Production yield improvement in a series system by a multithreshold CBM model

Mosè Gallo, Guido Guizzi, Pasquale Zoppoli

***Abstract*—**In many manufacturing environments, equipment condition has a significant impact on product quality, or yield. In this work it has been studied the case of a series of Pick and Place machines, characterized by a high value of basic components. So, in this kind of process it's necessary to rework all refused units caused by defective assembling. The approach we used in this work consider a condition based maintenance (CBM) model which is able to determine when it is economically convenient to make a preventive maintenance intervention on the machine in function of the number of refused units per unit of time produced by the process. We used the defection rate (number of refused units per unit of time produced by the process) as a parameter to decide when it's convenient to stop the machines, wich are in a series: so, every time one is stopped, it's neeeded to stop them all. We modeled the cost of the system and its productive behavior by an event driven simulator. The cost optimization consists in determining, by simulation, at what value the threshold (defection rate) should be fixed to minimize the overall maintenance and rework cost. The proposed model has clearly demostrated to improve the efficience of the process respect the nowaday, experienced based, management, but also respect a model based on the optimizing of the processes yield present in scientific literature.

***Keywords*—** condition based maintenance, multithreshold, pick & place, simulation, yield.

I. Introduction

THIS work has been accomplished in a plant that produces instruments for mobile radio networks, both with 2G and Edge technology, and also microwave systems. This plant has a large capacity, which is estimated in 900.000 circuit boards per year, with 500 million assembled components. The plant is composed of several assembling lines, Surface Mount Technology (SMT), with different configurations.

In this work, we have focalized our attention on the assembling line which produces components for indoor microwave network apparatuses. The study regard the series of Pick and Place (P&P) machines of the specific line, this because the company had specifically required assistance, since the lines yield was quite low, due to continuous maintenance interruptions.

Manuscript received March 20, 2007: Revised version received Nov. 29, 2007.

M. Gallo, G. Guizzi and P. Zoppoli are with the Materials and Production Engineering Department of the University of Naples "Federico II", piazzale Tecchio 80, 80125 Napoli ITALY (phone: +39 081 7682630; e-mail pasquale.zoppoli@unina.it).

The line considered is multi-product, the boards produced can mount from about 400 to almost 2000 components. The process line configuration is as following:

- Board Unloader
- Serigraphic MPM AP25S
- Conveyor + Lent 4x
- Siplace S25 HM
- Siplace 80 F5 HM
- Oven Omniflo 10
- Board Loader
- X-Ray Inspection Station (not in line)

On this line five Pick and Place (P&P) machines are present: the first three have the same configuration, mounting all two revolver heads with twelve segments each. The forth, also a S25, mounts one head with twelve segments and another head with six segments. The last P&P machine, F5, which has one IC head with six segments, which carries out a single assembly for every withdraw, for every Pick and Place cycle, necessary for the larger components.

Each one of these machines have an entrance or mouth, where in each of them are mounted feeders which introduce the necessary components for the assembly: this components are hosted in containers, which are substituted when the product changes.

As normally happens with this kind of manufacturing process, an important share of the costs are caused by reworking, in fact considering the high number of components which each board mounts and the fact that even a single component that is missing or incorrectly placed determines malfunctioning of the circuit. The eventual weldings that are missing, are discovered by the X-Ray station or along the next inspections, such as the "In Circuit Test". The following functional inspections, must be realized by an operator, this operation needs much more time if compared with a correct welding made on line. In case a component results crooked, first it must be disconnected and then correctly rewelded.

For these reasons it is essential that we contain the P&P's defectiveness. The scope that we have is to introduce and optimize a condition based maintenance policy on the series of P&P along the process line.

Before our studies the P&P's are maintained following the recommendations of machine producers, which prescribe a scheduled preventive maintenance. But the process line has evidenced a low yield, caused by frequent non-scheduled interventions: such interventions, in absence of any pre-determined criteria, are entrusted to the operators, whose limited experience, limited quantity of data and subjective valuations are used for the decision making. Analysis takes place only when the processes' yield becomes particularly low such to attract the managements attention.

The yield of the process line depends on countless factors, since, at the moment there aren't any intermediate tests, and therefore the intervention that are carried out, aren't always correctly aimed in the best direction, for this reason we want to determine a series of physical parameters that once monitored can indicate whether an intervention should be made or not. P&P machines are extremely complex and sophisticated, they supply a vast quantity of outputs, from which it is quite complicate to obtain significant data.

Once we've found which parameters best indicate the state of a P&P machine, we must determine the values of the thresholds that when crossed indicate the necessity of an intervention: the evaluation of this threshold will obviously be a point of equilibrium of a trade-off, seeing at one side the direct, indirect costs, and production lost regarding a maintenance intervention and at the other side, costs regarding a products defectiveness, a considerable share of this cost is in reworking the product.

II. STATE OF ART

A. SMT production yeld

The subject regarding SMT production yield and costs deriving from eventual reworks of defective products is very important under an economic point of view, for this reason it has been widely studied and analyzed. Particularly interesting for our specific study case result the works of Kamen, Goldstein [7] and others [9]. Their scope in one case was to analysis the relationship between the SMT process and the associated yield, in the other case it was to study the causing of mistaken placement of the components in a SMT process.

The approach is based on the concept of probabilistic network which defines the relationship between causes and effect of the machines state and quantitative inspections and measurements, such as the quantity of welding paste applied, precision in placing the component on the board, and the processes yield. The general form of this network is shown in figure 1.

