

ANOVA model based moving window approach for RtR control in high-mix semiconductor manufacturing industry

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Abstract — In this work, a new state estimation method based on run-to-run control for high-mix semiconductor manufacturing industry is proposed. This algorithm exerts moving window approach on the analysis of variance (ANOVA) model, MW-ANOVA approach, and employs the right pseudo-inverse of the context matrix to provide better estimate of the relative states including disturbances of each product and tool at next run. This approach takes the commonly encountered non-stationary disturbances, i.e., an integrated moving average with first order IMA(1,1) disturbance, into account. Comparing to the traditional t-EWMA algorithm, it provides better control performance, which can be verified by simulation examples.

Keywords — Run-to-run control; high-mix; MW-ANOVA approach; moving window approach.

I. INTRODUCTION

Recently, the semiconductor manufacturing industry has been one of the fastest developing industries in the world. Because of shrinking feature sizes and increasing wafer sizes, advanced process control (APC) has been introduced into the semiconductor manufacturing industry. And it has been successfully applied in many process steps such as diffusion, polishing, etch and lithography processes [1, 2, 3, 4]. Run-to-run (RtR) feedback control, an advanced process control approach, is the most commonly adopted control technique for semiconductor manufacturing industry.

The RtR approach is a discrete form of feedback control in which process recipes are modified between runs to minimize shifts, drifts and other forms of process variability [5]. Most current RtR algorithms are based on the assumption that there is only a single product fabricated in the manufacturing line [3,6]. However, this is far from reality. In fact, not only are there many different products, but usually new products are introduced and old ones are phased out. Another limitation comes from the economic conditions. The capital cost as a fraction of the revenue in the semiconductor industry is higher than that in other manufacturing industries [7]. Considering the high cost of manufacturing equipment, the manufacturers have to maximize the utilization of the tools, having as short idle time as possible. Therefore, the unique manufacturing characteristics of this industry are driving the researchers to develop enhanced sophisticated control algorithms to improve the product yield, throughput and capacity utilization rate and reduce the cost.

The semiconductor manufacturing process resembles an

automated assembly line in which many similar products with slightly different specifications are manufactured run to run by different tools. A specific combination of the product and the tool is known as a “thread” [8]. Each thread has its own control algorithm, which is only updated using information within that thread. The RtR control methods of single product can be applied to one thread. However, the number of threads can be up to thousands in a fab. It is cumbersome to maintain so many controllers, and the performance of the controllers will be degraded for those infrequent threads. Many new algorithms have been developed to address the issues raised with multiple threads in the semiconductor manufacturing industry. Firth et al. proposed just-in-time adaptive disturbance estimation (JADE) method which uses recursive weighted least squares method [7]. Pasadyn and Edgar investigated a new state estimation scheme based on Kalman filter [9]. Their method regarded a manufacturing area with all the tools, products and processes as a single interrelated system and assumed each system state was normally distributed around its current estimate with some variance. Wang et al. introduced a general framework for the non-threaded state estimation method which was based on the best linear unbiased estimate (BLUE) of a Gauss-Markov model [10]. Based on the general framework in [10], they proposed Bayesian-enhanced adaptive versions of the Kalman filter and RLS to handle non-stationary disturbances that often occur in semiconductor processes [11]. Based on Gauss white noise model and IMA(1,1) model, Prabhu et al. provided a new state estimation method for high-mix products [12]. This method combined with a moving window approach and least squares solution, and incorporated the noise influences into it to achieve better predictability and improve control performance. All of the algorithms in [7,9,10,11,12] used previous runs to estimate absolute state of each tool and product respectively. However, since in each production run, one product is performed on one tool, absolute individual states of products and tools are not observed [8].

