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Minimax Optimization for Recipe Management in High-Mixed Semiconductor Lithography Process

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***Abstract*—This study addresses the application of minimax optimization in the control design of complex dynamic systems of the semiconductor manufacturing. We highlight the main challenge in the control system of high-mixed wafer fabrication during the photolithography process called overlay control. In the semiconductor photolithography process, the sophisticated and high-mixed setting is generated by multiple recipe adjustments for the single scanner device. The high complexity will be moderated if there is a communication interface among the process variables. We design a communication protocol for the high-mixed photolithography process for overlay control. The proposed system is designed on the basis of the recipe management system for a distinct batches of recipes. The focal point of switching recipes performs as a communication hop, where aligning recipes together make a multi-hop communication system for recipe management. The proposed multi-hop communication system is optimized by the minimax decision rule to select the best parameter setting for each recipe and boost the overlay compensation.**

***Index Terms*—high-mixed manufacturing process; game theory; minimax optimization; communication system; photolithography process; recipe management.**

I. Introduction

In the semiconductor industry, hundreds of process variables apply to semiconductor devices. A specific combination of process variables (i.e., recipe plus tool) is named as a "thread" [1]. Each thread has its own control rule, and the process information can only be shared within the thread. In practice, due to sophisticated semiconductor manufacturing process, the process variables are frequently changing. Therefore, the number of threads can be reached to thousands in the high-mixed manufacturing process [2]. Maintaining so many threads within reliable and stable controller is difficult. Several studies have been deliberated upon by many authors to implement an effective control system in a high-mixed environment for the semiconductor industry (see Table I). Tan et *al.* [1] surveyed run-to-run (R2R) control algorithms in high-mix semiconductor manufacturing processes. Their review confirms that the attention of most researches is threaded R2R with exponentially weighted moving average (EWMA) design [3], [4], [5], [6], [7]. Besides, the EWMA-R2R controller is the most practical method in the real setting [8], [9].

According to Tan et *al.* [1], the threaded R2R controller has several drawbacks as follows:

- The number of threads increases as the manufacturing context augments.
- "Data Poverty" is caused by variation reduction in historical data for one thread due to partitioning data.
- Drift or shift occurs due to the long delay between adjacent lots in one thread.
- Information sharing within threads is impossible or inconsistent.

Most of the aforementioned works have attempted to assume independency among process variables. However, in practice, the effect of process variables on each other is not negligible. Therefore, in a high-mixed semiconductor manufacturing process, a smart recipe management system (RMS) is required to screen the production process and eliminate the uncertainties caused by mixed recipe process, where recipes can be considered as a set of instructions for production process of wafer.

As depicted in Fig. 1, RMS automates the process of communication among the components of the control process. When recipe information changes, RMS communicates with the database system to recall the best parameter setting associated with the new recipe. Subsequently, the control system can be updated with the new setting. In addition, taking the dependency situation into account, the controller can deal with noise or uncertainty caused by recipe replacement. On the other hand, each recipe has unique characteristic, associated with a number of different process parameters and conditions. Therefore, it would be a challenging task for the controller to optimize such a dynamic system.

Therefore, our research question is "how to optimize the control system in the presence of uncertainty and mixed-recipe process in semiconductor phototlithography process?"

To answer this question, a communication protocol is required to share the information among sequences of non-similar recipes (batch) in RMS. In general, the communication protocol among process variables for monitoring the production process can be formed in three major areas: 1) networked

Manuscript received August 27, 2018; firstly revised February 9, 2019; secondly revised June 19, 2019; accepted November 14, 2019.

This research is supported by Ministry of Science and Technology, Taiwan (MOST 108-2634-F-007-001; MOST 108-2634-F-007-008) and Micron Foundation.

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TABLE I. SUMMARY OF RESEARCH FOR CONTROLLING HIGH-MIXED SEMICONDUCTOR MANUFACTURING PROCESS.

