A Bayesian network based approach to improve the effectiveness of maintenance actions in Semiconductor Industry

Anis BEN SAID[1, 2], Muhammad Kashif SHAHZAD[2], Eric ZAMAI[2], Stéphane HUBAC[1], Michel TOLLENAERE[2]

[1]STMicroelectronics, 850 Rue Jean Monnet 38926 Crolles, France

anis.bensaid@st.com
stephane.hubac@st.com

[2]Univ. Grenoble Alpes, G-SCOP, F-38000 Grenoble, France CNRS, G-SCOP, F-38000 Grenoble, France

muhammadkashif.shahzad@g-scop.inpg.fr
eric.zamai@grenoble-inp.fr
michel.tollenaere@grenoble-inp.fr

ABSTRACT

The Semiconductor Industry (SI) is facing the challenge of high-mix low-volume production due to increasing diversity in customer demands. This has increased unscheduled equipment breakdowns followed by delays in diagnosis and ineffective maintenance actions that reduce the production capacities. At present, these challenges are addressed with mathematical approaches to optimize maintenance actions and their times of intervention. However, few studies take into account the ineffectiveness of maintenance actions, which is the key source for subsequent breakdowns. Hence, in this paper, we present a methodology to detect poorly executed maintenance actions and predict their consequences on the product quality and/or equipment as the feedback for technicians. It is based on the definition of maintenance objectives and criteria by experts to capture information on the extent to which the objective is fulfilled. Data collected from maintenance actions is then used to formulate Bayesian Network (BN) to model the causality between defined criteria and effectiveness of maintenance actions. This is further used in the respective FMECA defined for each equipment, to unify the maintenance knowledge. The key advantages from the proposed approach are (i) dynamic FMECA with unified and updated maintenance knowledge and (ii) real time feedback for technicians on poor maintenance actions.

1. INTRODUCTION:

The SI is characterized by fastest change in smallest period of time and has become a 300+ B$ industry in less than 60 years (Stamford, 2012; Dale, 2012). The demand in SI is mainly driven by end-user markets (Ballhaus, Pagella, and Vogel, 2009); hence, increasing diversity in customer demands with short product life cycles has resulted into a high-mix low-volume production. It increases unscheduled equipment breakdowns followed by delays in diagnosis and ineffective maintenance actions that reduce production capacities. This fact is shown in Figure 1, where unscheduled equipment breakdown is plotted against product mix using data collected from a world reputed semiconductor manufacturer for 2013. The blue curve represents number of different products whereas red curve is unscheduled equipment breakdown duration, in second. It can be seen that the variation of product mix has an important impact on production capacities; therefore, it is necessary to reduce variability of unscheduled breakdowns due to this fluctuation.
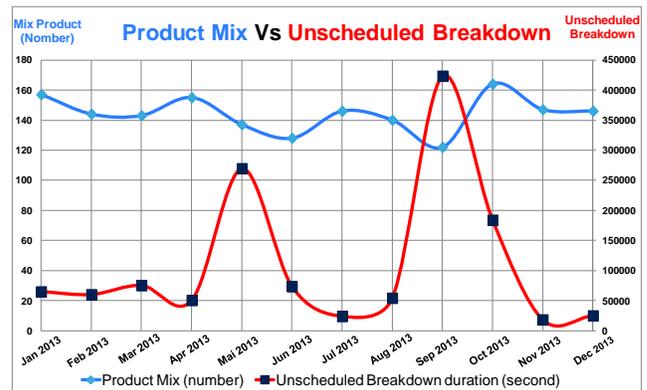

Figure 1. Product mix vs unscheduled breakdown

This complexity is treated in literature with mathematical approaches to optimize maintenance actions and their times of intervention. Vassilis and Christo (2013) used a Bayesian

classifier to recommend problem types based on historical case associated to specific event using sensor data. Multi-agent based approaches are also used in maintenance to dynamically schedule the actions (Aissani, Beldjilali, and Trentesaux, 2009). Weber and Jouffe (2006); Weild, Madsen, and Israelson (2009); Yang and Lee (2012); and Efthymiou, Papakostas, Mourtzis, and Ghyryssolouris (2012) present an application of Bayesian network for dynamic condition monitoring and diagnostic in order to support condition based maintenance (CBM) in the complex SI and aircraft industries. However, none of these above approaches take into account the effectiveness of the maintenance actions performed by technicians that serve as key source for variability in production capacities. Medina-Oliva and Weber (2013) proposed probabilistic relational model (PRM) with key performance indicators (KPIs) to monitor and report human effectiveness against maintenance strategies. The proposed approach, in this article, is different as we predict consequences of poorly executed maintenance actions as feedback to technicians, on product quality and equipment.

In this paper, we introduce the notion of defined criteria for maintenance functions based on equipment and maintenance types by experts. These are updated in failure mode effect and criticality analysis (FMECA) followed by maintenance checklists. The responses collected from technicians, while executing maintenance actions, serve as the knowledge base to model the consequences due to ineffective actions. This proposed methodology is implemented in dielectric (DIEL) workshop at the world reputed semiconductor manufacturer. The data is used to develop Bayesian network (BN) with an unsupervised learning that models causality between criteria and effectiveness of maintenance actions. The key benefits of the proposed approach are (i) dynamic FMECA to unify the maintenance knowledge and (ii) real time feedback to technicians on poorly executed maintenance actions. It also helps to renew experts' knowledge on equipment against increasing unscheduled due to fluctuations in product mix. This approach is not limited to SI and can be applied to any production line facing the challenges of reduced production capacities due to unscheduled equipment breakdowns.