Recently, some researchers have proposed to use the analysis of variance (ANOVA), a branch of statistical theory, to identify the relative state of products and tools [8,13,14]. ANOVA has also been applied to semiconductor industries in many different aspects such as control chart build-up and feedback variable selections [15,16]. Vanli et al. proposed a model selection approach that used ideas from the ANOVA model and stepwise regression literature to identify the context variables that contribute most to the autocorrelation and the offsets in the input and output data [13]. Ma et al. presented a novel state estimation method based on ANOVA model which estimated the relative states of each product and tool to the grand average performance [8]. However,

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this approach assumed that the tool states were unchanged from run to run and the process disturbances were stationary. But in semiconductor manufacturing process, the tool states are usually changing and their disturbances are non-stationary. Besides, both [8] and [9] assumed that the specific qualifying wafers must exist in every observed window. This assumption will increase the non-product test wafers, and thus reduce throughput capacity. Ma et al proposed a novel run-to-run control algorithm based on dynamic ANOVA approach to deal with the high-mix production [14]. The process model included a dynamic term to characterize the run-to-run disturbances such as a drift or other unknown disturbance of different tools, and used standard optimization techniques to estimate the states of tools and products. Whereas this method applied the optimization algorithm, its computational time may be too long.

In this work, a new state estimation method based on run-to-run control for high-mix manufacturing processes is proposed. This algorithm exerts moving window approach on the ANOVA model, which is called MW-ANOVA approach, and employs the right pseudo-inverse of the context matrix to provide better estimates of the relative states of each product and tool. This process model takes the commonly encountered non-stationary disturbances, i.e., an integrated moving average with first order IMA(1,1) disturbance, into account. Comparing to the t-EWMA algorithm, this method provide better control performance, which can be demonstrated by simulations.

The remaining parts of this paper are organized as follows. Section 2 introduces the plant and threaded EWMA algorithm, ANOVA model for the semiconductor manufacturing process, and presents the moving window approach based on ANOVA model to obtain state estimation. In section 3, the process with IMA(1,1) disturbance and a step fault is considered, some simulations are given to verify the effectiveness of MW-ANOVA method and compare the performance of t-EWMA algorithm and our approach. The final section concludes this paper.

II. THEORETICAL DEVELOPMENT

A. Plant and Threaded EMWA Algorithm

Product quality (the output) is the function of the manipulated variable (the input), the product characteristics and the manufacturing tools. The product and tool are often termed “manufacturing context”. Different product behaves differently due to factors such as differences in materials, configuration or layout of devices and interconnects, feature size, and overall chip size [7]. Consider a simplified multi-tool and multi-product process with a single output and a single input. The output can be explained into the linear function of the input, the product and the tool.

$$y(k) = bu(k) + a_{n(k)}^T(k) + a_{m(k)}^P(k) + \varepsilon(k) \quad (1)$$

where $n(k)$ ($n(k)=1, \dots$) denotes the n^{th} tool used at k^{th} run and $m(k)$ ($m(k)=1, \dots$) denotes the m^{th} product manufactured at k^{th} run; $\varepsilon(k) \in N(0, \sigma^2)$ is a

white noise with variance σ^2 and b is the process gain; $y(k)$ and $u(k)$ denote the output and input at the k th run, respectively; $a_{n(k)}^T(k)$ denotes tool characteristics of the specific tool $n(k)$ at the k^{th} run; $a_{m(k)}^P(k)$ denotes the product characteristics of specific product $m(k)$ processed at k^{th} run. However, the absolute value tool and product characteristics can't be estimated independently [9].

Threaded EWMA controller is widely used in mixed-run semiconductor manufacturing process control. Consider a simple linear process with a mixed run produced on a single tool.

$$y(k) = \beta_{m(k)}x(k) + \alpha_{m(k)} + \eta(k) \quad (2)$$

$$\hat{y}(k) = b_{m(k)}u(k_m) + \hat{a}_{m(k),k} \quad (3)$$

$$\hat{a}_{m(k),k} = \lambda(y(k) - b_{m(k)}u(k)) + (1 - \lambda)\hat{a}_{m(k-1),k-1} \quad (4)$$

$$u(k+1) = \frac{T - \hat{a}_{m(k),k}}{b_{m(k+1)}} \quad (5)$$

where $\alpha_{m(k),k}$ is the offset or bias, $\beta_{m(k)}$ is the static gain associated with the product $m(k)$, $\eta(k)$ is the disturbance associated with the tool at run k and $b_{m(k)}$ is the offline estimate of $\beta_{m(k)}$. Equation (2) denotes a semiconductor manufacturing process and it can be approximated by (3). The EWMA filter (4) is used to estimate the process offset $\alpha_{m(k),k}$ and the disturbance $\eta(k)$ at k^{th} run, where $\lambda(0 \leq \lambda < 1)$ is the EWMA tuning parameter. In order to keep the process output at a predetermined target T , the process recipe at $(k+1)^{th}$ run is denoted by (5).