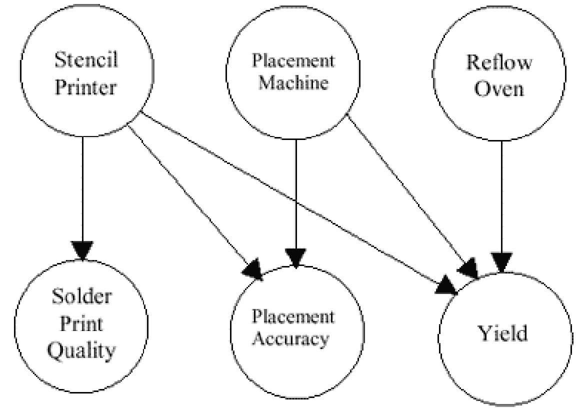

Fig. 1: Probabilistic network to evaluate the yield

The superior nodes indicate the states of the machines, the inferior nodes are parameters that can be objectively measured, while the arrows represent cause effect relationship. This network is able to indicate the state of a machine, measuring the three parameters indicated in the inferior nodes. To work, the network needs a previous evaluation of the conditioned probabilities. Particularly important is to determine the effect of different states of failure of the machine on the quality of the screen-printing, component placement and on the processes yield. For this we need to measure the different parameters during the different states of the machine. The experimental data was obtained by tests made on the machine Siplace analogue to the machine encountered in the plant of this study. Till now, we have examined:

- Intentional offset added on the P&P, corresponding to a calibration error
- Pads volume and height
- Nozzles pressure values, during functioning intervals

When we estimated the correspondence of the above factors with the placement accuracy of the components, only the first of them indicated a significant correlation. Let us note the significance of the non correlation between the quality of the screen printing, which, as we've seen, is calculated by measuring the volume or height of the welding paste placed on the circuit board, the evaluation is made by an optical instruments, and obviously measuring the components placement on the board. The components placement depends exclusively on the P&P's performance, neglecting accidental factors such as the detaching of a component due to human manipulation, aspects which are of limited importance.

The Siplace supply innumerous parameters related to it's functioning state: in particular, it registers the difference of pressure in presence or absence of a component on the machines nozzle (the nozzle is a pipette that is mounted on a segment, depending on which component must assemble on the board), in case the pressure difference results low for three times in a row, the machine automatically stops, but typically an operator starts the machine without a whatsoever intervention or even inspection. Problems of this type seem principally correlated with the malfunctioning of the same nozzles, which should by substituted at every board change and cleaned every work shift. Other gathered data regards the share of defective components, which is calculated as the quantity of refused components that the machine does not recognize, placing these components in a specific container. This problem, which is cause of immense expenses, has already been studied by the company, and it appears that such problem is not caused by the Siplace but by the feeders that supply the components for the Siplace. For this reason the feeders are replaced as soon as the percentage of refused components is more then 1%. A factor which appears to be significantly correlated with the P&P's placement errors, from the studies of Goldstein, Kamen and Asarangchai, and experimentally demonstrated on the Siplace S series, is with the segments offset, as a direct consequence it seems natural to monitor its value, to obtain information regarding the machines state. Unluckily this was not possible, the segments value of offset of each machine is accessible only in maintenance condition using the Siplace software Sitest [10]; the value of the segments offset is measurable when calibrating the head of the machine, or calibrating a single segment, operation which takes place after the disassembling and cleaning of the segment. In case this parameter results to be out of the prefixed range, calibration must be repeated. It is clear that his parameter can not give us any information regarding the functioning state of the machine, since this parameter is measured after a maintenance intervention: the cited study after all was formulated for correlating the segments offset with the placements offset, giving in this way a indirect measurement. Unfortunately, on this line we don't have an AOI instrument which is able to measure the placement offset on the output of the P&P; the only information that we have come from the X-Ray station, besides the fact that currently it isn't on line.

B. Condition based maintenance optimization

In the last years there have been many new models proposed about the optimization of a Condition Based Maintenance (CBM) system, but this is the first work orientated to organize all the new experimental data at disposal; with also highlighting the different efficacy of each model to resolve real problems through adapting and verifying the model at its best.

On this argument it's been done a vast bibliographic research, encountering 21 mathematical and simulative models regarding condition based maintenance.

There have been identified eight core aspects of the models, reassuming them in Table I, where for each work is indicated the reference and the models principle characteristics.

Table I: Features of models on maintenance policy

Reference	mathematical (m) -simulative (s)	discrete (d) - continuous (c)	perfect inspection (yes/no)	partial inspection (yes/no)	opportune maintenance (yes/no)	multi-threshold (yes/no)	failure (yes/no)	series (numb. of comp./no)
[21]	m	c	yes	no	no	no	no	1
[22]	m	c	yes	no	yes	yes	no	2
[23]	m	d	yes	no	yes	yes	yes	no
[24]	m	c	no	yes	no	no	yes	2
[25]	s	c	yes	no	no	yes	no	no
[26]	m	c	yes	no	no	no	yes	no
[27]	m	d	yes	no	no	no	no	no
[28]	m	c	yes	no	no	no	no	no
[29]	m	c	yes	no	no	no	no	no
[30]	m						yes	
[31]	m	d	yes	no	no		yes	no
[32]	s	c	no		no	no	no	2
[33]	m	c	yes		no	no	yes	no
[34]	m	c					yes	no
[35]	m	c	yes		no	no	no	no
[36]	m	d	yes		no	yes	no	no
[37]	m	d	yes		no	no	yes	no
[38]	m	c	yes		no	no	no	no
[39]	s	c	yes		no	no	yes	no
[40]	m	c	yes		yes	no	no	
[41]	s	d	yes		yes	yes	no	2

Modelling a real-world situation can principally happen by two ways: with simulations or with mathematical models. Currently 17 of the 21 works have chosen a mathematical approach [21 - 24, 26 – 31, 33 – 36, 38, 40]. These choices unfortunately could limit applications in industrial field, due to the firm hypothesises (even with one faulted hypothesis, all conclusions will fall attaining unreliable results) and also due to the difficulty of understanding and applying such models in real industrial background. In the only case of [25, 32 and 39] there has been a simulated approach of modelling using the Monte-Carlo Method, obtaining in the first cases an interesting way to model failures, while in the last case an innovating next-inspection policy. In [32] we are capable of studying a parallel configuration, which in case of failure of one unit produces a situation of extra-stress for the remaining unit. In [41] it's been used an event driven simulator to represent the wear process.

