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A BAYESIAN INDICATOR FOR RUN-TO-RUN PERFORMANCE ASSESSMENT USING INDUSTRAIL RISK

Taki Eddine Korabi
Guillaume Graton
El Mostafa El Adel
Mustapha Ouladsine

Laboratoire d'Informatique et des Systèmes
Avenue Escadrille Normandie-Niemen
Marseille, F-13397, FRANCE

Jacques Pinaton

STMicroelectronics
190 avenue Celestin Coq, ZI
Rousset, 13106, FRANCE

ABSTRACT

This paper proposes a performance indicator based on the Bayesian theory. This indicator is used for assessing the performances of Run-to-Run controllers. The indicator is calculated by analyzing four main points: the output/target error, the output dispersion, the out of tolerance (oot) rate and the industrial risk. The proposed Bayesian method has been tested on the Run-to-Run loops of a semiconductor manufacturing foundry.

1 INTRODUCTION

A semiconductor manufacturing foundry (FAB) is a factory in which slices of semiconductor material called wafers are produced (May and Spanos 2006). These wafers go through a long way of thousands of successive production steps (*i.e.* manufacturing route), before finally becoming a finished product. These steps are realized in several manufacturing areas such as photo-lithography, etch, chemical mechanical polishing (CMP), chemical vapor deposition (CVD), etc. The reader can refer to, (Del Castillo and Hurwitz 1997; Boning et al. 1996; Toprac et al. 1999).

Since the semiconductor industry is known to be extremely precise, any defect in the final product can lead to client dissatisfaction or additional costs. In order to avoid any damages, semiconductor manufacturers introduced physical measurement steps to the manufacturing route in a way that the product can often be checked (Moyne et al. 2000; May and Spanos 2006).

In reality, a measurement step is not an added value in the sense that it does not bring any direct plus to the final product. However, controlling every production step permits to reduce the industrial risk by avoiding unintended results at the end of the manufacturing cycle (Qin et al. 2006).

Therefore, different types of measurement are present in semiconductor industry, we can cite (among others) physical measurement such as Critical Dimension (CD) and thickness, electrical measurement such as Electrical Wafer Sorting (EWS) where every single site on every single wafer is checked, and defectivity wafer inspections where wafer defaults and contamination are detected. The obtained measurements are used to supervise the production machines and their capability for manufacturing products within specifications.

By using control charts, Statistical Process Control (SPC) is one of the main methods used to detect abnormal activities in production machines by detecting product drifts (Spanos et al. 1992). When a problem is detected, process control engineers put the equipment down and actions are taken in order to overcome the origin of the problem. SPC has, therefore, only a prevention role in the sense where it can trigger an alarm but it does not have any automatic control neither on the product nor the machine.

Thus, another type of process control techniques can be found in the semiconductor manufacturing field. It is called Run-to-Run (R2R) control (Edgar et al. 2000) where a run is a processing of a number

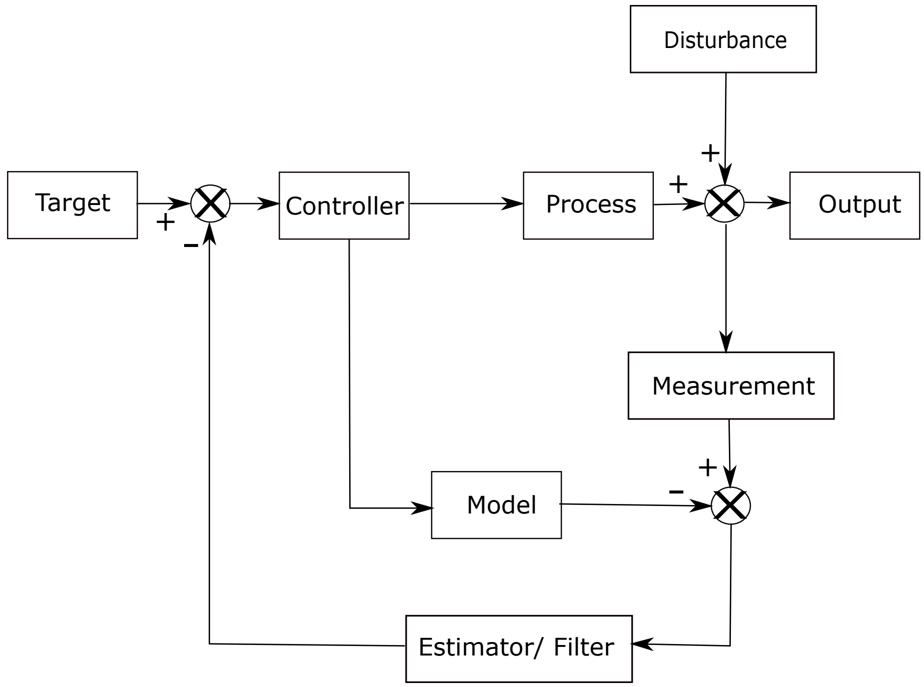

Figure 1: Run-to-Run regulation scheme.