B. MW-ANOVA Approach

The concept of ANOVA is used here to identify the disturbance states of the individual tools and products. It is assumed that disturbance $a_{m(k)}^P(k)$ is a constant and the condition of the tool changes from run to run. According to ANOVA model in [17], the output can be expressed as:

$$y(k) = b_{m(k)}u(k) + \mu + \tau_{n(k)} + p_{m(k)} + \eta_{n(k)}(k) \quad (6)$$

where μ is the overall mean of all observed tool and product combinations, $\tau_{n(k)}$ ($n(k)=1, 2, \dots$) represents the difference between the average results of all possible products on n^{th} tool and the overall mean at run k , $p_{m(k)}$ ($m(k)=1, 2, \dots$) represents the difference between the average results on all possible tools of the m^{th} product and the overall mean at run k , and $\eta_{n(k)}$ is a discrete-sampled stochastic dynamic disturbance attributed to n^{th} tool. Assume that there exists no interaction between tool $\tau_{n(k)}$ ($n(k)=1, 2, \dots$) and product $p_{m(k)}$ ($m(k)=1, 2, \dots$).

It must be noted that $\tau_{n(k)}$ is different from $a_{n(k)}^T(k)$ and $p_{m(k)}$ is different from $a_{m(k)}^P(k)$. $a_{n(k)}^T(k)$ and $a_{m(k)}^P(k)$ are absolute states of the particular tool and product. $\tau_{n(k)}$

and $p_{m(k)}$ must satisfy the ANOVA constraints.

$$\sum_{n(k)=1}^N \tau_{n(k)} = 0 \cdots \cdots \tau_{m(k)} = 0 \quad (7)$$

Considering the process discussed in (6), it is known that the disturbances follow IMA(1,1) model when the product states are static.

$$\eta_{n(k+1)} = \eta_{n(k)} + \omega_{n(k+1)} - \theta \omega_{n(k)} \quad (8)$$

where $\omega_k \sim (\cdot)$ is a white noise and θ is the known parameter of IMA(1,1) model.

If we consider the IMA(1,1) model for $\eta_{n(k)}(k)$ in (6), we have

$$\begin{aligned} \eta_{n(k+3)} &= \eta_{n(k+2)} + \omega_{n(k+3)} - \theta \omega_{n(k+2)} \\ &= \eta_{n(k+1)} + \omega_{n(k+2)} - \theta \omega_{n(k+1)} + \omega_{n(k+3)} - \theta \omega_{n(k+2)} \\ &= \eta_{n(k)} + \omega_{n(k+1)} - \theta \omega_{n(k)} - \theta \omega_{n(k+1)} + \omega_{n(k+3)} - \theta \omega_{n(k+2)} \\ &= \eta_{n(k)} - \theta \omega_{n(k)} + (1-\theta)\omega_{n(k+1)} + (1-\theta)\omega_{n(k+2)} + \omega_{n(k+3)} \end{aligned} \quad (9)$$

Thus the disturbance of each tool can be expressed as a linear combination of an earlier state and all the white noise terms from the earlier state to the current state.

Given the ANOVA constrain in (7), the ANOVA model can be represented into the matrix form.

$$\begin{aligned} \hat{Y}' &= \begin{bmatrix} \hat{Y} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} y_1 - b_{m(1)}u_1 \\ \vdots \\ y_K - b_{m(K)}u_K \\ 0 \\ 0 \end{bmatrix} \\ &= A \cdot X \\ &= \begin{bmatrix} I_{K \times 1} & A'_{K \times (N+M)} & A''_{K \times (K+N)} \\ 0 & \mathbf{1} \cdots & \cdots & \cdots \\ 0 & \mathbf{0} \cdots & \cdots & \cdots \end{bmatrix} \end{aligned} \quad (10)$$

with

$$A' = \begin{bmatrix} 1 & \delta_{1(m_1)} & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \delta_{1(n_K)} & \cdots & \cdots \end{bmatrix} \quad (11)$$

$$A'' = [A_1 \ A_2 \ \cdots] \quad (12)$$

$$X = \begin{bmatrix} \mu & \tau_1 & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \quad (13)$$

where A is an incidence matrix (context matrix), K is the number of historical production records, X denotes the