Reference	Main Contributions/Methodology	Comparison with Current Study
Tan et *al.* [10]	considering all conditions in [11], utilizing Bayesian model to estimate the singular state-matrix	not considering interaction among process variables
Harirchi et *al.* [12]	Considering the general conditions for independency and normality in [11], introducing a kalman-filter model to deal with unobservability (delay)	not considering interaction among process variables
Lee et *al.* [5]	Implementing a model based on threaded-EWMA for combined product-tool disturbance estimation (CPTDE)	their model is not working for Photolithography as a single tool process, when there is no effect of combination of products-tools
Chang et *al.* [13]	Utilizing k-mean clustering to deal with lack of historical information for rare data, when the general controller was set as threaded-EWMA	considering the low frequency products
Ai et *al.* [3]	Forecasting the cyclic behavior of each product/tool in a high-mixed system based on threaded-EWMA	considering a cyclic behavior due to high complexity in empirical data
Ma et *al.* [11]	Applying linear regression based on ANOVA model for independent process tools and products similar to [14], while considering the effect of each combination of tool-product as a constant variable in the model	not considering interaction among process variables, in addition, their model is not working for Photolithography as a single tool process, when there is no effect of combination of products-tools
Ai et *al.* [15]	Dealing with sudden fault using threaded-EWMA with the model called threaded predictor corrector controller (t-PCC)	not considering sudden fault in the current study
Ma et *al.* [16]	Considering the general condition for independency and normality in [15], they removed the assumption on unchangeable tools and proposed a stochastic dynamic disturbance attributed for tools as ARIMA(p, d, q)	not considering interaction among process variables
Firth et *al.* [14]	Considering indicator variable for each tool/product in a simple EWMA model for analyzing the interaction among variables, called just-in-time adaptive disturbance estimation (JADE)	non-threaded-EWMA
Zhen et *al.* [17]	Applying threaded EWMA for tool-based high-mixed system called tb-EWMA and product-based high-mixed system called pb-EWMA	not considering interaction among process variables

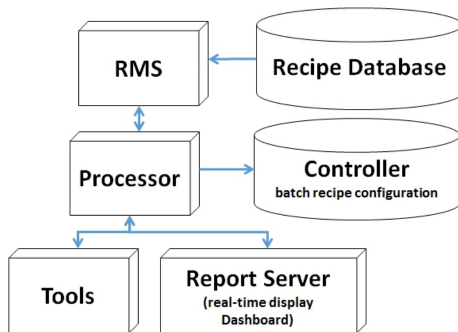

Fig. 1. Block diagram of a process recipe management and automation system in semiconductor industry according to [18].

control [19], 2) multi-agent system [20], and 3) cooperative control [21]. In association with aforementioned fields, assorted studies have been done (i.e., [22], [23]); However, semiconductor manufacturing lingers behind other industries. To date, only a limited number of studies have been identified these approaches in the semiconductor fabrication process (see [24]).

In this study, we aim to construct a robust communication design in RMS for each recipe to minimize the risk of mixed recipe system in semiconductor photolithography process. In the photolithography process, the most complicated task is to manage the overlay factors. RMS plays a vital role in framing a communication system during the photolithography process, such that by selecting the strategy under the extreme (worst) possible loading of other recipes can relief the misalignment. The problem of robust optimal design is formulated as a minimax problem ([25], [26]). Therefore, the contribution of this study is summarized as follows:

- introducing minimax approach to minimize the effect of mixed-recipe process and consequently, compensating misalignment during photolithography process of wafer fabrication.
- making a communication system for a batch of recipes in the single tool photolithography process considering interaction among recipes (not association).

The proposed communication system in this study is capable of minimizing the misalignment, employing the convex optimization of the minimax game model for self-interested recipes in a dependent dynamic process. EWMA controller is operated at this stage to compensate misalignment. Furthermore, a single-input-single-output (SISO) control model is considered for each overlay factor, where the association of all factors makes the multiple-SISO model.

The remainder of this study is organized as follows: Section 2 introduces the problem definition and assumptions. Section 3 proposes the minimax control system in the photolithography process with a discussion of the properties of threaded-EWMA. Section 4 exposes the numerical illustration of optimization based minimax theory and verifies the validation of the framework with simulation. Section 5 includes analysis of manufacturing data. Section 6, concludes the research, and provides the main results and recommendations for further research.

II. PROBLEM DEFINITION AND ASSUMPTIONS

The notation and terminologies used in this study are listed as follows:

i	the recipe index.
j	the overlay factor index.
k, t	the process run index, $1 \leq k \leq t$.
n	number of recipes in the system.
N	number of overlay factors in the system.
$u_{t,i}$	input variable for recipe i at run t.
$Q_{t,i}$	process output for recipe i at run t.
$d_{t,i}$	process disturbance for recipe i at run t.

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$E_{t,i}$	deviation from the target for recipe i at run t.
T	target of overlay factors.
β_i	process gain (parameter of EWMA controller) for recipe i.
α_i	parameter of EWMA controller for recipe i.
α^*, β^*	initial setting of α and β.
ω	fixed discount factor in EWMA controller.
$\mathbf{x}_{t,i}$	state vector of overlay factor in state-space model for recipe i at run t.
$\mathbf{x}_{t,-i}$	state vector of overlay factor in state-space model for all other recipe except recipe i at run t.
f, g	mapping functions in stat-space model.
R_i	recipe i.
J_{R_i}	cost function for R_i.
μ_i	the $N \times 1$ mean vector of normal distribution for R_i.
$\mathbf{\Sigma}$	the $N \times N$ covariance matrix of normal distribution.
δ_{t_i}	stochastic drift for recipe i at run t.
σ	the upper bound for the total overlay error.