This paper is divided in 3 sections. Section 2 presents a literature review on existing approaches and methods. The proposed methodology based on BN, case study and results are presented in section3. We conclude this article with the discussion and perspectives in section 4.

2. LITERATURE REVIEW

The review has been performed across three axes: (i) maintenance strategies, (ii) maintenance actions predictions and (iii) approaches to take into account the human factor during maintenance in the SI and complex production lines.

2.1. Design and Manufacturing Operations in SI

The design and manufacturing process of integrated circuit (IC) chip is presented in Figure 2 (Shahzad, Hubac, Siadat, and Tollenaere, 2011). In this process, customers request new products that go through a complex design using CAD tools and design libraries (reusable blocks of circuits). These are simulated to assess their compliance with technology specifications. Upon validation, design moves to the mask preparation step. These masks are glass plates with an opaque layer of chrome carrying target chip layout. They transfer product layout on silicon wafer through repetitive sequence of deposition, lithography, etching and polishing steps. The next step is called frontend manufacturing where thousands of transistors are fabricated on the silicon surface along with a network of interconnected wires to form an IC chip. The silicon wafers are then tested, cut, packaged and shipped to customers a.k.a. backend process. This complex manufacturing process consists of approximately 200+ operations, 1100+ steps and 8 weeks of processing time,. The cost of a production facility in SI with 600 production and metrology equipments is around 3.5 billion US dollars (Shahzad, Tollenaere, Hubac, and Siadat, 2011). The production capacity of a SI production line is measured in wafers manufactured per week. The case study performed in this paper is completed in 12 inches wafer production facility.
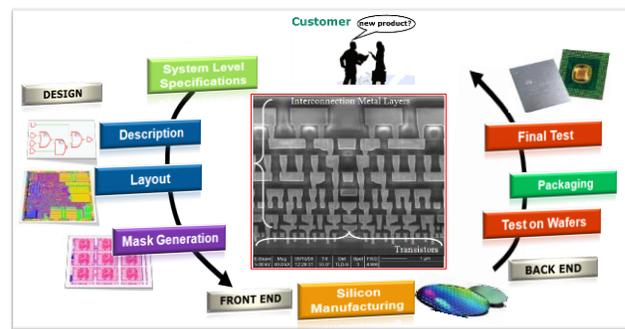
Figure 2. Design and manufacturing process for an IC chip

2.2. Maintenance Strategies

In the SI environment, maintenance is a key issue to keep such a high level of production and control capacity. The common maintenance practices in the manufacturing domain are corrective (run to failure), preventive (time and usage based) and predictive maintenances (Mili, Bassetto, Siadat, and Tollenaere, 2009). The corrective maintenance strategy is not suitable for the semiconductor manufacturing because it destabilize the production system; however, till now, the SI has relied on preventive maintenance (PM) as an alternative maintenance strategy to optimize capacities while ensuring product quality. The key disadvantages of PM are over and under maintenance. It decreases capacities due to maintenance when equipment is still in good health

and adds additional costs due to delayed maintenance. Besides these strategies, a new strategy known as predictive maintenance (PdM) is proposed, where maintenance actions are triggered depending on the condition of the equipment and in anticipation (prediction) of potential failure before they occur. This strategy has evolved in two forms as (i) non-predictive condition based maintenance (CBM) and (ii) predictive CBM. The non-predictive CBM is similar to the PM strategy but with the difference that maintenance decisions are taken based on surpassing thresholds on the key parameters used to monitor the health of equipment, instead of time based or usage based approach (Susto, Pampuri, Schirru, and Beghi, 2012); (Krishnamurthy, Adler, Buonadonna, Chhabra, Flanigan, Kushalnagar, Nachman, and Yarvis, 2005). The predictive CBM is far superior to PM and non-predictive CBM. It is because the maintenance actions are based on continuously monitoring equipment health followed by failure predictions and pre-failure interventions.

At present, unscheduled breakdowns are addressed with the mathematical approaches to optimize maintenance actions and their intervention time. Vassilis et al. (2013) employed Bayesian classifier to recommend problem types based on historical cases associated to specific event with sensor data. Weber and Jouffe (2006); Weild et al. (2009); Yang and Lee (2012); Efthymiou et al. (2012); and Bouaziz, Zamai, and Hubac (2012) used BN for dynamic condition monitoring and diagnostic to support condition based maintenance (CBM) in complex (e.g. SI and aircraft) industries. Mili et al. (2009) implemented dynamic FMECA based method to unify maintenance actions and prevent risks with qualitative information. Hubac and Zamai (2013) presented dynamic adjustment of maintenance policies based on CBM strategy approach allow to dynamically control and quantify equipment reliability in high mix flow industry. This shows that CBM is the dominant maintenance strategy being used to optimize maintenance actions. The mathematical and BN approaches are also found to be used for modeling purposes. However, none of these approaches take into account the effectiveness of maintenance actions that has emerged as a source of variability in dynamic environment like SI.