of wafers on a machine with subsequent measurement. A R2R controller is composed of three parts: a mathematical model, an observer (generally an EWMA filter) and a control law. The R2R controller uses the obtained measurement at run k to adjust the output at run $k+1$. Figure 1 summarizes the concept of Run-to-Run regulation.

Thanks to its simplicity and efficiency, R2R control has been successfully deployed in the semiconductor manufactures and permits to improve yield, process capability, and product quality. Unlike SPC, R2R control has a direct impact on the product since it permits the adjustment of the process output automatically in a run-to-run basis.

In order to estimate the efficiency and the relevance of the utilized process control techniques, several capability indicators such as Cp, CpK, Cpm have been introduced and used in the industrial world to evaluate machine capability in term of the manufacturing of a desired product (Chang et al. 2002). However, in the case of R2R control, if a problem is detected on the product, it may be a result of machine dysfunction, the mismatch between the model and the real system, the control law, or the parameters tuning of the observer (Del Castillo and Hurwitz 1997). In this case, the classical indicators like CpK can not evaluate the performance of the R2R controller because CpK is relevant in assessing machine capability but not other parameters. Moreover, CpK is related to Specification Limits which means that its value can be relatively acceptable if the limits are large enough.

In this context, other types of indicators have been used to rate and assess R2R controller's performances (Chen et al. 2009). However, to the best of the authors knowledge, those works have never been deployed in a real industrial environment. Indeed, works on Control Performance Assessment (CPA) are not applicable because they make conservative assumptions like assuming that the parameters of the system are known. This type of supposition is neither possible nor feasible in the industry, see for instance (Bode et al. 2004) and references therein. In this paper, we propose a novel R2R controller indicator based on the Bayesian theory (Carlin and Louis 1997; Yang and Lee 2012). This choice is motivated by the fact that this approach has been widely and successfully used in the industry notably in the semiconductor domain to detect different types of disturbances. Moreover, Bayes theorem is efficient in predicting a behaviour of a process

(Carlin and Louis 1997). The method is also intuitive and easily understandable. Which is very important in an industrial context since it will be used by both engineers and technicians. The indicator takes into account four main parameters: the distance to the target, the dispersion of the observations, the industrial risk and the out of tolerance rate. The indicator is tested on real data provided by semiconductor foundry. In order to demonstrate its efficiency, the indicator is compared with the Cpk capability index using the same industrial set of data.

The remainder of this paper is organized as follows. Section 2 describes R2R control theory as well as the used Bayesian approach and the treated problem is highlighted at the end of this section. The main results are revealed and discussed in section 3. Through an industrial illustration, Section 4 gives insights on how the developed method can be used in a manufacturing foundry. Finally, Section 5 provides some final conclusions and targeted perspectives.

2 BASIC STATEMENT

2.1 Introduction of Run-to-Run control

This section introduces the concept of R2R control and paves the way for the introduction of an indicator permitting to assess the performances of the regulation loop. First, let us introduce the main equations constituting a R2R controller starting with the studied system that is modeled as follows:

$$y_k = \alpha_k + \beta u_k, \tag{1}$$

where $k \in \mathbb{N}$ represents the run number, y_k is the system output, u_k the system input generated by the regulator, β is the system control gain and α_k is the intercept which is modelled by

$$\alpha_k = \alpha + x_k, \tag{2}$$

where α is a constant and x_k is the disturbance. The system has the following model

$$\hat{y}_k = a_k + b u_k, \tag{3}$$

where $\hat{y}_k$ is the estimated output, a_k and b are respectively the estimates of α_k and β. Note that b is estimated off-line while α_k is estimated recursively using a chosen filter. Due to its wide use in the semiconductor industry (Edgar et al. 2000), the Exponentially Weighted Moving Average (EWMA) filter is considered in this paper (Moyne et al. 2000)

$$a_{k+1} = \lambda(y_k - b u_k) + (1-\lambda)a_k, \tag{4}$$

where $\lambda \in [0,1]$ represents the tuning parameter of the EWMA filter. Once the estimate of α is obtained at every run k, the input u_k is also calculated in a recursive manner so that the output y_k meets the target T. This is made using a model inversion

$$u_{k+1} = \frac{T - a_{k+1}}{b}. \tag{5}$$

The aim is to found an indicator for the process described by the interconnection (1), (3), (4), and (5).