When discussing about condition based maintenance, it can be distinguished two kinds of dominions for the state of units or components: discrete and continuous state. In the first we have a certain number, finite or infinite, of states where the first state assumes the system "as new" and the last state securely is "system failed". The evolution of the systems state from new to fail comes by a stochastic process. In the second category the state of the model is described by the value assumed by a certain number of continuous variables. Agreeing with A. Barros, C. Berenguer and A. Grall [24], for most real systems the deterioration process, due to physical wearing, develops in an intrinsically continuous way in the continuous passing of time; for example erosion (case of hydraulic components) or corrosion (pipes). For these systems the concept of a "discrete state of wear" is an excess of simplification since the deterioration level has a clear physical meaning which is supported by the evaluation of the maintenance decision maker [25]. So, optimizing these models consists in determining the best number of wear thresholds and their position. When these thresholds are crossed there will be indications on which type of maintenance should be done (such as corrective, preventive, opportune) and also when the next inspection must occur; obviously the class and number of thresholds depend on the maintenance policy. In fact the three enunciated thresholds (corrective, preventive and opportune) have been considered by all models except 5 of them, which are [23, 27, 30, 36, 37].

In almost all real complex systems the wear condition of a system is function of numerous parameters, but if we consider each singular component alone, we could easily describe its state with a single parameter. There are two possible ways to consider the deteriorating process of a system. The first one is when to consider an increasing parameter which we call wear. The second one is a parameter of resistance, strength or performance, which decreases with time. In all works considered the deteriorating processes have always been described as a non decreasing parameter.

How does this parameter fluctuate in time? Indicating with x_k the value of wear of our unit in the k-th instant, such denotation has been used in most of the 21 works (figure 2). Let us formalize that:

- $x_0 = 0$;
- when $x_k=0$ what ever value k is, this means that the system or unit has been replaced becoming "as good as new";
- increments between two interval of time are not negative, casual, identically distributed and statistically independent;
- x_k - x_{k-1} is a quantity determined casually by a certain probability density function (pdf).

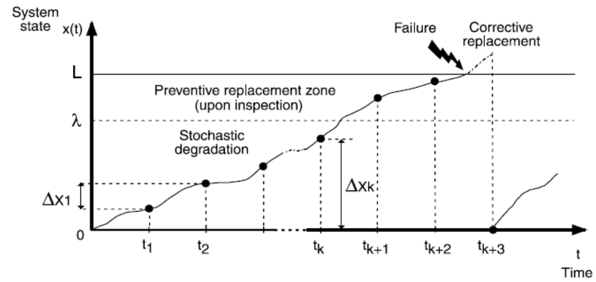

Fig. 2: example of a wear process [21]

Some studies to determine the casual increment of wear depend on generic "gamma processes", [21, 25, 28, 29, 33, 34, 35] and others, others are obligated for their particular mathematical structure to use determined cumulated density function (cdf) , such as exponential (in [2] or other). Differently from all other studies, in [26] there is not pdf used for shaping the increment of wear. The increments of wear depend simply on past values of wear which, after an inspection, are obviously certain and known. It's also interesting the technique for representing the deterioration used in [39] by Barata, Guedes Soares, Marseguerra and Zio, which calculate an increment of wear in the period of time that goes from k to k+1 depending on the value of wear in the instant k. This technique takes suggestion from a few studies performed on the deteriorating process of steel and cement. Totally different from the cases already considered are [23, 27, 30, 36 and 37] which describe the evolution from a state of wear to the next state independently of the current value of wear. At last some studies don't even consider a state of wear of the system assuming that it is impossible to know or measure, and that the only information obtainable is by observing if the system is in a state of failure or not [24, 32]. All the mentioned models consider an increasing continuous wear based on a gamma stochastic process. For example, let's consider [22], where the wear increments are drawn from an exponential distribution (exponential and erlang are particular generalizations of a gamma distribution), indicating with Δ(k,k+1)X(i) the increment of wear during the period of time with farthest instants k and k+1. With the apex of the variable X(i) we represent the wear for the i-th component of a system. This increment (Δ(k,k+1)X(i)) is always defined for every couple of instants t and t+1, and determined by a casual extraction from an exponential pdf:

$$\Delta_{(k,k+1)}X^{(i)} = \alpha_i e^{-\alpha_i x}, \ \forall \text{ component i}$$

The wears rate could be similar to what indicated in figure 3.

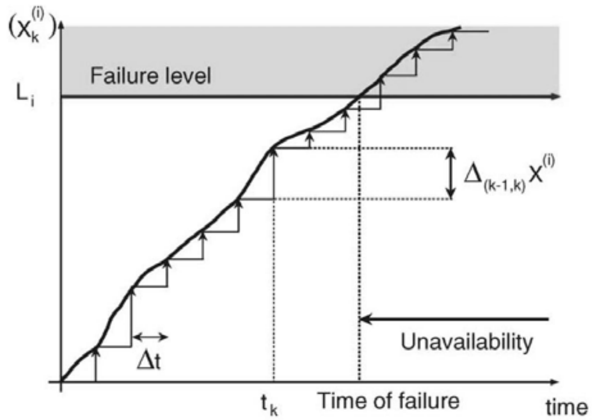

Fig. 3: wear increments with stochastically independent increase [22]

As already seen, simulative models are more capable, respect analytic models, of representing realistic industrial applications as they can consider aspects that would analytically be impossible to develop.

Regarding CBM models they must take in consideration a certain grade of aleatority when carrying out a measurement, allowing to describe a more realistic model. It will then be up to the designer or user to decide the accuracy of each measurement depending on the real process that we want to model.

Concerning the modelling of failure, despite what has been supposed in literature until now, for a future development of the research the assumptions could be:

failure should be possible at any condition of deterioration;

units or components should never cross the limit of sure failure;

failure is unequivocally evident, and so it should not be established only after an inspection.

Industrial maintenance stops cause an internal production imbalanced situation. It is obvious to try to equilibrate this aleatority with internal buffers. The buffers dimension is a issue that has been widely treated in literature, but only one work [30] formulates a way to determine a buffers size using as inputs mean times between failure and maintenance time. This study is very interesting under an economic point of view, it could be fairly attractive to include this kind of economic aspects in a CBM model, it would give the possibility to optimize the size of the buffer respecting maintenance processes.

None of the considered models have tried to integrate a CBM policy with a production plan. To do this it is necessary that the increment of wear of a unit should by implemented with the units working cycle. With the modeling liberty granted by simulative methods, it would be possible to model this situation by letting the parameter wear increment every time interval, only if the component considered actually worked in that same interval; and more we could assure that the casual wear increment depended even on the type of work done.