A. Semiconductor Photolithography Process

The semiconductor photolithography process as the bottleneck in the wafer fabrication [27] is a lengthy and costly process. A wafer goes several times under the lithography process during the fabrication, and each time regarding the fabrication's step, the recipe is different. Any noise or level of uncertainty in the lithography process will cause misalignment between the scanner device, laser beam, and wafer substrate, called overlay error. The mixed-recipe process is one of the sources of uncertainty. Overlay error measures in both horizontal and vertical dimension and several variables such as rotation, translation, and expansion are affecting on overlay error. Practitioners called these variables as overlay factors. For more information in this field one can refer to [28] (challenges in photolithography process), [29] (state-space modeling of overlay error), [30] (photolithography effects on other fabrication steps), and [31], [32], [33] (advanced process control for overlay error compensation).

For the semiconductor's process engineers, the first challenge is to conduct a recipe confliction for each machine, so that the steps of the protracted process and the sharing process of the tool variations and disturbances have minimal effects on the production quality. The recipe confliction motivates the immensely dynamic nature of the patterning process for each wafer. Recipes naturally are independent (self-interested). However, when they apply sequentially on a single tool, then the parameter setting of the tool for each recipe depends on the sequence of past recipes.

Therefore, this study aims to design a communication system for the mixed-recipe photolithography process to minimize the effect of recipe confliction on the misalignment of overlay factors. The proposed model intends to indicate the dynamic collaborative attitude among the self-interested recipes which can be updated through the communication hops.

B. The Foundation of Communication System

The communication protocol is defined as a set of rules that allows the data transfer and exchange between the RSM and control system. In the first place, following components are composed the layout of communication system:

- *process parameter*: the corresponding parameter of each recipe in the presence of other recipes; these information are store in *database system*
- *hop*: the run when there is a switch in recipe.
- *batch*: a sequence of recipes together from the current run to the run just before the first recipe appears again in the chain. These information are store in *RMS*.

The structure of the communication system is designed based on a switching hop [34] which transfers information from one hop to another. Several switching hops (multi-hop) handle the data transformation task to serve the dynamic formation of the system. Batches are made to lessen the system optimization. Process parameters are saved, update and recall in database system through RMS for each batch instead of each recipe. RMS contains all sets of distinct batches that the system has experienced since the first run.

To address the low similarity and collaboration in a communication system, recipes consider to be self-interested agents and sequentially communicate on a network of distinct batches. In a self-interested multi-agent based system of photolithography process, the recipes' utility function [35] interpreted as the minimum expected value of overlay error.

To compensate the misalignment in photolithography process, for each overlay factor, a SISO controller is considered, when all associated overlay factors can make a multiple SISO controller together. The threaded EWMA control model is designed for optimization and estimation of the control system's parameters on the basis of R2R control.

To clarify the utilization of proposed communication system, following questions are answered in next sections:

A) How is the structure of the multi-hop communication system for mixed-recipe photolithography process?
B) How RMS, database system, and controller communicate with each others?

C. Multi-hop Communication System for High-Mixed Recipe Process

Consider a system with mixed-recipe process. A simple case of system with a mixed-recipe is when each recipe periodically applies to the process after a certain number of runs (fixed drift). For a system with fixed drift, the action for the current run is based on the previous run when the same recipe was used (Fig. 2 left-side). If the recipe allocation is random (stochastic drift, δ_t), the action for current run is performed based on the output of the previous run, when the same recipe was used with the same drift (Fig. 2 right-side). The system becomes even more complicated with a dynamic allocation system and in the presence of other recipes.

To illustrate this situation, consider Fig. 3 with dynamic recipe process, random drift, and more than two recipes in the system for 20 runs of historical data. Tables II summarized

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Fig. 2. Mixed-recipe process with fixed-drift (left) and random-drift (right) for the system with two recipes. The star under each recipe shows the communication hop at the run of changing recipe.

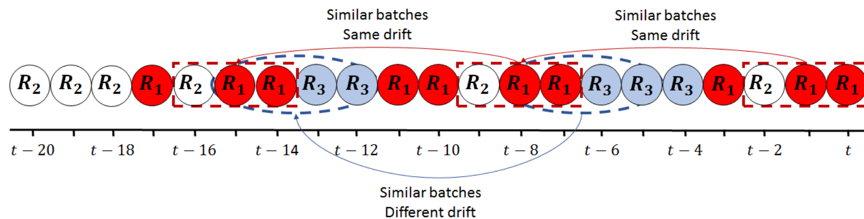

Fig. 3. Mixed-recipe process with random drift and random sequence

the information of all batches in Fig. 3. In this example, at the current run (t), $R_1R_1R_2$ makes a batch. Looking at historical data, the similar batches were made at run $t-7$ and $t-14$. The same situation repeated for second batch at run $t-8$ and $t-15$, and for the fifth batch at run $t-12$. Therefore, for recalling the parameter setting for R_1 at current run (t), it is required to find the similar batch in the past which compensated the misalignment and resulted the best output. Note that, the batch making and similarity rule is not valid for 7th batch at run $t-13$ due to different drift (gap) to meet the latest similar recipe in the chain.