2.2 Bayesian theory

The indicator proposed in this paper is based on the well-known Bayes' Theorem (Carlin and Louis 1997):

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(B|A)\mathbb{P}(A)}{\mathbb{P}(B)}, \tag{6}$$

where $\mathbb{P}(A|B)$ is the conditional probability of A occurring given that B is true. This probability is also called posterior probability, $\mathbb{P}(B|A)$ is the conditional probability of B occurring given that the proposition

A is true, $\mathbb{P}(A)$ and $\mathbb{P}(B)$ are the probabilities of observing respectively A and B. These probabilities are independent. An alternative form of Bayes' theorem is presented in the form

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(B|A)\mathbb{P}(A)}{\mathbb{P}(B|A)\mathbb{P}(A) + \mathbb{P}(B|\bar{A})\mathbb{P}(\bar{A})}, \tag{7}$$

equation (7) is obtained from

$$\begin{aligned} \mathbb{P}(B) &= \mathbb{P}(A \cap B) + \mathbb{P}(\bar{A} \cap B) \\ &= \mathbb{P}(B|A)\mathbb{P}(A) + \mathbb{P}(B|\bar{A})\mathbb{P}(\bar{A}), \end{aligned} \tag{8}$$

in the original equation (6).

The second form of the Bayes' theorem (7) is the one which will be used in the rest of the paper. Disturbance detection using Bayes theorem has been introduced in (Wang and He 2007). The idea was to use the prior probability $\mathbb{P}(A)$ to detect eventual future disturbances on the system. The method was called Bayesian detection and has been able to detect both step and impulse disturbances by calculating the posterior probability $\mathbb{P}(A|B)$.

3 MAIN RESULT

3.1 Bayesian indicator proposition

In this paper, a similar approach to Bayesian detection is used for Run-to-Run control assessment. The proposed indicator will also use the industrial risk to evaluate the efficiency of the regulation loop. First, we consider that the whole state space Φ is partitioned in two sub-spaces Φ_N and Φ_D, where Φ_N is the subspace of the tolerated observations and Φ_D is the subspace of the non-tolerated observations (See Figure 2).

Notice that if the regulator is performing well, non-tolerated observations are not supposed to be observed. Moreover a tolerance limit (TL) will be fixed later in the paper. We introduce the likelihood function of a single tolerated observation for a system under Run-to-Run control where Gaussian distribution $\mathcal{N}(0,\sigma^2)$ is assumed

$$\mathbb{P}(y_i|\Phi_N) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{-y_i^2}{2\sigma^2}\right]. \tag{9}$$

By defining the space Y_k regrouping all the observations y_i with $i \in \{1,\ldots,k\}$, $k \in \mathbb{N}$ by

$$Y_k = \{y_1, y_2, \ldots, y_k\}, \tag{10}$$

and by assuming that all the observations y_i, $i \in \{1,\ldots,k\}$ are independent and identically distributed,one can write

$$\mathbb{P}(Y_k|\Phi_N) = \prod_{i=1}^{k} \mathbb{P}(y_i|\Phi_N). \tag{11}$$

By replacing (9) in (11) one obtains

$$\mathbb{P}(Y_k|\Phi_N) = \frac{1}{(\sqrt{2\pi\sigma^2})^k}\Psi(y), \tag{12}$$

where $\Psi(y) = \exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{k} y_i^2\right]$. In parallel to tolerated observations, Gaussian distribution $\mathcal{N}(d,\sigma^2)$ is also assumed for non-tolerated observations and the equivalent likelihood function is given by

$$\mathbb{P}(Y_k|\Phi_D) = \frac{1}{(\sqrt{2\pi\sigma^2})^k}\Psi(y-d). \tag{13}$$