III. The proposed approach

A. The CBM model

Condition Based Maintenance (CBM) is a maintenance policy wich aims to prevent component failure in a system, by controlling certain wear parameters and activating maintenance intervention when these parameters pass pre-determined thresholds. Deciding what value should the thresholds be arranged at, the same thresholds that determine a maintenance intervention, requests that we know the law that describes the deterioration of the components and also an economic valuation of convenience. Let us remember that our final goal is to minimize the overall maintenance cost, considering that if we arrange the threshold at a low value, we will be more protected against accidental failure but such an arrangement will necessarily involve many maintenance intervention, which obviously have their costs. Instead if we were to place the thresholds at high values we would have limited maintenance intervention, with limited associated costs, but the risk of sudden and unannounced failures with costs that quickly become considerable.

The multithreshold CBM is a more complicated deciding system where the thresholds for each component indicate a different wear state of the unit and as a consequence different decisions. Let us start describing the models inspection method. This model does not consider a continuous control of the state of wear, but inspections at discrete time every predetermined interval; in this way we can model the real act of inspection and associate to each inspection a determined cost and time consumption. In such a case the decision policy of the system can place one or more “alarm” thresholds between which the inspections become more frequent; in this way we would be able to keep under a better control the evolution of the components parameter of wear, trying to avoid unexpected failures.

A particularly interesting case are serial systems, because when a component of a serial system fails the whole system must be stopped, involving serious economic losses, except in the case inter operational buffers are present along the production line. In cases of a stop the cost is very consistent because it considers the unproductively of the production line, but also the costs to reactivate a normal flow of production, so it is typically convenient to use this time of inactivity for maintenance intervention on other components that in a close future would need preventive maintenance; this maintenance anticipating will be indicate such as “opportune” maintenance.

The CBM model we used has to be representative of a real production system; each single resource can be modeled as deterministically or stochastically time consuming. The model keeps trace of the actual working time of a component. In fact a component will work only when it receives a work in progress from a precedent unit; in case the precedent unit is stopped (for failure or preventive maintenance) or in case of a temporary unbalance on the working line (caused by the stochastic working process), the following unit has to attend. After a discrete period of time the parameter wear, for each single component, will be increased for a value equivalent to the real operating time.

In all models based on CBM policy it is very important that inspections are correctly modeled. The models closeness to a real situation depends mainly on this aspect. All decisions that will be taken depend directly on inspection values, inspection errors will bring to corrupted maintenance decisions; in fact depending on the value of wear measured the system must decide what to do: preventive maintenance, opportune maintenance or delay in till the next inspection. Every single measurement is effected by uncertainty; this circumstance cannot be ignored because a casual event during a measurement can bring to wrong decisions. Therefore, in the model each measurement of wear will be considered to be not perfect, but affected by an error with a Gaussian distribution with null mean and standard deviation depending on the kind of measuring process.

The model considers three kind of threshold for each unit:

- preventive maintenance
- opportune maintenance
- alarm

The last kind of threshold can be present in a growing number, where they indicate a reduction of the period of time between inspections.

In most of the models examined, a component is considered to be in a state of failure when its parameter of wear passes a certain value, indicated as the failure threshold. This approach does not take in consideration the possibility that a unit can fail before it achieve a specific value of wear, for extraordinary events. Some of the models considered that the state of failure of a unit is noticed only with an inspection act. This hypothesis is unrealistic, except in cases where we define that a failure threshold is a value of maximum wear after which we necessarily must replace the component because it doesn't guarantee a proper function. Wanting to place the model with the most general non restrictive hypothesis possible, the hypotheses that we used are:

- failure of a component is possible at any value of the parameter wear;
- a wear limit which when is crossed by the wear parameter automatically brings the component in a state of failure does not exist.
- the probability of failure depends on the state of wear of each single component
- when a component goes in a state of failure, it is instantly acknowledged and automatically implies the stop of the production line.

For this reason, we must build a continuous function defined in R+ , which must return the probability of failure depending on a certain parameter. In scientific field, time is commonly used as parameter of the probability distribution function. The probability function that has been used in this model is a Weibull, which is much more versatile then other, more common functions, such as the Gaussian or exponential. The parameter that describes the weibull function is wear, instead of the more commonly used time, depending on the fact that all units don't necessarily work continuously. This hypothesis is totally coherent with the CBM philosophy, which aims in measuring and controlling the state of wear of a unit to decide on eventual maintenance interventions. The fact that we have picked a weibull distribution does not compromises the model validity because in any case we can modify the probability density function used according to the components technologic characteristics.

In a series production line, stops caused by maintenance interventions on different components create an unbalanced situation along the production system. Wanting to have certain flexibility and contain different unit productivity, it would certainly be useful to insert along the line interpretational buffers. In this model we've considered only one buffer placed at the centre of the N units, in this way the line can be studied as if they were two distinct lines partially independent. Each machinery inside the two branches work as if between then there is a buffer with null capacity. When a unit stops, the other units of the same branch, once concluded the WIP, must stop too.

Instead, the units belonging to the other branch can work normally untill the capacity of the buffer allows it. The buffer capacity is not sufficient to cover the whole period of unproductively caused by a maintenance intervention or a failure. In fact the buffer that we've considered is "realistic"; it represents a limited possibility to separate the production line. If we would have considered a production line with an interpretational buffer that has an infinite capacity, it would not have sense to study the two branches together. In the sphere of economic valuation of our system we have considered the buffers costs as the buffers capacity for the unit storing cost per time for each component stored.

Unlike most article publication on this subject, whatsoever intervention is not considered instantly, every maintenance intervention (corrective or preventive), as inspections, are considered time consuming. The period of time considered for each act can be determined by deterministic formulas or stochastic parameters. All this in the intent to move the model closer to reality. The time for an inspection of maintenance act can also stochastically vary depending on different parameter for different causes such as employees, or kind of maintenance act.

At last, we have introduced the possibility to have a limited amount of maintenance resources. Let's consider N element series, of which K of these N components need a maintenance intervention (which means that at least one component is in a state of failure, or the parameter wear has crossed the preventive threshold while the other K-1 components have crossed the opportune maintenance threshold), the model checks that K is not larger then M, where M is the max number of maintenance units (maintenance teams, technicians or component replacements). If K < M is true K maintenance acts will be accomplished, in the other case only M interventions will be made while the remaining K - M will be postponed in till the next production stop.