2.3. Maintenance Actions Predictions

In the past, it was very difficult to predict equipment failures due to the unavailability of fault detection and classification (FDC) and maintenance data; however, today its availability with artificial intelligence (AI) techniques has enabled the failure prediction. There are several PdM based maintenance approaches proposed in recent papers for the SI e.g. classification methods (Baly & Hajj, 2012), filtering and prediction approaches (Susto, Beghi, and DeLuca, 2011); (Schirru, Pampuri, and DeNicolao, 2010) and regression methods (Hsieh, Cheng, Huang, Wang, and Wang, 2013); (Susto, Pampurin, Schirru, and Beghi, 2012). An innovative approach, integrated failure prediction

(Susto, McLoone, Pagano, Schirru, Pampuri, and Beghi, 2013), is presented with the hypothesis that the data collected is based on full maintenance cycle runs in compliance with runs to failure policy. Here, the objective is to capture the evolution of failures from initial safe conditions. However, this approach does not take into account the influence of parent-child relation between different equipment modules and suggest to model failure evolution for each module. It is also adapted from support vector machine (SVM) technique, a very well know classification method in machine learning (ML). Not all the equipment monitoring parameters are relevant in predicting a specific failure; hence, different approaches are used for the combination of relevant parameters e.g. discriminated analysis to get linear combination of parameters (Gertsbakh, 1977). Similarly, a linear combination function of parameters with the maximum contribution to the tool condition can also be found with principal component analysis (PCA) or singular value decomposition (Stamatis, Mathioudakis, and Papailiou, 1992). The predictive CBM needs accurate model for equipment failure predictions. The most commonly used techniques are AI and ML based predictive CBM with different types of data; however, none of them use effectiveness of maintenance actions as criteria for prediction.

2.4. Human Factor in Maintenance

This paper highlights the importance of such factors to implement an effective predictive maintenance process. There are few studies that use effectiveness of actions in the equipment maintenance. Trucco, Cagno, Ruggeri, and Grande (2007) focus more on risk analysis associated to human and organizational factors and in their study used a fault tree analysis (FTA) with BN model. In this framework, Léger, Weber, Levrat, Duval, Farret, and Iung (2009) also proposed a methodology to integrate operator and human actions for probabilistic risk assessment. Medina-Oliva et al. (2013) takes into account the notion of human effectiveness. They propose a probabilistic relational model (PRM) to integrate maintenance system interactions with enabling system, and impact of maintenance strategies and human effectiveness on production line performance.

Our approach is different as we focus on detecting poorly executed maintenance actions and predicting their consequences on the product quality and equipment, as feedback to technicians. It provides an opportunity for continuous improvement. This approach also offers dynamic unification of maintenance knowledge as well as a source to renew knowledge of maintenance experts. The BN is taken as the target modeling method due to its structural ability for causality. This study is based on hypothesis that ineffective maintenance actions is one of the reason for decreasing unscheduled equipment breakdowns in the SI, challenged with high-mix low-volume production. The next section will detail our proposal approach.

3

3. PROPOSED METHODOLOGY

The proposed 3-step methodology is presented in Figure 3 below. In this methodology, step-1 corresponds to the criteria and consequence definition for maintenance actions, depending on the effectiveness of human by maintenance experts. The checklists for the target equipment and maintenance type are modified to capture information on the extent to which the associated objectives are fulfilled. The initial BN between maintenance functions, objectives, criteria, failure modes, effects and causes is developed using experts' knowledge from FMECA. Moreover, updated checklists are deployed on the production line to capture qualitative and quantitative information as evidence to evaluate the believed causality by experts. The BN is then learned from this collected data with supervised learning in step-2. This is compared with the knowledge based BN and any structural changes found are fed to step-1 for knowledge unification and renewal in the FMECA. The learned BN is continuously updated with the new evidence collected from the production line and is fully capable to detect and notify not only the effect of product mix, but also feedback to the technicians as potential consequences.
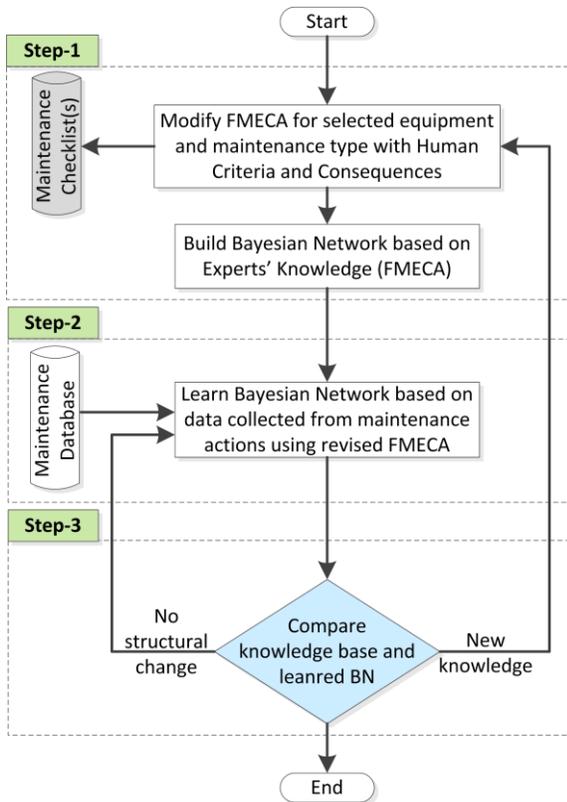