Notice that d stands for the mean of non-tolerated observations as shown in Figure 2

$$d = \frac{\sum_{i=1}^{k} y_i}{k}, \tag{14}$$

By replacing the newly introduced notations in the Bayes' theorem (7) one obtains

$$\mathbb{P}(\Phi_D|Y_k) = \frac{\mathbb{P}(\Phi_D)\mathbb{P}(Y_k|\Phi_D)}{\mathbb{P}(\Phi_D)\mathbb{P}(Y_k|\Phi_D) + \mathbb{P}(Y_k|\Phi_N)\mathbb{P}(\Phi_N)}, \tag{15}$$

where $\mathbb{P}(\Phi_D)$ is the prior probability of non-tolerated observations, $\mathbb{P}(\Phi_N) = 1 - \mathbb{P}(\Phi_D)$ is the probability of tolerated observations. By substituting the obtained results (12) and (13) in (15) we obtain

$$\mathbb{P}(\Phi_D|Y_k) = \frac{\mathbb{P}(\Phi_D)}{\mathbb{P}(\Phi_D) + \mathbb{P}(\Phi_N)\exp\left[-\frac{\left(\sum_{i=1}^{k} y_i\right)^2}{2k\sigma^2}\right]}. \tag{16}$$

See Appendix A for the demonstration of (16).

3.2 Tolerance concept

The obtained indicator in (16) permits to calculate the posterior probability of non-tolerated observations under R2R control. In others words, it permits to know if the regulator performs well and if it is optimally tuned. Indeed, obtaining a value relatively close to 0 means that the probability of obtaining undesired values is relatively small (i.e, it will have optimal performances). On the other side, having a value relatively close to 1 means that the probability of having undesired values is relatively high and that the regulator is not optimal. However, one may ask this question: how can we calculate the prior probability $\mathbb{P}(\Phi_D)$? The answer depends on the exigence that we want to impose to the regulator since $\mathbb{P}(\Phi_D)$ is estimated by calculating the Out of Tolerance (*oot*) rate.

$$oot = \frac{\#non\ tolerated\ observations}{\#all\ observations}, \tag{17}$$

where, $\#non-tolerated\ observations$ refers to the number of non-tolerated observations, and $\#all\ observations$ is the number of all observations.

In order to obtain the value of *oot*, the number of non-tolerated observations needs to be calculated. For that, a limit between tolerated and non-tolerated observations needs to be fixed. One may use Upper Control Limit (UCL) and Lower Control Limit (LCL) in (18) as a limit between tolerated and non-tolerated observations.

$$\begin{aligned} UCL &= \mu + 3\sigma \\ LCL &= \mu - 3\sigma, \end{aligned} \tag{18}$$

where μ stands for the mean of normal observations. Here, we assume that $\mu = 0$. However, these limits are not relevant in a case of normal distribution because the number of observations exceeding these limits can be too small which means that the exigence on the regulator is small. Thus, smaller limits (tolerance limits) will be used in this paper, these limits are defined as follows

$$\begin{aligned} UTL &= \mu + \rho\sigma \\ LTL &= \mu - \rho\sigma, \end{aligned} \tag{19}$$

where UTL is the Upper Tolerance Limit and LTL is the Lower Tolerance Limit. ρ is the tolerance coefficient fixed by the user. Hence, every single observation is compared to the tolerance limits, and if it exceeds these limits, the number of non-tolerated observations is incremented. Note that for the rest of the paper, we set $\rho = 1$. The *oot* rate is then calculated as shown in (17). The proposed indicator in (16) allows to see if the regulator is behaving well or not by taking into account three parameters: the distance to the target y_i, the run-to-run dispersion σ, and the oot rate $\mathbb{P}(\Phi_D)$. However, it does not take into account the effect of the industrial risk in this evaluation. In the next section, the industrial risk will be introduced to the indicator and a relationship between the optimal behavior of the indicator and the risk will be proposed.

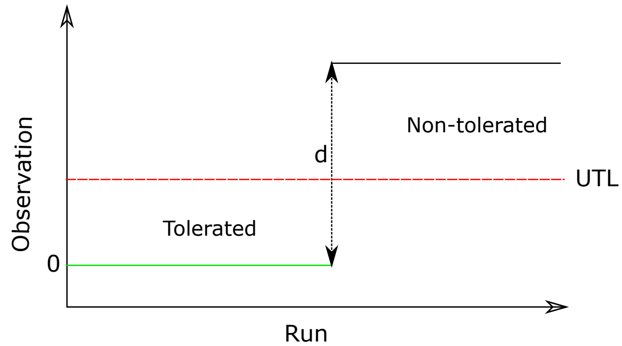

Figure 2: Description of the two modes of operation for a R2R controller.