B. Selection of monitoring parameter

Non of the data at hand seems to be a good parameter for indicating the P&P's state: The technical data proposed by the machine doesn't seems to be correlated with the machines performance, as indicated by various academic and industrial studies. The will to apply a condition based maintenance policy (CBM) based on one or more parameters, results to be frustrating, due to the fact that it is complicated to define a stress parameter corresponding to our scope [31].

On the contrary, to follow a maintenance policy based on time scheduling doesn't seem to be suitable, because of the limited results and often unscheduled intervention necessary. These intervention are implemented by evaluating, in a non-systematic way, the products' yield increases: but the yield depends also on the differences between the countless components, by errors generated along the whole production line, and therefore not only by the P&P. From the types of errors that are present in the table of troubleshooting of the SMT line:

- Open
- Solder balls
- Cold welding / voids
- Short
- Missing component or misaligned
- Only the last seems to be caused by the P&P machines.

We decided to formulate another index, in terms of Defect Per Million of Opportunities (DPMO). Where we considered only the boards with a component missing or misaligned, noticeable by the report on the ABC analyses on refused circuit boards.

Considering only the refused boards of our interest, we considered the number of opportunities to generate a defect, which varies from board to board depending on the number of components on each of them. Furthermore, we must be able to determine which P&P machine, of the five in the process line, committed the error, this because our intent is to develop a model for interventions on the single machine. The necessary information has been obtained by accessing the NC assembly files: these files contain the assembling sequence for every product. The files are loaded on the processes line central computer, which programs the P&P's activity, by indicating for each machine the components and the segment that mounts each component, the position on the board is obtained by the CAD file of the board, also the set of nozzles that each head must use for the different products.

From these file we've obtained:

- The number of components mounted by each machine for each product
- Knowledge of which machine to associated a missing component

Information regarding processing time, are acquired from files, relative to each P&P, that contain data regarding running time, waiting time, stop time and also information on the product that has been processed. Using an electronic data sheet we've been able to calculate the daily DPMO's of the five machines, based on samples of the four principal products processed by the line, with various dimensions and composition. The expression used is the following

$$Dpmo = \frac{E}{\sum_i Ci \cdot Ni} \times 10^6 \qquad (1)$$

Where

E = number of errors committed by the machine in the samples that we have considered

Ci = number of components per board referred to product i

Ni = number of circuit boards of the product i considered

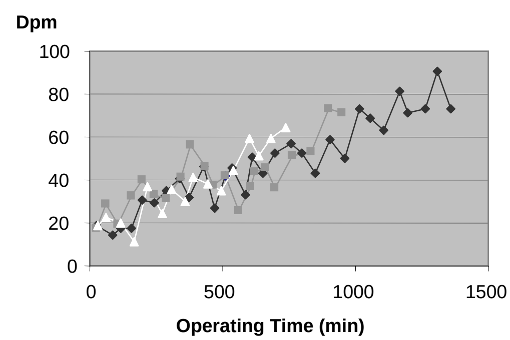

Fig. 4: DPMO for machine 1

All the data has then been gathered in another sheet where information is inserted for each machine regarding processing time expressed in minutes, the cumulated function of processing time starting from the last maintenance intervention held (intervention of cleaning and calibration of the revolver heads are also considered as maintenance), and the DPMO. In this way we were able to study how the DPMO varies when the processing time grows, this for each single P&P. The information in our hands, however, is limited, it appears evident that the performance has a certain trend, as we can observe from figure 4 which reports the performance of machine 1.

C. The simulation model

Once that we determined the parameter that will guide us in deciding if or if not to carry out maintenance, we need to have an objective criteria so to determine the values of the thresholds: for this reason, we've decided to implement a simulation model of maintenance on the P&P series. Once modelled the process line it will be possible to optimize it by using the cost function built by considering all maintenance costs, production loss and expenses due to the non quality of the products. We decided to use for simulating or model a event driven simulator, in particular Arena.

A model that well adapt to our needs must consider two fundamental aspects: it must simulate the process line, this is accomplished by modeling the PCB (printed circuit boards) as entities that flow through the different blocks in the simulated environment, each block represents elementary tasks or logic steps, while this is done the simulator must note the deterioration of the P&P performances. The simulator must also contemporary replicate maintenance processes, since the two processes are linked together: the DPMO, factor which determines whether or not to carry maintenance, will depend on the number of PCB's processed by all machines, while a maintenance intervention will influence the availability of the machines and therefore on the possibility of them working.

Given the vast heterogeneity of the two processes, where in the first case we have entity/product, and in the other entity/machine, or better, opportunity of a maintenance intervention, it is convenient to develop two distinct model that interact through global variables and Signal modules that send signals to other modules Hold situated in the first sub-model.

The sub model production is roughly built as following: The model starts with six Create modules, which generate the batches of the different products; then there is a logical structure that determines if two following boards are of the same kind, in this way, as soon as the first machine receives a new batch, the process stops for a time adequate for the setup process. Next we have five sub sectors which represent the five P&P's: in each one of them, the simulator occupies the resource/machine for a period of time imitating the processing time. The period of time for each machine referred to each product is extracted from a probability distribution which has been determined from real process data. We also simulate casual micro-stops which are not correlated with DPMO values. At the end of the process line, we will separate the products depending on the kind, once separated the products they have to pass through a Counter, in all six, one for each kind of product, these counters register the number of products and they are annulled on a daily basis, continuing along our model there are also six Record modules that account the value generate by the P&P process line, such calculation is made for each single circuit board on a zero defect basis.

The logical structure of the model that is oriented to maintenance aspects must respond to the following necessities:

- Evaluate the opportunity of accomplishing maintenance on all machines depending on the thresholds, fixed on consideration from the DPMO, in this why we can exploit the process stop to anticipate a maintenance intervention, saving on inducted maintenance costs.
- Simulate when necessary, maintenance processes by activating and shutting down the process line in the model
- Account the costs deriving from maintenance intervention and also reworking defected products
- Restore the machine to a functioning state after the process has had a micro-stop

We've decided to model these aspects with a closed loop. In this loop, at time zero, there will be created a series of entities representing each single P&P, these entities will never be disposed, they will circulate in the model for the entire time of the simulation.