D. Network of RMS and Multiple-SISO Controller

The schematic of the proposed multi-hop communication system for the multiple-SISO controller is represented by Fig. 4. A multiple-SISO system is considered to comprise the case when multiple overlay factors together are inducing overlay error. The system consists of the multi-hop recipe communication system and a sequence of SISO controllers. RMS center composes the batch system based on the recipe similarity checking and helps to update the corresponding parameter for a random recipe in the multiple-SISO controller. The corresponding parameters will be updated when the new recipe launches into the system and enhanced the overly error. In Fig. 4, the order of communication hops from newest to the latest run are $t-1, t-2, t-3, t-6, t-8, t-9, t-11, t-13, t-15$, and $t-16$.

Admitting the communication along RMS and the control system, at each hop the information can be updated (if it is required) in database system before reaching the next hop. For updating the parameter settings in the control system, RMS can search the relevant information in database center, which matches the corresponding batch of the applied recipe and select the best setting that can compensate the worst situation.

E. Minimax Optimization System for Compensating the Overlay Error

Consider a production line including n recipes with each recipe having its own specific parameter setting. In a real situation, the monitoring system has little information about the action of current recipe given by the sequence of past recipes and only limited historical data are available. Sometimes, the communication system for batch similarity checking is disabled due to lack of historical data. In this situation, RMS itself is unable to update the control plant with the best parameter setting. Therefore, expert knowledge and human decision making are required for parameter selection.

In this study, the minimax strategy is applied to empower the control system and reduce the role of human decision making in a fully automated wafer fabrication process. The corresponding process is as follows:

Lottery function: Probability distribution of each possible action.

Utility function: The result or outcome of selecting a specific action.

Action's definition: Concerning the mixed-strategy decision [36] where more than one action can play in lottery function, given that the action at time t will have a better utility function than at time $t-1$. The action's definition for each recipe is the corresponding parameter setting for that recipe given the matching batch.

Strategy selection: To optimize the utility function each recipe can play different actions. One action is to keep the same parameter setting as previous recipe in the system which called "fix" strategy. Alternative strategy is to search among the historical data and find the parameter setting which caused the optimal utility among the others or called "update" strategy.

The recipe always starts with fix strategy. RMS checks the "fix" strategy with historical data and if the recipe had a better performance with another parameter setting which minimize the overlay error, changes the status of recipe to "update" strategy. With "fix" strategy controller does not require to optimize the objective function and simply can wait for the next run and the system response.

III. Minimax Optimal Control Solution for R2R Controller

Minimax optimization is widely applied in control system design [26]. In addition, it plays a key role in many areas

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TABLE II. SUMMARY OF BATCHES AND SIMILARITY MATCHING IN FIG. 3

Batch No.	Batch order (left to right)	Run	Drift to next similar recipe	Matched batches
1	$R_1R_1R_2$	$(t, t-1, t-2)$	$\delta_t = 1$	8,15
2	R_1R_2	$(t-1, t-2)$	$\delta_{t-1} = 2$	9,16
3	$R_2R_1R_3R_3R_3$	$(t-2, t-3, t-4, t-5, t-6)$	$\delta_{t-2} = 7$	-
4	$R_1R_3R_3R_3$	$(t-3, t-4, t-5, t-6)$	$\delta_{t-3} = 4$	-
5	$R_3R_3R_3R_1R_1R_2$	$(t-4, t-5, t-6, t-7, t-8, t-9)$	$\delta_{t-4} = 1$	-
6	$R_3R_3R_1R_1R_2$	$(t-5, t-6, t-7, t-8, t-9)$	$\delta_{t-5} = 1$	13
7	$R_3R_1R_1R_2$	$(t-6, t-7, t-8, t-9)$	$\delta_{t-6} = 6$	Batch 14 cannot match with batch 7, because the drift of batch 14 is unknown.
8	$R_1R_1R_2$	$(t-7, t-8, t-9)$	$\delta_{t-7} = 1$	15
9	R_1R_2	$(t-8, t-9)$	$\delta_{t-8} = 2$	16
10	$R_2R_1R_1R_3R_3$	$(t-9, t-10, t-11, t-12, t-13)$	$\delta_{t-9} = 7$	-
11	$R_1R_1R_3R_3$	$(t-10, t-11, t-12, t-13)$	$\delta_{t-10} = 1$	-
12	$R_1R_3R_3$	$(t-11, t-12, t-13)$	$\delta_{t-11} = 3$	-
13	$R_3R_3R_1R_1R_2$	$(t-12, t-13, t-14, t-15, t-16)$	$\delta_{t-12} = 1$	-
14	$R_3R_1R_1R_2$	$(t-13, t-14, t-15, t-16)$	-	
15	$R_1R_1R_2$	$(t-14, t-15, t-16)$	$\delta_{t-14} = 1$	-
16	R_1R_2	$(t-15, t-16)$	$\delta_{t-15} = 2$	databse-
17	R_2R_1	$(t-16, t-17)$	$\delta_{t-16} = 2$	-
18	$R_1R_2R_2R_2$	$(t-17, t-18, t-19, t-20)$	-	-
19	$R_2R_2R_2$	$(t-18, t-19, t-20)$	$\delta_{t-18} = 1$	-
20	R_2R_2	$(t-19, t-20)$	$\delta_{t-19} = 1$	-
21	R_2	$(t-20)$	-	-