3.3 Industrial risk and main result

The industrial risk is defined by the consequence in term of cost resulting from a certain technical decision. In semiconductor manufacturing field, the industrial risk is defined by the number of wafers scraped after taking a production decision. In the case of this indicator, the industrial risk is related to the number of scrapped wafers if the indicator tells that the Run-to-Run controller is optimal while it is not. In this context, the semiconductor industry introduce the so-called Acceptable Risk (@R), which is defined by the maximal "acceptable" number of lost wafers. This number can not be exceeded without any consideration no matter which decisions have been taken. Generally speaking, whatever the result communicated by the indicator, the decision related to this result should not lead to a number of lost wafer exceeding the value of the Acceptable Risk. The goal here is to introduce the industrial risk in the calculation of the performance indicator in (16) in a way that will permit to avoid an exceeding of the @R.

Proposition 1 Considering that a fixed value of $@R$ is available, and that the value of the posterior probability $\mathbb{P}(\Phi_D|Y_k)$ in (16) can be calculated, an estimation of the number of products at risk under the R2R control (1), (3), (4), and (5) can be expressed by

$$I = @R(\mathbb{P}(\Phi_D|Y_k)),\ I \in [0, @R]\,. \tag{20}$$

The proposition in (20) can be seen as the number of wafers at risk, which are under the control of the evaluated regulator. In other words, the indicator evaluates the performances of the regulator in term of the wafers that are in risk regarding the behavior of this regulator. The result of the indicator will be compared with two main values: accident and excursion. Both values were introduced to quantify quality and performance losses. Indeed, it can be said that a loss may be due to an accident such as a bad adjustment or a faulty metrology machine while an excursion may be the result of a more significant problem. Therefore, these two values represent the number of lost wafers if an accident or a excursion occur. Note that an accident value is always smaller than an excursion.

4 INDUSTRIAL CASE STUDY

In this section, a test of the proposed indicator is realized on 49 regulators. Note that this indicator is already used in the studied foundry for assessing the majority of the regulation loops. Generally, a regulator is defined by a combination of different manufacturing contexts such as layer, recipe, tool, product, etc. called threads (see for instance Figure 3).

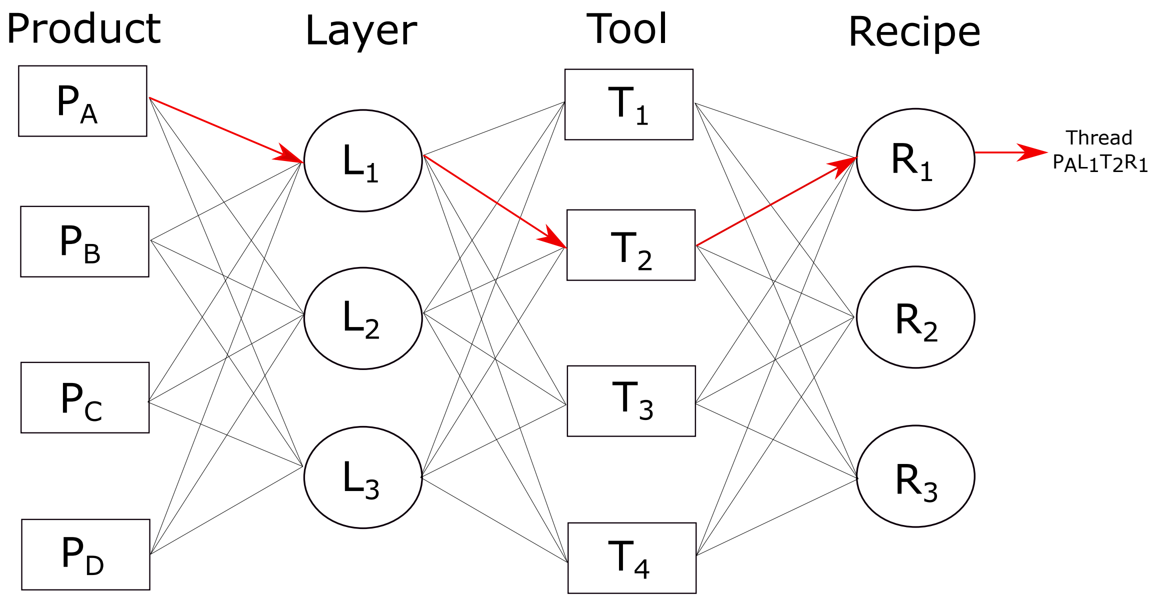

Figure 3: Illustration of a thread for run-to-run control.