state to be estimated, and A' is the incidence sub-matrix with relation to the tool $\tau_n(n=1, \dots)$ and the product $p_m(m=1, \dots)$. $\delta_{n(n_k)}$ and $\delta_{m(m_k)}$ are Kronecker deltas, which are equal to 1 when n and m are equal to the tool $n(k)$ and product $m(k)$ of the record at k^{th} run. Since each record contains one product being manufactured on one tool, we can get that

$$\sum_{j=1}^N A'_{ij} = 1 \cdots \cdots A'_{ij} = 1 \quad (14)$$

In (12), the incidence sub-matrix A'' denotes the relationship between N tool disturbances and their white noise sequences for the K historical records. Here, we take the n^{th} ($n=1, 2, \dots$) tool disturbance for example and assume that the n^{th} tool appears K_n times during the $K(K_1 + K_2 + \dots)$ historical records. The context matrix $A_n \in \mathcal{R}^{K \times (K_N + 1)}$ of the n^{th} tool disturbance can be expressed as follows.

$$A_n = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 1 & -\theta & 1 & \cdots & 0 \\ \vdots & & & \ddots & \vdots \\ 1 & -\theta & 1-\theta & \cdots & 0 \\ 1 & -\theta & 1-\theta & \cdots & 1 \\ 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \quad (15)$$

where the number of nonzero line is K_n and we assume that the n^{th} tool appears in former K_n runs. In fact, the matrix A_n is decided according the actual situation.

Then we can get the whole expression of the context matrix A .

Notice that the matrix structure ensures that the number of row is always less than or equal to number of columns. It is clear that the rank of the context matrix A in (10) is often insufficient if we ignore the tool disturbances, while A will always be full row rank after the tool disturbance is considered.

Next, the ANOVA model is combined with moving window approach, i.e. MW-ANOVA approach. In a moving window approach we consider the last K runs of the process, irrespective of whether all the possible contexts are present in those runs. If any context to be used in next run is not available in the moving window, we just adopt the last available estimate for that context. The context matrix evolves as the window moves, i.e., we recalculate A after every run based on the latest K measurements and the corresponding contexts.

A moving window ensures that the computational effort is steady over time and will not balloon up with more and more data. Also, the moving window approach allows us

to consider all the latest measurements without having to remove rows according to same thread which have identical context combinations. However, the selection of window size is a trade-off between maximizing the use of available data and minimizing the computation time. For initial runs, the window size is limited by the available data. Once we have enough data, we may restrict the matrix to a reasonable size based on the available computational time.

Therefore, to solve for X in (10), we use the right pseudo-inverse of A . Then the estimate is given by the following equations:

$$\hat{X} = A^T (AA^T)^{-1} \hat{Y}' \quad (16)$$

Then the estimated error of the $(K+1)^{th}$ run is

$$\hat{e}_{K+1} = C_{K+1} \bullet \quad (17)$$

$$C_{K+1} = \begin{bmatrix} 1 & \delta_{1(n_{K+1})} & \dots & \dots & \dots \\ & 1 - \theta & 1 - \theta & \dots & \dots \end{bmatrix} \quad (18)$$

where C_{K+1} denotes the entire context matrix at $(K+1)^{th}$ run.

The control objective is to maintain the process output as close to target as possible. Given a set of predicted state \hat{X} , the dead-beat control action in the next run is given by:

$$u_{K+1} = \frac{T - \hat{e}_{K+1}}{b_{m(K+1)}} \quad (19)$$

III. SIMULATION STUDY

In this section, a series of simulation tests are designed to verify the effectiveness of the proposed ANOVA model based moving window RtR control approach in various operation scenarios. In this example, there are three products (P1,P2,P3) produced on one tool and the plant can be expressed in Eq.(2). Set $\alpha = [2 \ 3 \ 4]$, $\beta = [1.5 \ 2 \ 2.5]$, $b = [1 \ 1.5 \ 2]$ and $T=0$. The disturbance is expressed by IMA(1,1) model with $\theta=0.2$ and $\sigma^2 = 0.25$, as in Eq.(8).

The product for each run is randomly selected based on a given probability of occurrence. In the next simulation examples, the probability distributions of product P1, P2 and P3 for this case are 0.1, 0.6 and 0.3, respectively.