Figure 3. Proposed three-step methodology

3.1. Including Human Factors with Proposed Extension in FMECA (Step-1)

The FMEA approach was initially conceived by US military (MIL-18372) to find failure modes of system components, evaluate effects and propose counter measures. The formal description of FMEA is given by the New York Academy of Sciences (Coutinho, 1964). This was further extended as the FMECA by NASA to ensure desired reliability of the space systems (Jordan, 1972). There are different diversifications of this approach (Reifer, 1979) as software failure mode and effects analysis (SWFMEA), design FMEA, process FMEA and system or concept FMEA etc. The traditional 5-step FMECA process is presented in Figure 4, below.
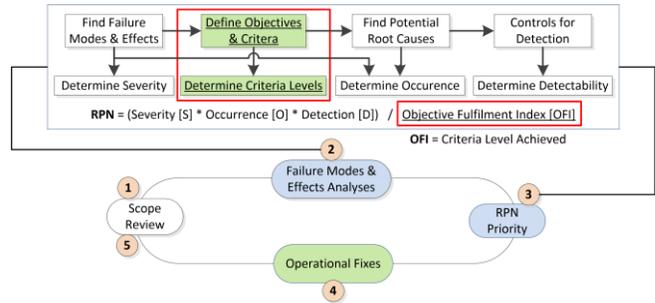
Figure 4. Proposed FMECA with objectives and criteria

It starts with clear description of the scope e.g. maintenance type (preventive maintenance) followed by important functions identification for further analysis (step-1) by experts. The potential failure modes, effects and causes are listed along with occurrences, severity and detection (step-2). We propose the inclusion of objectives and criteria definition for each identified function and inclusion of criteria levels while calculating risk priority number (RPN). The severity, occurrence and detection are multiplied followed by division with criteria level for RPN (step-3). It is because RPN decreases if a criterion linked to the defined objectives is fulfilled at highest criteria level, a.k.a. objective fulfillment index (OFI). The RPN is assigned with threshold that triggers the priority to select failure modes for operational fixes (step4). The results are finally evaluated and reviewed (step-5). This 5-step process is repeated until RPN number falls below the threshold.

The proposed approach is implemented and tested in one of the eight workshops (dielectric DIEL) in SI production line. In this production area, a thin film of electrical insulation is deposited on the wafers. These layers serve to insulate different zones with transistors and interconnections. This deposition is completed with chemical vapor deposition (CVD) process using plasma technology at temperature < 400°C to avoid structural changes in previous layers. This workshop is one of the critical workshops in SI production line and is often turn into bottleneck with reduced production capacities and increasing unscheduled equipment breakdowns. Hence, the role of effective maintenance actions becomes critical. The DIEL equipments use multiple recipes and chemical gases due to high-mix low-volume production that destabilizes the equipment. The FMECA analysis is done on all equipment by experts for each type of

maintenance. In this case study, we have selected PM-FMECA in DIEL workshop to clean process chamber, for the purpose of demonstration. Each FMECA is then translated into checklist that comprises a sequence of maintenance actions. The key functions in this PM are equipment and personal security, ventilation of the process chamber, dismantling foreline, leak test with helium etc. We present FMECA analysis for PM procedure to clean process chamber (Figure 5). In this analyses, we presented only

normalized RPN* is computed with and without OFI that clearly reflects the decrease in the associated risk due to human actions effectiveness (Figure 6). In this figure, failure modes are plotted along x-axis and normalized RPN* on y-axis for confidentiality reason. The three functions in FMECA analysis are associated to an objective, whereas each objective is linked with multiple fulfillment criteria and levels to capture the effectiveness of maintenance actions. The criteria are defined at chamber or equipment

Title : PM procedure for cleaning Process chamber --> Actual Risk (FMECA Analyses)

(a)

Function	Objective	Criteria Definition	Criteria Levels	Potential Failure Mode	Potential Effects of Failure	Potential Cause/ Mechanism of Failure	Current Controls Prevention	Current Controls Detection	(S) SEV	(O) OCC	(D) DET	OFI	Current RPN = (S*O*D)	Knowledge based RPN = (S*O*D) / OFI
Personal and Equipment Security	Protection of machine against mishandling / Equipment Level	Sequence of checklist actions is respected	No=1, Yes=2	Actions execution order is mixed based on the experience of technician	Contamination of process chamber	Technicians are not provided with the feedback of consequences of random execution of actions	Trainings and certifications	No detection	8	7	6	2	336	168
		Only the screen described in the procedure are used	No=1, Yes=2	Prescribed screen is not conculted during the maintenance operation	Contamination of equipment	Technicians prefer their expeirence then using prescribed actions as FMECA and respective checklists are considered static	No control for prevention	No detection	6	7	5	2	210	105
		Action on the equipment is carried out without training and certification'	No=1, Yes=2	Some maintenance actions are executed without training and certification	Risk to damage equipment due to poorly executed actions	Urgence, lack of trained maintenance professionals or undermining the importance of formal training and need	Trainings and certifications	No detection	9	7	7	2	441	221

(b)