For each entity the modules Assign will provide them with a series of factors such as hour cost of the personnel, the thresholds (sogliemac, is a five per two matrix where each row is associated to a machine and the two columns indicate the two thresholds that we've considered, one indicating the necessity of a preventive maintenance, the other is an opportune maintenance thresholds which allows a maintenance intervention only if at least another machine needs a preventive intervention), and other parameters useful for simulating maintenance time. In particular, the last parameter announced will be read from the matrix ptman where each row is associated to the intervention time of each machine: in this way we can associate different maintenance intervention time to each single machine (in our particular case, the fifth machine, Siplace F5, has different maintenance times, because it has a IC head and not a revolver head as the first four).

Once the entities are create they'll queue themselves in a module called Hold, of the kind "wait for signal". A specific signal will come once a day from the sub model "daily chronometer", and every time it is necessary to restore the process model following a micro-stop. When the signal is emitted, the Hold module releases all five of the entities, sending them to the following module Decide that will appropriately direct them along the model. This module determines if the signal is determined by breakdown or if it's the daily inspection that evaluates the prospect of a maintenance intervention. In the first case, the functioning machine (entities) will be sent again to the module Hold, while the machines in breakdown will be sent to the restore sub model. In this sector the machine will employ the resource operator for a certain time, after that the parameter on is restored to the value of 1, the entity returns to the module Hold where it came from.

Instead if the signal is associated to the "end of the day", the entities will all be addressed to the module " time allocation": here the entities will be associated to a maintenance time that will be casually extracted from a probability distribution. The following module Record will register the data in the module Set, costs for each machine, day by day, deriving from reworks by using the function DPMO and also considering the number of boards produced, this aspect will be explained letter on.

Next we have the module "if to stop process": here the simulator compares the variable DPMO with the attribute spre, with is the value of the threshold that once is crossed by DPMO, starts the maintenance process. The value of the attribute spre is obtained from the matrix sogliemac. The module "maintenance decision" will evaluate the machines conditions, and consequently address the entities to:

- Preventive maintenance
- Opportune maintenance
- The module Hold at the beginning, waiting for a new signal

D. The input data

Once concluded the structural modeling, it is necessary to proceed with a quantity modeling, determining the values of parameters and the form of the probability distribution so to be able to simulate the P&P's process line that we want to study. In particular we will need:

Time

- Production time of all products on every machine
- Setup time
- Maintenance time for each machine
- Restore time in case of micro-stops

Cost

- Maintenance costs
- Reworking costs
- Generated value for product
- Variations of the DPMO
- Resources
- Buffer

To analyze the data that we've gathered obtaining the distribution that will be used in the model, we have used the software Minitab and a component of the simulator Arena, Input Analyzer, which can be used to determine the quality of adapting the data to a probability distribution function, carrying out for this scope a Chi-square and Kolmogorov – Smirnov test.

One of the most important factors of this model is given by how the DPMO index varies, because it is on this factor that the maintenance decisions are made. For this reason we are interested in determining an aleatority function which describes the DPMO's increments in function of the working time per machine. To determine this function we proceeded as following:

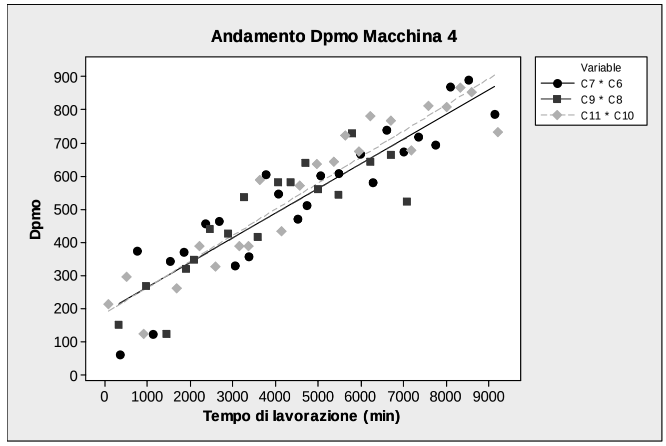

Fig. 5: DPMO for machine 4

In first place, we've observed that after cleaning and calibrating the segments, the DPMO values would not tend to zero, but to a significant value, similar after every intervention.

Since we could have the value of the DPMO only at the end of a day (we've chosen to use a daily basis in evaluating the DPMO variations, since the line produces a couple of hundreds PCB per day; a smaller time interval would bring to have a limited number of samples from which we can gain information), we operated with a linear regression of the data, so to estimate the value of the DPMO at time zero; we have observed that there aren't many differences between different series of data form similar machines, as indicated in the example figure 5, referred to machine 4.

We proceeded in estimating the researched value using a linear regression of the generalized series of data for every machine. The results indicate similar DPMO starting values for the first four Siplace S25 Hm, therefore we decided to fix the starting DPMO value for all four at the average starting DPMO, different case regards the fifth machine, which is a F5 Hm.

Continuing with the first four machines, we have that the linear regression calculated has this expression:

DPMO = 186 + 0,0766 T

With a value of R2=84,9%

The mean value of the first four P&P machines result to be 185, which will be the value placed, after every maintenance intervention, to the DPMO variable. For the fifth machine (different to all the others) the mean that has been calculated is 450. These values have been considered as deterministic and not aleatority given the limited deviations of the samples, the limited number of samples, in particularly regarding the Machine 5, but more important then all because of the fact of the limited sensibility demonstrated by the model regarding these values; fact that has been confirmed by various simulated runs of the model that we have made.

After determining the starting value for the DPMO's, we've gathered in separated tables data relative to each machine. From these tables we calculated the increment per minute per every day, using the formula brought below:

$$\frac{Dpmo_{k+1} - Dpmo_k}{T_{k+1} - T_k} \tag{2}$$

The values obtained have then been analyzed using the Input Analyzer, so to adapt them to a distribution. As the results we have obtained that some are better described by a Weibull while others by a Gaussian. This fact may depend on the limited quantity of the samples at hand. Given the nature of the phenomenon's that are responsible for the deterioration of the P&P performance, it is logical to consider a Gaussian distribution. In any case, we preferred to maintain the distributions that we have determined with the samples available.

At this point we must specify that as we said, the data available derives from a daily production basis, the numerosity of the sample is variable, and in the same way, also the time of authentic production is variable between a measurement and another.