In the studied case, the regulator is defined by a combination of two contexts, recipe and tool. In this example, we will use the indicator presented in (20) on 49 different threads in order to evaluate their performances and the obtained values are compared with the two values of accident and excursion. In this example, the standard industrial value of the Acceptable Risk (@R) is arbitrary fixed to 500 wafers. For confidentiality reasons, the true value used in the studied FAB is not disclosed. However, the proposed methodology is not affected by this choice. Also, the fixed value of accident and excursion are respectively 200 and 300. The oot rate is calculated using data from the previous 3 months and the run-to-run dispersion has been estimated using the same set of data. it is important to notice that the dataset satisfies the condition of normality, thanks to the large number of observations.

The idea is to highlight all the sub-optimal regulators so that necessary actions can be taken for making the regulator more optimal. Note that, the sub-optimality of the regulator may be the result of a mismatch between the system (1) and the used model (3) in R2R control. It also can be the results of non-adapted sampling frequencies (Nduhura-Munga et al. 2013), or poorly tuned parameters (Moyne et al. 2000). Figure 4 shows the obtained results for the 49 threads. The data have been collected for a period of 3 months in 3 different areas (deposition, diffusion, and etching).

In Figure 4, the number of threads exceeding the accident limit is 4. Which means that these threads need to be examined and actions have to be taken so that they become more efficient. As an example, the first thread (Thread 1) has been pointed as sub-optimal because the value of the indicator exceeds the accident limit. Let us see the plot of the observations concerning Thread 1 so that a comparison between the proposed indicator and a classical capability index such as CpK can be done. Figure 5 summarizes the collected observations for Thread 1 where a number of 1000 has been considered

In the plot 5 of Thread 1 observations, a number of 4 out of control has been detected. Also, the dispersion is important between Run 220 and Run 630. Now, let us see what is the value of the capability index CpK (Chang et al. 2002)

$$CpK = \min\left(\frac{USL-\mu}{3\sigma}, \frac{\mu-LSL}{3\sigma}\right), \tag{21}$$

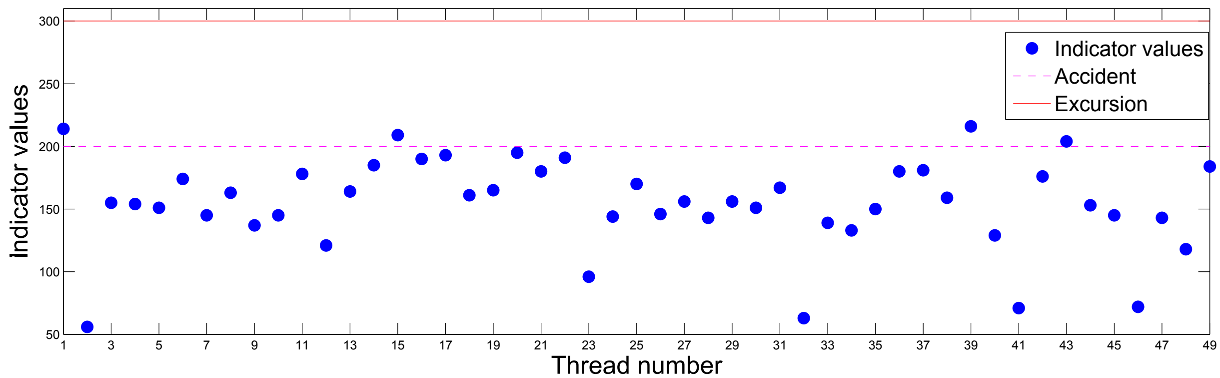

Figure 4: Performances evaluation of 49 threads in STMicroelectronics FAB.