Function	Objective	Criteria Definition	Criteria Levels	Potential Failure Mode	Potential Effects of Failure	Potential Cause/ Mechanism of Failure	Current Controls Prevention	Current Controls Detection	(S) SEV	(O) OCC	(D) DET	OFI	Current RPN = (S*O*D)	Knowledge based RPN = (S*O*D) / OFI
He Purge	Switch off plasma Evacuate by products / Chamber Level	plasma?	On=1, Off=2	Plasma ON	defectivity	RF on	see prevetion for RF on	alarm equipement alarm E-star	7	3	1	2	21	11
		backstreaming?	Yes=1, No=2	Backstreaming	defectivity/abort	TV regulation problem	see prevention for PTV regulation pb	alarm equipement alarm E-star	8	3	1	2	24	12
		Chamber at right temperature?	>80°C =1, = 80°C =2, <80°C= 3	Backstreaming	defectivity/abort	Wrong TV opening set up	hardware capability respect	alarm equipement alarm E-star	9	1	2	3	18	6
		Flush with He?	No=1, Yes=2	Chamber too cold	deposition rate HS	Step time too long	Recipe creation	Infilm	9	4	1	2	36	18
		Chamber pressure?	<7torr=1, =7torr=3, >7torr=2	Chamber too cold	deposition rate HS	He flow too high	Recipe creation	Infilm	7	3	1	2	21	11
		Chamber SCCM settings?	<2000sccm=1, =2000sccm=3, >2000sccm=2	No flush with neutral gaz	defectivity/abort	MFC failure	see prevention for MFC failure	alarm equipement alarm E-star	2	4	2	3	16	5
	Equipment Level	RF?	On=1, Off=2	RF ON	abort	communication failure, bug soft	NA	alarm equipement alarm E-star	4	3	2	2	24	12
		Mass flow controller (MFC) failure?	Yes=1, No=2	MFC failure	Flow not at setpoint	Communication or hardware issue	MFC calibration after PM	alarm equipement alarm E-star	7	4	2	2	56	28

(c)

Function	Objective	Criteria Definition	Criteria Levels	Potential Failure Mode	Potential Effects of Failure	Potential Cause/ Mechanism of Failure	Current Controls Prevention	Current Controls Detection	(S) SEV	(O) OCC	(D) DET	OFI	Current RPN = (S*O*D)	Knowledge based RPN = (S*O*D) / OFI
Chamber ventilation	Purge all gaz lines and residual outgasing (chamber lines) / Chamber Level	Back streaming?	Yes=1, No=2	Backstreaming	defectivity	pumping step too long	NA	Infilm	8	2	2		32	16
					defectivity/abort	TV regulation problem	see prevention for PTV regulation pb	alarm equipement alarm E-star	7	3	1	2	21	
					defectivity/abort	Wrong TV opening set up	hardware capability respect	alarm equipement alarm E-star	9	3	1		27	
		Purge all gas lines	Yes=2, No=1	Gas lines not purged	Residues in gas line	Base pressure too high	NA	alarm equipement alarm E-star	8	4	1	2	32	16
		PTV regulation problem?	Yes=2, No=1	PTV regulation pb	Residues in gas line	Communication or hardware issue	PTV replaced during PM	alarm equipement alarm E-star	7	3	1	2	21	11
	Equipment Level	Pump failure?	No=2, Yes=1	Pump failure	Pressure not at setpoint / equipment abort	Communication or hardware issue	Pump replaced in PM	Supervision available for pump & abatement support to detect / alarm equipement alarm E-star	9	4	1	2	36	18

Figure 5. FMECA analysis on PM procedure to clean process chamber

three functions *(i)* personal and equipment security (Figure 5a), *(ii)* HE (helium) purge (Figure 5b) and *(iii)* process chamber ventilation due to space limitations (Figure 5c). However, the severity, occurrence and detection values have been changed due to confidentiality.

The objectives (functions), criteria definition and criteria levels are the columns added in addition to traditional FMECA columns, by the experts. The defined criteria levels (1 to 3) are the objective fulfillment indices (OFI) which are judged and responded by technicians during PM. The

levels, where applicable. It can be observed that, for the PM procedure under discussion, detection is already optimized with strong preventive controls where risk values, range from 1-2 and 1-4, respectively, for functions 2 and 3 (see Figure 6).

However, these are quite high for function 1. It is because, this function depends on the effectiveness of maintenance actions performed by technicians. The proposed approach enables us to reduce the risk associated with human factor for all maintenance action in a given maintenance

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* The RPN values are normalized for confidentiality purposes.

procedure. The benchmarked target RPN* with OFI are modest, whereas effective RPN* with OFI actually achieved in the case study are highly significant and result in optimizing the production capacities due to unscheduled equipment breakdowns (see section 4).

Figure 6. Comparison of normalized RPN* and RPN*/OFI

FMECA is very effective in collecting experts' knowledge and risk quantification; however, its static nature cannot predict in real time the failure modes and their effects on the equipment and products. For this reason, Bayesian network modeling approach is selected as the target method due to its inherent abilities to model causal relations between variables from FMECA (Garcia & Gilbert, 2011). The effectiveness of FMECA structure to build causal nets like Bayesian network is also demonstrated by (Lee, 2001) and (Weber, Suhner, and Iung, 2001). The BN is an artificial intelligence (AI) technique for probabilistic reasoning under uncertainty (Kjærulff & Madsen, 2006); (Jensen and Nielsen, 2007); (Pourret, Naïm, and Marcot, 2008). Bayesian networks are institutive approach for modeling human like decision-making problem with probabilistic reasoning under uncertainty. The Bayesian network (graph) comprises of the nodes (random variables) and directed edges (links, arcs) between nodes. The directed edges represent the influence of nodes in the network.