The way we formulated the increment values by the minute are to intend as constant between each interval, which in this case is a day. For this reason the function results to be a step function.

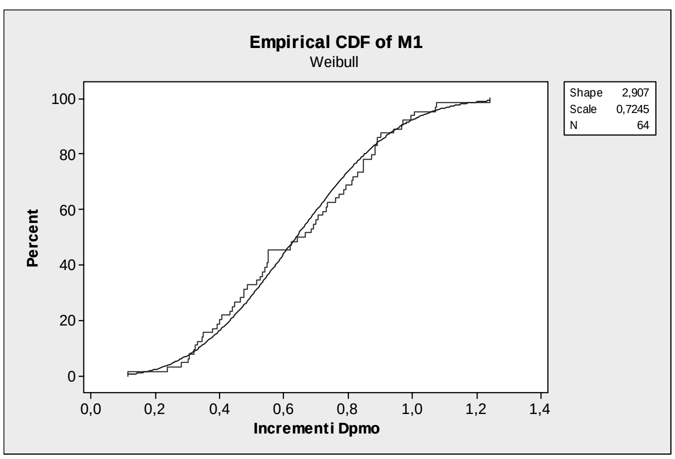

Fig. 6: CDF for machine 1

If we would use the distributions obtained, in our model, Arena would casually extract an increment of the DPMO for every simulated minute, we would have hundreds of extractions every day, this would sum up as an almost constant increment at the end of the day, since the mean would stochastically converge to the mean of the distribution that is given.

To reproduce the same conditions with which we calculated our functions, for each machine, Arena will extract only one casual value from the distributions that we feed to the program, this value will be the increment of every minute during that day, in an analogues way of how we treated the samples that were available.

The cost deriving from the rework of the defected boards is essentially caused by the fact that the missing or misaligned component must be, once found by the X-Ray station (and after the operator has correctly confirmed the investigation, which not always happens) removed and rewelded by an operator. We don't consider the cost of the component because it should have been present on the card and therefore it is already accounted. Remains to be evaluated the cost of the operators time and the cost of the occupied station for the interval of time necessary to correct the faulted board.

The hour cost of the reworking station is estimated by the firm to be 78,65€. So now we must calculate the average time to correct a defected board, for each product. The company has collected the reworking time for each single product, this data considers the time necessary to correct different kinds of errors per circuit card.

To estimate the value of our concern we simply divided the average time of reworks for the number of defects per board, considering only the defected circuit boards. Obtaining in this way a mean value of the time necessary to correct a generic error for all the different products. This value that we've acquired must by related to the different DPMO's of each machine.

Table II: error opportunity per product or machine

Product	M1	M2	M3	M4	M5
36	202	60	46	80	42
50	223	196	130	160	58
68	348	218	174	148	80
92	346	371	307	268	48

We built a matrix product/machine, where in every cell are indicated the corresponding number of components mounted per each board. So these are the number of components that can generate errors, since at the X-Ray station we don't verify the correct functioning of the component but only its placement. The expression used to evaluate the reworking costs will be:

$$\sum_m \sum_p \frac{C \cdot T_p \cdot N_p \cdot Dpmo_m Opp_{pm}}{10^6} \tag{3}$$

Where:

C = Hour cost of production

T = Time for reworking a defected board, expressed in hours

N = number of produced boards

Opp = number of components projected per board
m,p = machine and product index

Once built the model, we economically optimized it by using another tool of Arena, which is Optquest. As control variables, which are the variables that Optquest varies while optimizing, we obviously have chosen the opportune and preventive maintenance thresholds.

The objective function, which is to maximize, is defined as Net Generated Value, given from the difference between Gross Generated Value (obtained from SAP data, which calculates the value of every product on the basis of a production cycle with zero defects) and the reworking and maintenance costs.

IV. Results

The optimization has indicate a series of values of the preventive and opportune maintenance threshold quite close, this is comprehensible given the fact that setup costs following a machine stop are insignificant if compared with other costs, but also the limited number of technicians limiting the maintenance interventions to maximum two at a time.

The processes first optimized solution has been casually chosen, since simulated logic it not implemented in the plant.

Subsequently we made a simulated run with the optimized solutions. Using a procedure developed in two phases, we first evaluated the length of the run with 50 replications, so to obtain the mean of the objective function with a confidence semi-interval not more then 1%. The results obtained presented an increment of the net generated value of 7.98% respect the net generated value of the line during the period of gathering the data, thanks to a very important reduction of the reworking costs.

To verify that this improvement is associated to the using of a DPMO metric, and not only caused by the optimization, we built an alternative model where the logical and cost structure remained the same, and we changed the logic in maintenance decisions basing ourselves on the processes yield (the same logic that the process line used). To do this, we calculated the values of the yield from the DPMO's, which remained in the background of the model, for each product we would foresee the maintenance thresholds, the expression used is:

$$Dpu_{pm} = \frac{Dpmo_m \cdot Opp_{pm}}{10^6} \tag{4}$$

$$Y = e^{-DPU} \tag{5}$$

Even this model has been optimized, neither the less, as we can see from the following results, the model based on the DPMO's presents a net generated value +4.19% respect the yield optimized model.

$$YIELD = Y_{P\&P} \cdot Y_{nonP\&P} \tag{6}$$

The data that has been actually observed in the plant, when simulated for an equal period of time of the other two models, generates the following results:

Net generated value	67921.26
Gross generated value	96233.47
Rework costs	27042.27
Maintenance costs	1269.94

While the DPMO model generates these values:

Net generated value	73340.44
Rework costs	18955.54
Gross generated value	94581.40
Prev. maintenance costs	2106.20
Opp. Maintenance costs	179.22

The comparing model based on the processes yield, has given:

Net generated value	70392.88
Rework costs	25608.30
Gross generated value	96926.20
Maintenance costs	925.02

In conclusion, the model that we have built appears to be in grade, using the DPMO metric, to offer more precise information regarding when to carry a maintenance intervention.

Furthermore, the models flexibility will allow in future, as done here with the other model, to compare different decision processes with limited changes.