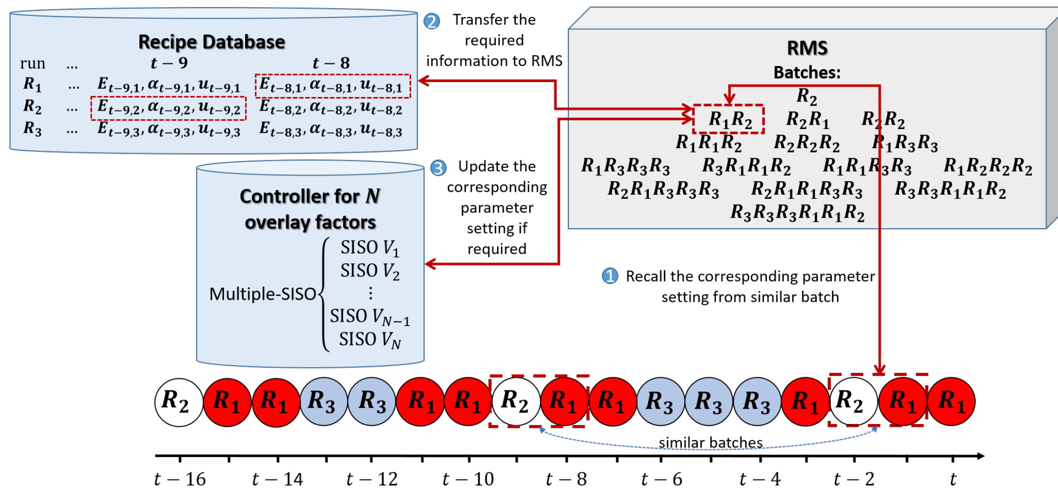

Fig. 4. Multi-hop communication system for multiple-SISO controller for overlay error compensation, where $V_1, \ldots V_N$ are overlay factors, and for each overlay factor one SISO controller is assigned. In step 1 and 2, recipe similarity is checked and control plant is updated through RMS based on database system. In step 3, before moving to the next hop, if the control parameters had any change the information in RMS and consequently the database system will be updated.

of research, including game theory, optimization, and computational complexity [37], [38], [39]. In this study, minimax theory is applied for decision making and compensating the misalignment in the lithography process of wafer fabrication and selecting the best parameter setting (strategy) for threaded the EWMA-R2R controller in high-mixed recipe environment.

A. Threaded EWMA Controller

EWMA is a well-known control model for R2R control design in semiconductor manufacturing [40]. Consider a simple SISO process with the mixed recipe situation, then a linear form of the threaded-EWMA controller for calculating the process output and input for recipe i at run t is shown as [41]:

$$Q_{t,i} = \alpha_{t,i} + \beta_{t,i} u_{t,i} + d_{t,i}, \qquad (1)$$

$$u_{t,i} = u_{t-1,i} - \frac{\omega}{\beta_{t,i}} E_{t-1,i} \qquad (2)$$

where $\alpha_{t,i}$ and $\beta_{t,i}$ are unknown parameters to be estimated from the data by tuning the algorithm and will be updated after each run. According to the engineers' domain knowledge, ω is usually fixed at 0.3. The bias of control system is set to:

$$E_{t,i} = Q_{t,i} - T. \qquad (3)$$

In real setting disturbance $d_{t,i}$ is unmeasurable. In this situation, the optimization objective can be defined for the estimated value of $u_{t,i} + d_{t,i}$, called $\hat{u}_{t,i}$. Therefore, the equivalent optimization problem in (3) for EWMA controller can be minimized by the expected squared deviation of output and

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target value in (4) for a given $\beta_{t,i}$ and ω as follows:

$$\begin{aligned} \min \quad & E[E_{t,i}^2] = (\hat{Q}_{t,i} - T)^2 \\ s.t. \quad & \hat{Q}_{t,i} = \hat{\alpha}_{t,i} + \beta_{t,i}\hat{u}_{t,i} \\ & \hat{\alpha}_{t,i} = \omega(\hat{Q}_{t,i} - \beta_{t,i}\hat{u}_{t,i}) + (1-\omega)\hat{\alpha}_{t-1,i} \\ & \hat{u}_{t+1,i} = u_{t,i} - \frac{\omega}{\beta_{t,i}} E_{t,i} \\ & \hat{\alpha}_{t,i}, \hat{Q}_{t,i}, \hat{u}_{t,i} \in \mathbb{R} \end{aligned} \tag{4}$$

