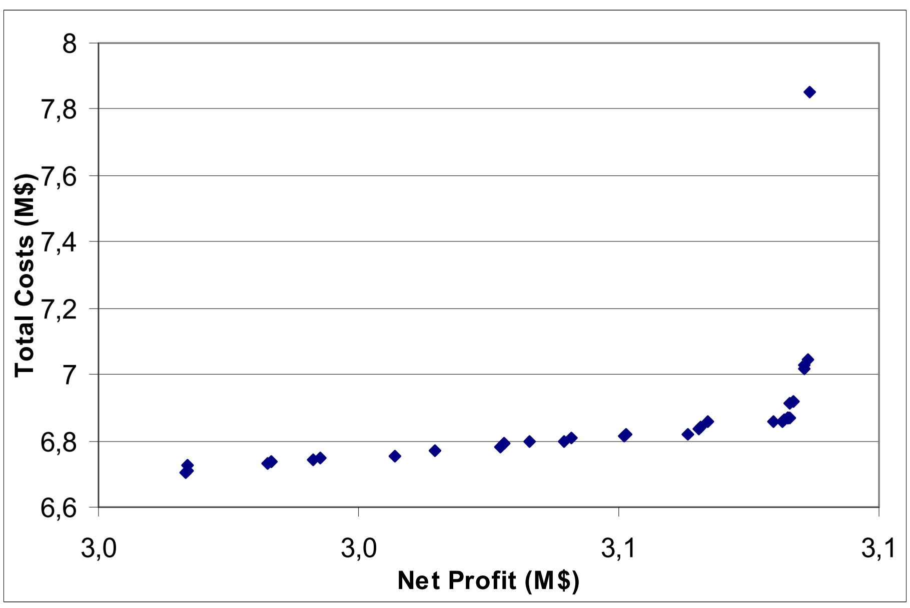

Fig. 5. Pareto front obtained in the optimization process

Additionally, Table 7 details the periodicities and cost-profit values of the PM activities shown in Fig. 5:

Wc1	Wc2	Wc3	Wc4	Wc5	Wc6	Net Profit (€)	Total Cost (€)
57	24	217	287	101	49	5073840	11569746,08
259	203	276	287	36	254	4958660	11391119,09
259	220	284	287	36	137	4944400	11376236,31
259	234	284	287	36	128	4934460	11363711,18
261	21	49	287	36	170	5069720	11557158,79
261	21	282	283	36	244	5072660	11558294,87
261	24	120	287	36	137	5078500	11824125,91
261	24	120	287	36	170	5078700	11819128,42
261	24	168	283	36	74	5079760	11864908,78
261	24	217	287	36	49	5074500	11577481,48
261	24	217	287	36	231	5073900	11570285,34
261	24	217	287	36	254	5073840	11569746,08
261	24	276	287	36	74	5075560	11658237,44
261	24	276	287	36	102	5080300	13330001,56
261	24	276	287	36	102	5073260	11551843,41
261	24	276	287	36	137	5078820	11839544,71
261	24	276	287	57	143	5080480	13209311,2
261	24	276	287	36	186	5078780	13088264,73
261	24	276	287	36	254	5075040	11644593,44
261	24	284	287	36	137	5074240	11575248,3
261	24	284	287	36	143	5072840	11561591,77
261	72	217	287	36	231	5049060	11529753,47
261	72	282	287	36	231	5050680	11557092,2
261	74	217	283	36	49	5048160	11520395,78
261	77	217	287	36	214	5045100	11494831,02
261	88	276	287	36	137	5038940	11503122,02
261	104	120	287	36	214	5027520	11491780,06
261	107	217	287	36	143	5026920	11484713,39
261	128	271	287	57	196	5011400	11474116,47
261	129	120	287	36	170	5009660	11458363,92
261	143	168	287	36	74	4999720	11453174,76
261	156	168	287	36	137	4992060	11442624,64
261	156	168	287	36	254	4991260	11423301,86
261	156	217	287	36	143	4992340	11441827,68
261	156	217	287	36	170	4991340	11429164,3
261	182	271	287	36	170	4972380	11407934,91
261	182	276	287	36	280	4973340	11402901,84
261	199	271	287	36	128	4960780	11378041,99
261	229	272	287	36	163	4939140	11369356,24
261	231	282	283	36	170	4937080	11361320,55
261	249	168	283	36	254	4924000	11340232,17
261	249	217	283	36	254	4924860	11351080,1
261	249	271	283	36	196	4925160	11354773,53
261	249	276	287	36	102	4924580	11339726,48
261	249	276	287	36	254	4924500	11337625,08
261	249	284	287	36	58	4924680	11343427,54
261	282	120	287	36	170	4900260	11297333,11
261	282	237	287	36	170	4900680	11305358,67
261	282	276	287	36	170	4902120	11337373,85
261	282	276	287	36	254	4900700	11306826,13

Table 7. PM periodicities and objective values of the obtained Pareto front

As it was stated previously, the developed MOP offers solutions which are situated in a Pareto optimal front. Thus, the analyst can select externally the best maintenance strategy, since it has to be considered simultaneously possible additional restrictions imposed over the solutions after having them. Hence, they can analyze afterwards how every solution of each Pareto set score in cost and profit criteria. Additionally, the Pareto front generated satisfies the constraint imposed to the problem. Each one of the elements calculated in the Front is related to critical age or deterioration levels when a preventive activity must be executed. So, the decision maker can select a solution of the Pareto front in accordance with his preferences knowing that the elected solution will accomplish all the imposed constraints.

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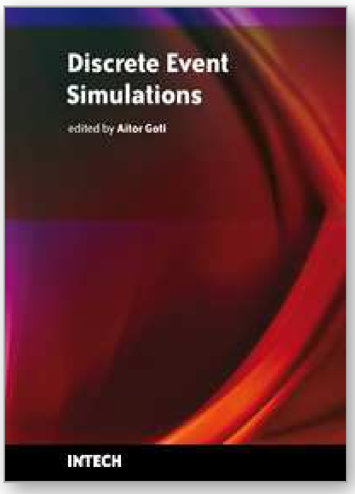

Discrete Event Simulations
Edited by Aitor Goti

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Considered by many authors as a technique for modelling stochastic, dynamic and discretely evolving systems, this technique has gained widespread acceptance among the practitioners who want to represent and improve complex systems. Since DES is a technique applied in incredibly different areas, this book reflects many different points of view about DES, thus, all authors describe how it is understood and applied within their context of work, providing an extensive understanding of what DES is. It can be said that the name of the book itself reflects the plurality that these points of view represent. The book embraces a number of topics covering theory, methods and applications to a wide range of sectors and problem areas that have been categorised into five groups. As well as the previously explained variety of points of view concerning DES, there is one additional thing to remark about this book: its richness when talking about actual data or actual data based analysis. When most academic areas are lacking application cases, roughly the half part of the chapters included in this book deal with actual problems or at least are based on actual data. Thus, the editor firmly believes that this book will be interesting for both beginners and practitioners in the area of DES.

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