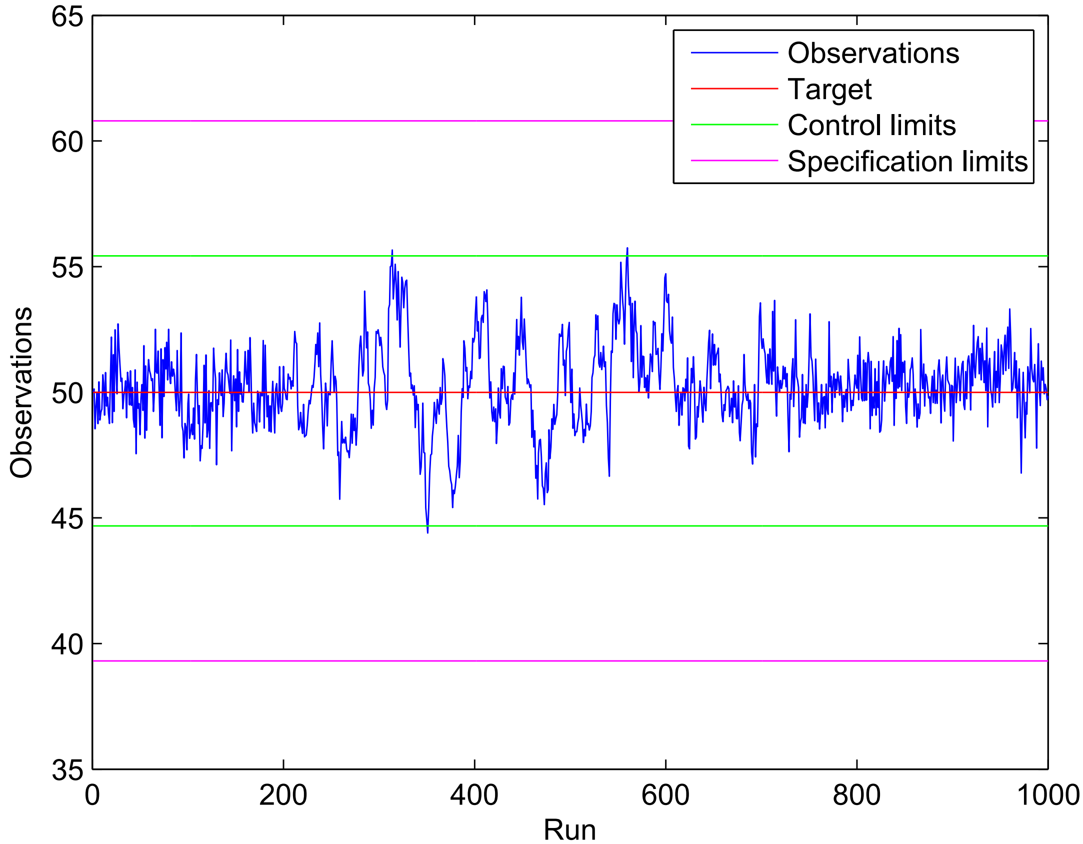

Figure 5: Collected observations for 1000 runs of Thread 1.

where USL and LSL stand respectively for Upper and Lower specification limits, these limits are fixed by the customer and are related to the product. The obtained value of Cpk for Thread 1 is

$$CpK_{Thread\ 1} = 1.8 > 1.67,$$

which is a satisfying value of Cpk. The main inconvenient of CpK is that it gives a good capability value when the product is centred and under specification, which does not necessarily mean that the regulator has optimal performances. However, the studies concerning Thread 1 show that the regulator is not optimal and that a re-tuning of its parameters is necessary. Therefore, the use of the proposed Bayesian indicator was more efficient in detecting the sub-optimality of Thread 1.

5 CONCLUSION

In this paper, a Bayesian indicator for Run-to-Run control assessment is proposed. The indicator uses 4 main parameters in evaluating the performances of a regulation loop: error between the target and the observed output, the dispersion of the output, the out of tolerance rate, and the industrial risk. The efficiency of this indicator has been proved using an industrial example with data from a semiconductor FAB. At the end of this paper, the indicator has been compared to the classical capability index, CpK and the results have been discussed.

In future works, the indicator will be deployed for assessing the R2R loops in a semiconductor foundry. The method may also be used for adapting the sampling frequencies in an automatic manner according to the regulator needs.