B. Minimax Controller for Discrete-Time System

For discrete-time controller in state-space model, consider a class of SISO system as follows:

$$\begin{aligned} \hat{x}_{t,i} &= f(x_{1,i}, ..., x_{t-1,i}) + g(x_{1,i}, ..., x_{t-1,i})\hat{u}_{t,i} \\ \hat{Q}_{t,i} &= \hat{x}_{t,i} \end{aligned} \tag{5}$$

where unknown f and g functions are bounded and no prior knowledge is required for bounding. To keep the model in (5) controllable, we assume the following assumptions:

Assumption 1: $\lim_{t\to\infty} E\left(\widehat{\mathbf{Q}}_t\right) = T$

Assumption 2: $\lim_{t\to\infty} var\left(\widehat{\mathbf{Q}}_t\right) < \infty$

As discussed before, the objective of control system in this study is to minimize the overlay error in the case of worst decision making for parameter selection given by a specific recipe, or in another word to minimize the effect of maximum value of all possible disturbances for each recipe.

From game theoretical approaches, under necessary condition for optimality [42], Nash equilibrium shows that each agent receives a pay-off that is equal to its alignment's min-max value. To putexplain it simply, the min-max strategy is the one which minimizes the payoff of an agent in a situation where all other agents (denoted by x_{-i}) play their worst performance on the system. In this study, recipes are playing the role of agents. For achieving the best performance of monitoring systems, we consider the case with the worst possible values of $E_{k:t-1,-i}$ within a batch with $(t-k+1)$ runs. Therefore, the performance of the system can be improved by the following augmented optimization model [43], [44]:

$$\arg\min_{i}\max_{-i} J(\hat{Q}_{t,i}, \hat{u}_{t,i} | Q_{k:t-1,-i}, u_{k:t-1,-i}) \tag{6}$$

Regards to the district-time linear state-space model in (5) the optimal solution of (6) can minimize the cost function, $E_{k:t-1,-i}$, given the worst decision in the past within the same batch.

C. Minimax Controller for Threaded EWMA

The game of proposed distinct multi-hop communication system for recipe management can be considered as the sequential decision-making problem [45].

Consider n recipes in the game, when the game has been already playing for $t-1$ times and since run k the game is playing in a new batch; at run t, the ith recipe plays an action given the action of all other recipes in past within the new batch. In fact, the action of ith recipe at run t is the response to the action of previous recipes which returns by cost function $E_{t,i}$ in (3). Therefore, with the minimax control strategy the control cost in (4) is the difference between the cumulative cost of ith recipe and the cumulative cost of the worst action from previous recipes in the same batch. That is:

$$J_{R_i} = \min_i(\hat{Q}_{t,i} - T)^2 - \max_i \sum_k^{t-1} (\hat{Q}_{k,-i} - T)^2 \tag{7}$$

To illustrate that how the minimax controller with the help of RMS can optimize the objective function in (7), consider recipe sequence in Fig. 3, when run $t-20$ is the first run in the production process. For the first round ($t=1$), the recipe R_2 receives the cost of $\arg\min(\hat{Q}_{1,2} - T)^2$. For the second round ($t=2$), again recipe R_2 receives the cost of $\arg\min(\hat{Q}_{2,2} - T)^2$, and subsequently at run $t=3$, once more, R_2 receives the cost $\arg\min(\hat{Q}_{3,2} - T)^2$. However, the parameter setting from the first run to third run remains the same, as recipe is the same. In run $t=4$, for batch $R_2R_2R_2R_1$, when R_1 installs into the system plays the minimax response such that the cost function of recipe R_1 at $t=4$ is minimized the maximum cost of recipe R_2 since run $t=1$.

Although the cost function in (7) can guarantee the minimum cost in a batch of recipes [46], we need to consider the case when large $(\hat{Q}_{t,i} - T)^2$ and large $\sum_k^{t-1}(\hat{Q}_{k,-i} - T)^2$ make the total cost small. To avoid this situation, it is required that any set of output and input values are bounded by $\sigma \in \mathbb{R}^+$ such that:

$$\forall k, i, \quad \left|\hat{Q}_{t,i}\right| \le |\hat{u}_{t,i}| \le \sigma \tag{8}$$