The conditional probabilities computed from the input data corresponds to the quantitative part of the Bayesian model. The structure of the Bayesian network (graph) is the qualitative model that represents causal dependence and inter-dependence between variables. The name "Bayesian" is conceived from Mr. Thomas Bayes' surname (Peter, 2012), who proposed formulae to compute conditional probabilities (a.k.a. Bayes theorem) (equation 3.1). The formalism is read as probability of an event A knowing the evidence on the occurrence of event C and is also referred as "Bayes condition".

$$P(A \mid C) = \frac{P(A,C)}{P(C)} = \frac{P(C \mid A)P(A)}{P(C)} \qquad 3.1$$

In the BN, prior probabilities are provided in the absence of evidence, whereas conditional probabilities are dynamically updated with new information as input to a network, a.k.a. a posteriori probabilities. For n variables, 2n-1 joint probabilities result in huge numbers; however, resulting

Bayesian network encodes knowledge so that key and less important information is easily identified (Pearl, 2000). The Bayesian network is developed with minimum computations and is easy to understand (Kjærulff & Madsen, 2006). It is an efficient method, because of inherent assumption of interdependence about variables; hence, it requires expert intervention for the definition of the structure (directed edges).

The advantages of using Bayesian network is its inherent ability to deduce the inter-causal reasoning (Kjærulff & Madsen, 2006). The Bayesian network is gaining popularity due to its graphical structure with probabilistic networks to express causal interactions and direct/indirect relations. The notion of causality empowers Bayesian network with the human like reasoning under uncertainty. The ability of the Bayesian networks to handle causal independence, results in efficient inference even with large number of variables. They have superiority over rule based systems (RBS) due to their capabilities for deductive, abductive and inter causal reasoning. The Bayesian network is an interesting choice for statistical modeling due to its efficient learning and inference algorithms (Zou & Bhanu, 2005).

Figure 7. Experts' knowledge based BN model

Initial BN model is developed based on experts' knowledge from FMECA file. The data collected to build initial BN, presented in Figure 7, are three principle PM objectives, the criteria to fill each objective, failure modes and their effects on equipment and products. As per proposed methodology (Figure 2), this static knowledge based BN structure will be compared with the learned BN model using data collected from the production line maintenance operations. The expert knowledge based BN model is divided into four classes of nodes with different colors as maintenance objectives (red), criteria (orange), failure modes (green) and effects (SandyBrown). It is based on the a priori probabilities which are computed from severity, occurrence and detection values, and the prior from experts. In this BN model, solid nodes are discrete variables whereas dotted nodes e.g.

chamber temperature, SCCM (see figure 6-b) and pressure are continuous variables which are discretized. The direction of the associations is drawn as per knowledge from FMECA. This BN is implemented using Bayesialab 5.0 and for demonstration purposes the chamber pressure node is set as the target variable for interactive inference, as presented in Figure 8. This figure contains an example to exploit the experts knowledge modeled as a static BN model.

The Figure 8a predicts potential failure modes for a given set of values for objective and criteria nodes. It shows that, in the presence of backstreaming, pressure <7.5 Torrs, temperature <80, and SCCM between 1500 and 2001, the likely failure modes are cold chamber, backstreaming error and RF errors. Similarly, figure 8b presents that, for the same criteria and objective settings, likely effects are defectivity, abort and high deposition rate. The experts can interactively change the probabilities to analyze the knowledge discovery by this static BN model. Moreover, this model is based on initial experts judgment and do not take into account the effect of changing equipment behaviors due to changing high-mix of products. In next section, we learn this BN from the data collected across the production line in DIEL workshop.

(a)

(b)
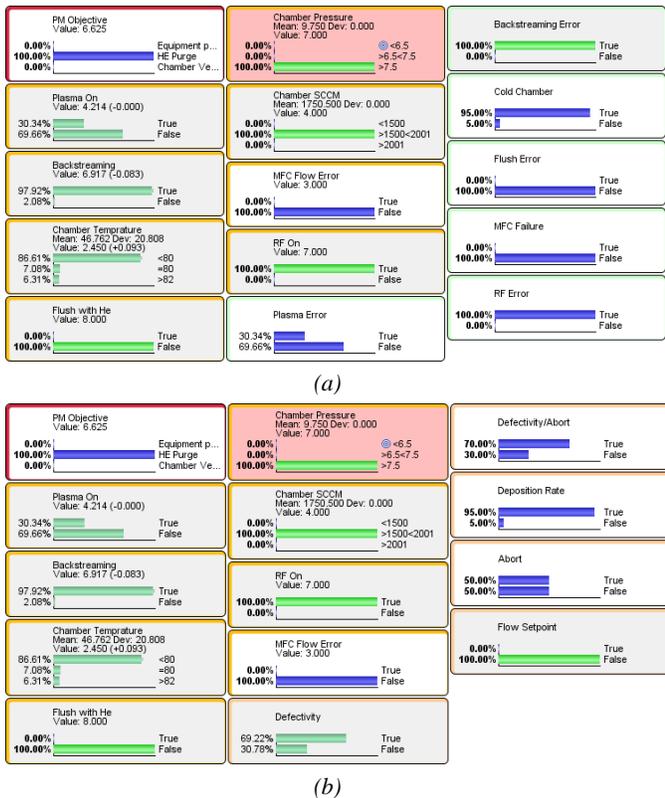
Figure 8. Experts' knowledge based BN model