A. Moving Window Size

We now analyze the influence of moving window size on the mean square error by the proposed approach. The moving window size is increased from 5 to 80 in increments of 5. The relation between the mean square error and moving window size is shown in Fig 1.

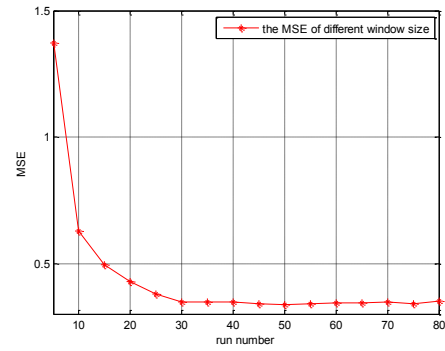


Fig 1 Effect of moving window size on mean squared error

If t-EWMA is used, the MSE is 0.5326. Comparing with MW-ANOVA approach, the MSE is larger than that of t-EWMA when window size is less than 10. Once the window size is larger than 10, the MSE of MW-ANOVA approach is smaller than that of t-EWMA filter. Thus, if enough data are available, MW-ANOVA approach will have better estimation than EWMA filter. It is theorized that the MSE of the moving window approach decreases when window size increases because more information is available with higher window sizes. In reality, the opposite is the case. In Fig 1, the MSE is the minimal when the window size is 50. When the window size increases, the MSE becomes larger. At the same time, the computing time is an essential factor to decide the window size in real industry application. Thus, the optimal window size is designed as 50 in the following simulations.

B. Process with IMA(1,1) disturbance

Compare the proposed MW-ANOVA algorithm with t-EWMA method. For the t-EWMA method, the tuning parameter λ is set 0.8. The MSE of different product and the overall MSE of the two approaches are shown in TABLE I. The variance and mean of the output under the two control algorithms can be seen in TABLE II. The product 1 is infrequently fabricated in this simulation example. The MSE of this product controlled by t-EWMA algorithm is 1.8334, while the MSE of it controlled by WM-ANOVA approach is 0.6270, which drops 65.20%. The individual product control performance is shown in Fig 2-Fig 4. The responses of the 1000 runs by the proposed approach and t-EWMA algorithm are shown in Fig 5. It can be seen that the control performance of MW-ANOVA approach is much better than t-EWMA algorithm.

TABLE I The MSE Different Products with IMA(1,1) Disturbance and The Overall Control Performance of The Two Approaches

Method	MSE _{p1}	MSE _{p2}	MSE _{p3}	MSE
MW-ANOVA method	0.6270	0.3838	0.3060	0.3882
t-EWMA method	1.8334	0.3910	0.6028	0.5974

TABLE II Performance of The Two Algorithms

Method	Variance	Mean
MW-ANOVA method	0.3855	-0.0060
EWMA method	0.6975	-0.0206

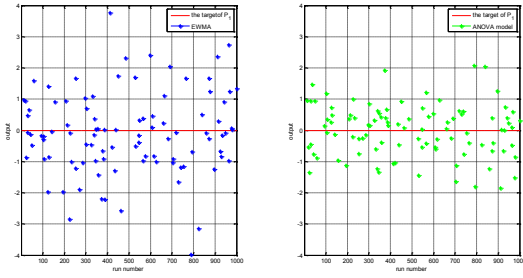


Fig 2 Outputs of product 1 under the control of EWMA and MW-ANOVA (the left-EWMA and the right-MW-ANOVA)

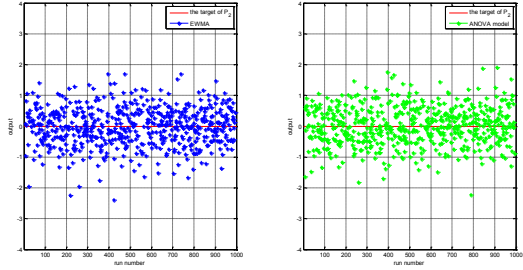


Fig 3 Outputs of product 2 under the control of EWMA and MW-ANOVA (the left-EWMA and the right-MW-ANOVA)