Therefore, the corresponding EWMA controller in (4) with the minimax objective in (7) and convergence rule in (8) can be updated as follow:

$$\begin{aligned} & J_{R_i} = \min_i(\hat{Q}_{t,i} - T)^2 - \max_i \sum_k^{t-1} (\hat{Q}_{k,-i} - T)^2 \\ s.t. \quad & \hat{Q}_{t,i} = \hat{\alpha}_{t,i} + \beta_{t,i}\hat{u}_{t,i} \\ & \hat{\alpha}_{t,i} = \omega(\hat{Q}_{t,i} - \beta_{t,i}\hat{u}_{t,i}) + (1-\omega)\hat{\alpha}_{t-1,i} \\ & \hat{u}_{t+1,i} = u_{t,i} - \frac{\omega}{\beta_{t,i}} E_{t,i} \\ & \left|\hat{Q}_{t,i}\right| \le |\hat{u}_{t,i}| \le \sigma \\ & \hat{\alpha}_{t,i}, \hat{Q}_{t,i}, \hat{u}_{t,i} \in \mathbb{R}, \quad \sigma \in \mathbb{R}^+ \end{aligned} \tag{9}$$

Algorithm 1 represents our proposed methodology for minimax-EWMA controller to summarize the procedure of overlay error compensation.

IV. Illustration and Simulation

A. High Frequency Recipes

To evaluate the performance of the proposed communication framework in controling the misalignment under high-mixed recipe structure, the proposed model in this study is compared with the threaded-EWMA [17] and non-threaded-EWMA (JADE) [14] as the most similar cases in Table I. At the beginning we consider all recipes appear during production

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Algorithm 1: minimax-EWMA Controller

Set $t = 0$;
Initiate α^* and β^*;
Set σ as the upper bound of overlay error;
for $i : 1 \rightarrow n$ **do**
    Initiate "fix" strategy for R_i *at run* $t = 0$;
end
for $k : 1 \rightarrow t$ **do**
    Find the strategy of R_i *given the value of* (E_{-i}, E_i) *at runs* $t = 1, ..., k-1$;
    if *strategy of* R_i *is "update"* **then**
        Find $\arg\min J(\hat{\mathbf{Q}}_i, \hat{\mathbf{u}}_i | \mathbf{Q}_{-i}, \mathbf{u}_{-i})$ *within the current batch;*
        if $\left|\hat{\mathbf{Q}}_i\right| \leq |\hat{\mathbf{u}}_i| \leq \sigma$ **then**
            system is convergence;
        else
            Find $\arg\min J(\hat{\mathbf{Q}}_i, \hat{\mathbf{u}}_i | \mathbf{Q}_{-i}, \mathbf{u}_{-i}, \alpha^*, \beta^*)$;
        end
        Update database with new $(\alpha, \beta, E_{k,i})$;
    end
end

process with the same and high frequency. The illustrative simulation scenario is conducted as follows:
Step 1: Consider recipe R_i with input variable u_{ij}, for $i = 1, ..., 5$, $j = 1, ..., 5$ for ith recipe and jth overlay factor.
Step 2: Generate 1000 samples for each recipe from $MVN(\mu, \mathbf{\Sigma})$ where μ_i's are a 5×1 mean vector of $\overrightarrow{0}, \overrightarrow{1}, \overrightarrow{2}, \overrightarrow{3}, \overrightarrow{4}$ (represent the impulse shift), respectively, and $\mathbf{\Sigma}$ is a 5×5 diagonal matrix with diag $\{10, 5, 1, 0.5, 0.1\}$ (represent the effect of very large or small disturbance). The generated random variable describe the cumulative value of $u_i + d_i$ for each recipe during t runs.
Step 3: Set T for all overlay factors to zero.
Step 4: Mix all recipes' data randomly to build up a new dataset with 5000 instances and five overlay factors.
Step 5: Initialize the setting of the control system at the current run for each recipe with the configuration of last run where the same recipe is applied to the system.
Step 6: Update the initial setting of control system if and only if the estimated value of process input and output of current run for each overlay factor improve the overlay error.
Step 7: Consider the multiple-recipe SISO system, the controller optimizes the objective function in (9) for minimax-threaded-EWMA, the objective function in (4) for threaded-EWMA, and the model in [14] for non-threaded-EWMA (JADE).
For the individual overlay factors and recipes, the estimated input and output values are implemented for the similarity performance between the proposed minimax-EWMA and standard threaded EWMA/non-threaded EWMA controllers. The box plot is applied to visualize the controller's performance of overlay factors as illustrated in Fig. 5 and Fig. 6. Consequently, the minimax-EWMA has better compensation performance and closer to the target than the standard threaded EWMA and non-threaded EWMA, given the input and output values of overlay factors.

Comparing the variation of input with the output variables in both simulation results confirm the excellent effects of convergence rule in (8), which means the proposed communication system tightens up the excellent performance boundary, and eventually achieves a lower cost in the presence of an extensive disturbance, in compared to the system without communication protocol. Yet, the proposed model cannot compete with non-threaded model in this context.
When the variation increases and the unmeasurable disturbance makes a tangible shift in overlay factors, RMS can be update by the controller to deal faster with process shift, while simple system loses its stability. However, unlike the excellent performance of proposed minimax controller encounters with impulse shift and process disturbance, the range of estimated input cannot compete with the estimated value of benchmark models.