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A APPENDIX

Replacing $\mathbb{P}(Y_k|\Phi_D)$ and $\mathbb{P}(Y_k|\Phi_N)$ by their expressions (12) and (13) in (15) we obtain

$$\mathbb{P}(\Phi_D|Y_k) = \frac{\mathbb{P}(\Phi_D)\Psi(y-d)}{\mathbb{P}(\Phi_D)\Psi(y-d)+\mathbb{P}(\Phi_N)\Psi(y)} \tag{22}$$

putting $\mathbb{P}(\Phi_D|Y_k) = \mathbb{P}_l$, $\mathbb{P}(\Phi_D) = \mathbb{P}_s$, and $\mathbb{P}(\Phi_N) = 1-\mathbb{P}_s$ we obtain

$$\mathbb{P}_l = \frac{\mathbb{P}_s\Psi(y-d)}{\mathbb{P}_s\Psi(y-d)+(1-\mathbb{P}_s)\Psi(y)}, \tag{23}$$

by setting, $y_i^2 = (y_i-d)^2 - d^2 + 2dy_i$ we obtain

$$\mathbb{P}_l = \frac{\mathbb{P}_s}{\mathbb{P}_s + (1-\mathbb{P}_s)\exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^k 2dy_i - d^2\right]}. \tag{24}$$

Now, let us remark that,

$$\begin{aligned} \textstyle\sum_{i=1}^k(2dy_i - d^2) &= d\left(\textstyle\sum_{i=1}^k 2y_i - \sum_{i=1}^k d\right) \\ &= d\left(2\textstyle\sum_{i=1}^k y_i - \sum_{i=1}^k d\right) \\ &= d\left(2\textstyle\sum_{i=1}^k y_i - kd\right), \end{aligned} \tag{25}$$

and by replacing d by its equivalent equation in (14), we obtain

$$\sum_{i=1}^k (2dy_i - d^2) = \frac{\left(\sum_{i=1}^k y_i\right)^2}{k}, \tag{26}$$

finally, by substituting the obtained result (26) in (24) one obtain

$$\mathbb{P}_l = \frac{\mathbb{P}_s}{\mathbb{P}_s + (1-\mathbb{P}_s)\exp\left[-\frac{1}{2k\sigma^2}\left(\sum_{i=1}^k y_i\right)^2\right]}, \tag{27}$$

which ends the proof.

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AUTHOR BIOGRAPHIES

TAKI EDDINE KORABI received the M.S. degree in automatic control from université de Lille 1, France, in 2016. He is currently a member of the Technical Staff with STMicroelectronics Process Control group, Rousset, and a Ph.D. student of Aix Marseille université, Marseille, France. He is also a member of Laboratoire d'Informatique et des Systémes (LIS), Marseille, France. His research interests include run-to-run control, sampling strategies in the semiconductor manufactures, and Interconnected systems. His email address is taki.korabi@st.com.

GUILLAUME GRATON is Associate Professor He received from Orleans University in 2005 his Ph.D. on "System diagnosis using finite memory observers. Application to the Common Rail system". He joined the LIS laboratory in 2007. With 13 years experience in research in automatic control, his skills are oriented to complex system control, diagnosis and monitoring. He has numerous references in the field of fault detection applied to Diesel engines, but also in the field of nonlinear system control. For 5 years, his research interest is focused on the improvement of semiconductor manufacturing lines. His email address is guillaume.graton@centrale-marseille.fr.

EL MOSTAFA EL ADEL received Ph.D. degrees in Automation and Computer Science from University of Sidi Mohamed Ben Abdelleh and LESSI Lab, Fs Morocco. Since 2004, he is Associate Professor at Aix-Marseille University and the Information Sciences and Systems Lab. (LIS) France. His research interests include control systems, fault diagnosis and fault tolerant control, monitoring of product quality and control performance, virtual metrology applied in semi-conductor manufacturing. His email address is EL-Mostafa.el-adel@lis-lab.fr.

MUSTAPHA OULADSINE is Professor and head of LIS He received his Ph.D. in Nancy 1993 in the estimation and identification of nonlinear systems. In 2001, he joined the LIS laboratory in Marseille (France), which he is heading since 2006. His research interests include nonlinear estimation and identification, neural networks, diagnosis and control and their applications in the vehicle and aeronautic domains, he published more than 100 technical papers in international conferences and journals. His email address is mustapha.ouladsine@lis-lab.fr.

JACQUES PINATON is manager of Process Control System group at ST Microelectronics Rousset, France. He is an engineer in metallurgy from the Conservatoire National des Arts et metiers d' Aix en Provence. He joined ST in 1984. After 5 years in the process engineering group, he joined the device department to implement SPC and Process Control methodology and tools. He participated in the startup of 3 fab generations. He is leading various Rousset RD programs on manufacturing science including programs on automation, APC, and diagnostics. His E-mail address is jacques.pinaton@st.com.