References

[1] Ning-Cheng Lee., *Reflow soldering processes and troubleshooting: SMT, BGA, CSP and Flip-chip technologies* , Newnes, 2002

[2] Varteresian J., *Fabricating printed circuit boards*, Newnes, 2002

[3] Strauss R., *SMT soldering handbook*, Newnes, 2°ed. 1998

[4] Masri Ayob, *Optimisation of surface mount device placement machine in printed circuit boards assembly*, University of Nottingham, 2005

[5] Gomez-Villa J., *A characterization for a placement machine in a surface mount technology assembly line*, University of Puerto Rico Mayaguez Campus 2005

[6] Tegethoff M., Chen T., "Defects, fault coverage, yield and cost, in board manufacturing" , presented at the 1994 International Test Conference

[7] Kamen E., Goldstein A., Creveling D., Sahinci E., Xiong Z., *Analysis of factors affecting component placement in SMT electronics assembly*, Georgia Institute of Technology, Atlanta

[8] Ho S., Xie M., Goh T., "Process monitoring strategies for surface mount manufacturing processes", The international journal of flexible manufacturing systems, 15, 95-112, 2003

[9] Kamen E., Goldstein A, Asarangchai O., Fraser A., Klatka K., Belmonte J., Huber R., "Analysis of factors that affect yield in SMT assembly", SMT Express, volume 2, issue n°4, 19/4/2000

[10] AA.VV., *Siplace Sitest: software guide 503.xx,* Siemens, 2003

[11] Jarrell D., Sisk D., Bond L., *Prognostics and CBM, a scientific crystal ball*, Nuclear Technology (2004)

[12] Kelton D., Sadowski D., Sadowski R, *Simulation with Arena*, McGraw-Hill

[13] AA.VV., Arena® *professional edition reference guide* - Rockwell Software, 2000

[14] Smith D., *Reliability, maintainability and risk*, Butterworth Heinemann, 6° ed. 2001

[15] AA.VV., *S-20, S-23 HM, F4, F5, HS-50 Trouble Shooting Guide,* Siemens, 2001

[16] AA.VV., *Siplace 80S-15/F3/G Lista di riferimenti, messaggi di errore V10.x,* Siemens, 1999

[17] AA.VV., *Siplace S-25 HM versione software 502.xx Istruzioni per l'uso*, Siemens, 2001

[18] AA.VV., *Manutenzione ordinaria dei Sistemi di Piazzamento SIPLACE Prospetto generale*, Siemens, 1999

[19] AA.VV., *Agilent 5Dx Service Guide - Agilent, manual version B*, 2003

[20] AA.VV., *Siplace Sitest: software guide 503.xx - Siemens*, 2003

[21] Grall A., Berenguer C., Dieulle L., "A condition-based maintenance policy for stochastically deteriorating systems", Reliability engineering and system safety (2002)

[22] Castanier B., Grall A., Berenguer C., "A condition-based maintenance policy with non-periodic inspections for a two unit series system" Reliability engineering and system safety (2005)

[23] Kececioglu D., Feng-Bin Sun, "A general discrete time dynamic programming model for the opportunistic replacement policy and its application to ball bearing systems", Reliability engineering and system safety (1995)

[24] Barros A., Grall A., Berenguer C., "A maintenance Policy Optimized with imperfect monitoring and/or partial monitoring", Annual reliability and maintainability symposium (2003)

[25] Castanier B., Berenguer C., Grall A., "A sequential condition-based repair/replacement policy with non-periodic inspections for a system subject to continuous wear", Applied stochastic models in business and industry (2003)

[26] Christer A.H., Wang W., "A simple condition monitoring model for a direct monitoring process", European journal of operational research (1995)

[27] Ohnishi M., Kawai H., Mine H., "An optimal inspection and replacement policy for a deteriorating system", Journal of applied probability (1986)

[28] Dieulle L., Berenguer C., Grall A., Roussignol M., "Continous time predictive maintenance scheduling for a deteriorating system", Annual reliability and maintanability symposium (2001)

[29] Liao H., Elsayed E.A., Chan L.Y., "Maintenance of continuously monitored degrading system", Preprint submitted to Elsevier Science (2004)

[30] Van der Duyn Schouten F.A., Vanneste S.G., "Maintenance optimization of a production system with buffer capacity", European journal of operational research (1995)

[31] McCall J.J., "Maintenance policies for stochastically failing equipment: a survey", Management science (1965)

[32] Barros A., Berenguer C., Grall A., "Maintenance policy for a two components system with stochastic dependences and imperfect monitoring", Preprint submitted to Elsevier science (2005)

[33] Park K.S., "Optimal continuous wear limit replacement under periodic inspection", IEEE transaction on reliability (1988)

[34] Park K.S., "Optimal wear limit replacement with wear dependent failures", IEEE transaction on reliability (1988)

[35] Newby M., Dagg R., "Optimal inspection and maintenance for stochastically deteriorating systems", Preprint of Norwegian Institute of Technology

[36] Chiang J.H., Yuan J., "Optimal maintenance policy for a Markovian system under periodic inspection", Reliability engineering and system safety (2001)

[37] Teresa Lam C., Yeh R.H., "Optimal maintenance policies for deteriorating systems under various maintenance strategies", IEEE transaction on reliability (1994)

[38] Dieulle L., Berenguer C., Grall A., Roussignol M., "Sequential condition based maintenance scheduling for a deteriorating system", European Journal of operational research (2003)

[39] Barata J., Guedes Soares C., Marseguerra M., Zio E., "Simulation modelling of repairable multi component deteriorating systems for 'on condition' maintenance optimization", Reliability engineering and system safety (2002)

[40] van der Duyn Schouten F.A., Vanneste S.G., "Two simple control policies for a multicomponent Maintenance system", Operations research (1993)

[41] Guizzi G., Santillo C.L., Zoppoli P., "Condition Based Maintenance: Implementation and optimization of a two-unit serial system model with multi-threshold policy", 8th International Conference on "The modern information technology in the innovation processes of the industrial enterprise" Budapest, Ungheria. (2006)

[42] Dekker R., Wildeman R., van der Duyn Schouten F., "A review of multi-component maintenance models with economic dependences", Mathematical method of operations research (1997)

[43] Dekker R., "Applications of maintenance optimization models: a review and analysis", Reliability engineering and system safety (1996)

[44] Yam R.C.M., Tse P.W., Li L., Tu P., "Intelligent predictive decision support system for Condition Based Maintenance", Advance Manufacturing Technology (2001)