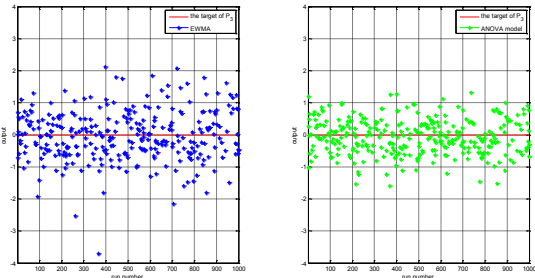


Fig 4 Outputs of product 2 under the control of EWMA and MW-ANOVA (the left-EWMA and the right-MW-ANOVA)

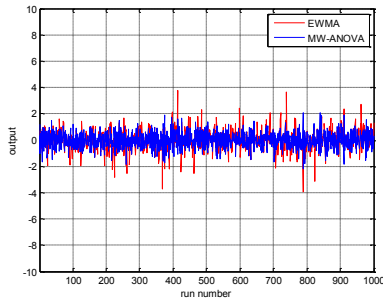


Fig 5 Response under the control of EWMA and MW-ANOVA approach

C. Process with IMA(1,1) disturbance and a step fault

For many semiconductor manufacturing processes, the fault such as an abrupt change of tool conditions can result in the magnitude of the output changing greatly which would be recognized as a step fault. In the following example, there is a step fault with magnitude 5 at 300th run. In this simulation example, the product 3 is fabricated at 300th run. The responses by the proposed MW-ANOVA approach and

t-EWMA algorithm are shown in Fig 6 and Fig 7, respectively. The MSE of different product and the overall MSE of the two approaches are shown in TABLE III. It should be noted that for t-EWMA, there are many spikes as shown in Fig 6 when a step fault happened. The MW-ANOVA method experiences only one large spike and goes back to the target rapidly. In Fig 7, it is obvious that it can make the output return to the target without delay. The proposed method has higher convergence speed than t-EWMA approach. The variance and mean of the output by the two control algorithms is shown in TABLE IV.

TABLE III The MSE Different Products with IMA(1,1) Disturbance and a Step Fault and The Overall Control Performance of The Two Approaches

Method	MSE _{p1}	MSE _{p2}	MSE _{p3}	MSE
MW-ANOVA method	0.4757	0.3242	0.4842	0.3883
t-EWMA method	1.9795	0.3798	0.7799	0.6662

TABLE IV Performance of The Two Algorithms with a Step Fault

Method	Variance	Mean
MW-ANOVA method	0.3886	0.0059
EWMA method	0.6625	0.0190

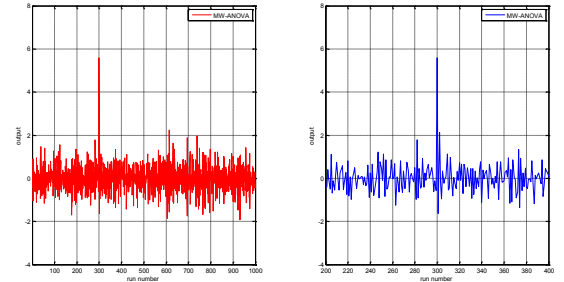


Fig 6 Response under the control of MW-ANOVA algorithm with a step fault

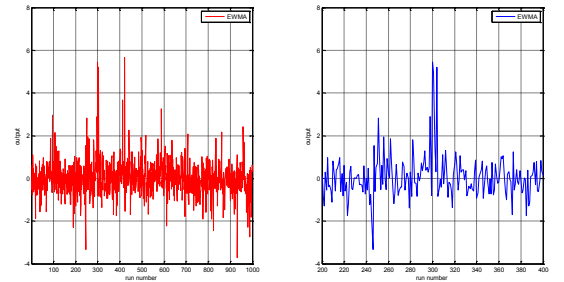


Fig 7 Response under the control of t-EWMA algorithm with a step fault

IV. CONCLUSION

In this work, a new state estimation method based on run-to-run control is proposed. This algorithm exerts MW-ANOVA approach and employs the right pseudo-inverse of the context matrix to provide better estimates of the relative states of each product and tool. The ANOVA model in this paper takes the commonly encountered non-stationary disturbances, i.e., IMA(1,1) disturbance, and a step fault into account. The approach gives the estimates of the disturbances and gives the respective RtR control algorithm. Comparing to the EWMA algorithm, this method provide better controlling performance, which is verified by the simulations.

In the future, the high-mix system with fixed or random metrology delay will be discussed.

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