3.2. BN Model for Effectiveness of Maintenance Actions and Analyses Results (Step-2)

The PM checklist modified form the revised FMECA (Figure 6). It is approved and deployed on the production line as a pilot case study for four months prior. In this period, revised PM checklist is executed 223 times on 15 equipments in the DIEL workshop. The historic data of maintenance checklist executions, equipment states and parameters such as RF, pressure and chamber temperature, and product measurements like defectivity and deposition rate are collected to learn new model. In order to learn new BN structure using these data, three unsupervised learning algorithms (EQ, Taboo and Taboo order) were used working on a set of heuristics to reduce the search space. The objective function used in these algorithms is the minimum description length (MDL). It takes into account "correlation" plus structural complexity of the causal network and establishes "automatic significance thresholds" (Rissanen, 1978); (Bouckaert, 1993). These algorithms result not only in the network, but also in the associated conditional probabilities. The MDL score is used as a criteria to select the lowest score network.

The equivalence class (EQ) is an efficient algorithm for structural learning as it significantly reduces search space. It is based on the assumption that two BN structures are said to be equivalent if the set of distributions that can be represented with one of those structures are identical to the set of distributions that can be represented with the other (Chickering, 2002); (Munteanu & Bendou, 2001). The Taboo search algorithm is useful in refining the network based on a given structure; hence, it gives better results when initial structure is developed with experts' knowledge or using some other unsupervised learning algorithm. This algorithm also has the capability to learn network from scratch but in this case, it is less efficient than EQ. Therefore, we use it in combination with EQ where EQ provides an initial structure followed by Taboo to improve it based on the MDL score. Taboo order (Teyssier & Koller, 2005) is an exhaustive search algorithm that offers more accurate results, but takes more time than simple Taboo search. This method searches the space in the order of Bayesian network nodes by choosing parents of a node between nodes appearing before it, in the considered order.

The learned network serves as a reference network and is cross validated using 50 randomly generated datasets, based on the distribution of responses collected through survey from employees with added noise. As a result, we retain the network with best fit. The threshold in our case is 75%. The learned BN along with its contingency fit are presented in Figures 9a and 9b. The learned BN using unsupervised learning in Bayesialab is presented below in Figure 9. The dataset is divided into randomly selected 75 and 25% rows for learning and testing. The contingency fit is observed to

be 77 and 72%, respectively. The threshold of 75% is used as a criteria to accept the model.

(a)

(b)

Figure 9. BN learned from Data using unsupervised learning

3.3. Knowledge Discovery: (Step-3)

The structural difference in experts' knowledge (Figure 7) and learned (Figure 9a) BN models is presented below in Figure 10. The learned BN model shows new knowledge as new arcs from potential failures to causes. It must be noticed that the checklist flow execution error/failure in the BN model learned from production line data results in chamber and equipment contaminations. The plasma and backstream error are found to be correlated with defectivity. It is important to note that while learning BN model from data, certain arcs were forbidden. e.g. arcs from criteria, failure modes and effects are not allowed to loopback towards objectives. Similarly, the arcs from failure modes and effects towards criteria are also not allowed. The color of each node in this new BN model corresponds to its respective class (objectives, criteria, failure modes, effects).

Figure 10. Structural difference in BN models and knowledge discovery

(a)

(b)

Figure 11. Learned BN model for knowledge exploitation and feedback to technicians

The newly learned BN model based on data collected from production line is set to similar test settings as presented in Figures 8a and 8b, above. Figure 11a predicts plasma error, backstreaming, cold chamber, MFC and RFC failures against backstreaming and cold chamber as identified by static BN model for the same objective and criteria settings. Figure 11b predicts defectivity, abort, flow setpoint issue and high deposition rate as potential effects against abort, defectivity, and high deposition rate. The new knowledge generated from this learned BN models (Figure 10) serves dual purpose as it provides continuous renewal of experts' knowledge and updates FMECA. This BN model also generates feedback with predictions on likely failure modes and effects based on the level of fulfillment of defined criteria.

4. CONCLUSIONS, DISCUSSION AND PERSPECTIVES

The new BN model was deployed on the production line to provide feedback to technicians during maintenance, on potential failure modes and effects, if the expected criteria level is not reached. The data collected on failure occurrence and normalized RPN* upon subsequent deployment of this methodology, over a four months experiment, is presented in Figures 12a and 12b. RPN* has greatly decreased because the said BN model has improved not only detection, but also reduced failing actions occurrences by providing feedback to technicians.
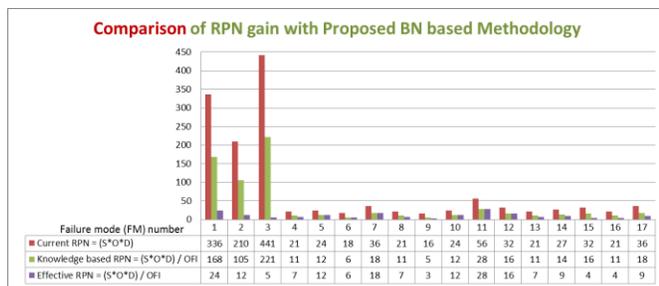
(a)
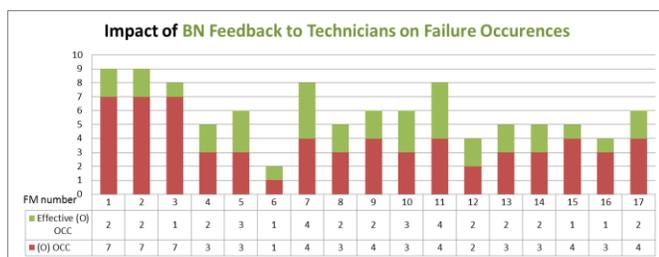
(b)

Figure 12. Impact of proposed BN based methodology on risk and failure occurrences

The proposed methodology demonstrates that effectiveness of maintenance actions by technicians has a strong impact on the subsequent risk, failure occurrences and ultimately on the equipment unscheduled breakdowns. This study has also concluded that providing feedback to maintenance personals

on the consequences of their actions improves failure occurrences that have direct impact on the production capacities. It also highlights the need to renew experts' knowledge with high-mix low-volume impacting the equipment behaviors.

There remain some open ended issues e.g. what is the learning time or excursion frequency, before the BN model predictions and structural changes are used to renew experts and FMECA knowledge? Similarly, it should be interesting to introduce a multi-agent based technology to share the knowledge, captured through BN model on one equipment, for other similar equipments in the same workshop. We still need to find an answer that the proposed BN model should be developed at an equipment level or one generic model for all the equipments in a production line would be efficient. These questions are presently investigated by the authors.

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BIOGRAPHIES

Short biographies of authors can be found below:

Anis BEN SAID: Mr. Ben Said is a PhD student at Grenoble University and STMicroelectronics (CIFRE). He has completed his electrical engineering degree from ENIM, Tunisia in 2010. He also holds a Master's degree in industrial engineering from Grenoble INP in 2011. He has one year of professional experience in automobile diagnosis consulting. His research interests include equipment usage optimization and maintenance action effectiveness.

Muhammad Kashif Shahzad: Dr. Shahzad completed his PhD from University of Grenoble and STMicroelectronics in 2012. At present, he is working in the European research project INTEGRATE in collaboration with STMicroelectronics and G-SCOP research lab. His research focus is on the equipment usage optimization, production scheduling and engineering data management. He holds Bachelor's degrees in Mechanical Engineering and Computer Science from Pakistan and Master's degree in industrial engineering from Grenoble INP with distinction. He has six years of professional experience in industrial information systems and databases with special interests in data/information extraction and integration methodology and statistical modeling.

Eric Zamai: Eric Zamaï was born in France in 1971. He received a Ph.D with distinction in electrical engineering from the University of Toulouse, France, in 1997. He is currently an associated professor at the Grenoble Institut of Technology (Grenoble INP) and does his research at the Laboratory of Grenoble for Sciences of Conception, Optimisation and Production (G-SCOP). His research interests include supervision, diagnostic, prognostic, and management and control of production systems. He also teaches in Grenoble INP engineering school of ENSE3. His subjects are design of real time system, control and management, logic and PLC programming.

Michel Tollenaere: Dr. Michel Tollenaere is a Professor of Information System and Project Management at Grenoble University and the scientific advisor at his university in the domain of industrial engineering. He is the team leader of the SIREP (Information system and multiple representations of the product) research group within G-SCOP Laboratory and is responsible for industrial partnerships. He has supervised 15 PhD thesis in partnership with EADS, Renault, Peugeot, Alcan, STMicroelectronics; Siemens; he is the author of 19 international papers, 2 books, and is a member of many scientific committees as IDMME, ICED... He specializes in the areas of PLM, Knowledge Management, Risk Management, Industrial Process Modeling and Industrial Information Systems. Recognizing DFM (design/manufacturing interface modeling) as being complex, necessarily relates his work to PLM and knowledge management.

Stephane Hubac: Stephane Hubac is Expert on the yield enhancement and Fab productivity projects at STMicroelectronics. Since 1981, he has worked in many disciplines within the semiconductor industry including manufacturing, memory device design, process & equipment engineering in lithography, dry etching and dielectric deposition, process control, Quality methods implementation and R&D. He joined CR2 Alliance (Freescale, NxP, ST) in the initial phase of the project as a project manager; responsible for the selection of 300mm plasma etching, dry stripping equipment then manufacturing and R&D ramp-up has an AREA Manager (Etch, Strip, APC programs) and ISOTS audit supervisor for Fab qualification. He has been leader of the CR2 Alliance APC project and Process Control Area manager in the Crolles 2 Alliance R&D and fabrication facility at Crolles, France. He has special interest in teaching and is currently associated with the Grenoble University as visiting Professor on process control and plasma physics. His special interests include R&D on DFM methods, yield enhancement, productivity and process control.