B. Low Frequency Recipes

The effect of recipe-based controller on low frequency recipes is critical due to inability to track parameter variations. Therefore, designing a system that controlling the low frequency recipes by shared information from past large frequency recipes in a the high-mixed semiconductor manufacturing process is essential.
In practice, the high frequency recipes are controlled by individual recipe-based EWMA and the same information from high frequency recipes are used for low frequency recipes. In the system without communication system the production information of high frequency recipes is used to help update the process parameters for low frequency recipes. On the other hand, without the communication protocol the quality of low frequency recipes is hard to maintain, because controller loses corresponding information between runs. The communication protocol helps that low frequency recipes obtain the correct control parameters, when they use in the next runs.
We claim that the performance of low frequency recipes can be improved by the information from large frequency recipes, using the proposed communication system in this study. To proof this, consider R_5 is a low frequency recipe (probability of use is $< 5\%$). The simulation scenario in last section is repeated with 95% of simulated data assigned to R_1-R_4 recipes equally (1200 instances per recipe) and only 5% of data are belong to R_5 (200 instances). The result of estimated input and output of the individual overlay factors for R_5, for the proposed minimax-EWMA and standard threaded EWMA/non-threaded EWMA controllers is illustrated in Fig 7.
From Fig. 7, we can see that how the performance of low frequency products can be improved by the information from similar batches included high frequency recipes. However, other communication-less models cannot compensate the effect of impulse shift, although they are more powerful than minimax-EWMA in reduction the variation. One of the reason that other models perform better than minimax-EWMA in compensating the variation for low frequency recipes may back to the fact that the communication-less models consider the fix parameter setting regardless the recipe scheduling for the entire of production process, unless out of control phenomena happen.

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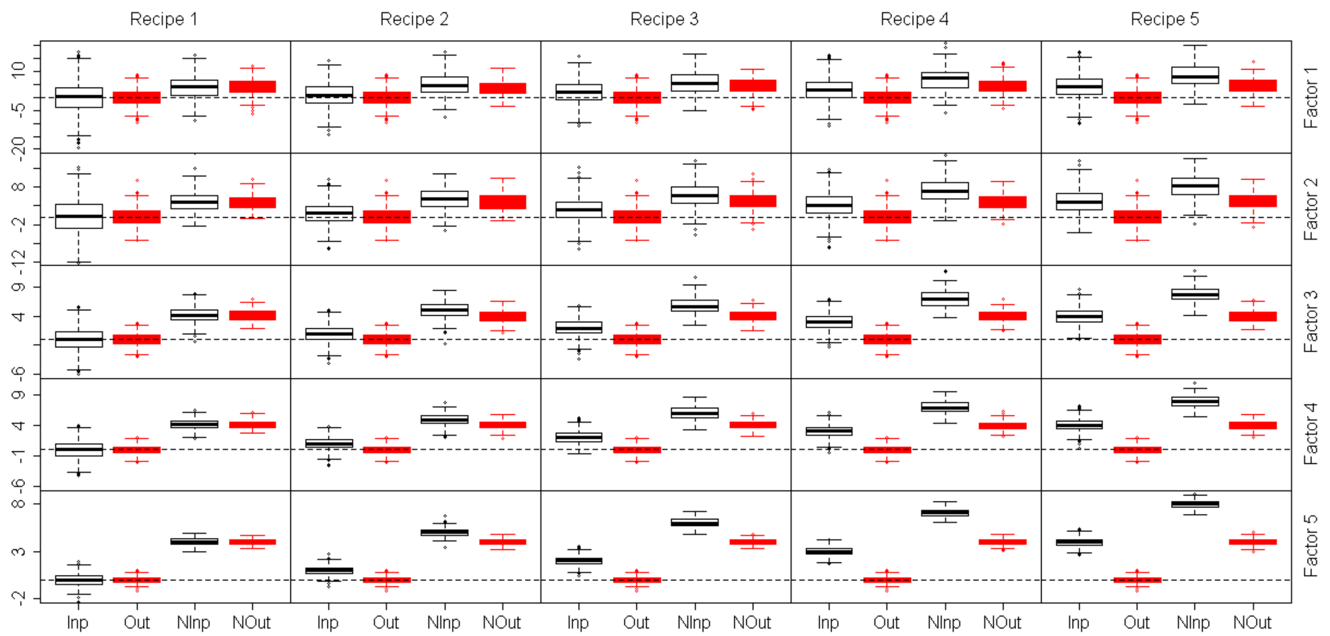

Fig. 5. Simulation results of estimated input (white) and output (red) of five process variables for minimax threaded-EWMA controller vs. simple threaded-EWMA controller for recipes 1-5, when "Inp" and "Out" refer to input and output of model with communication protocol and "NInp" and "NOut" address to the input and output of simple controller. Horizontal dash lines show the target value, T.

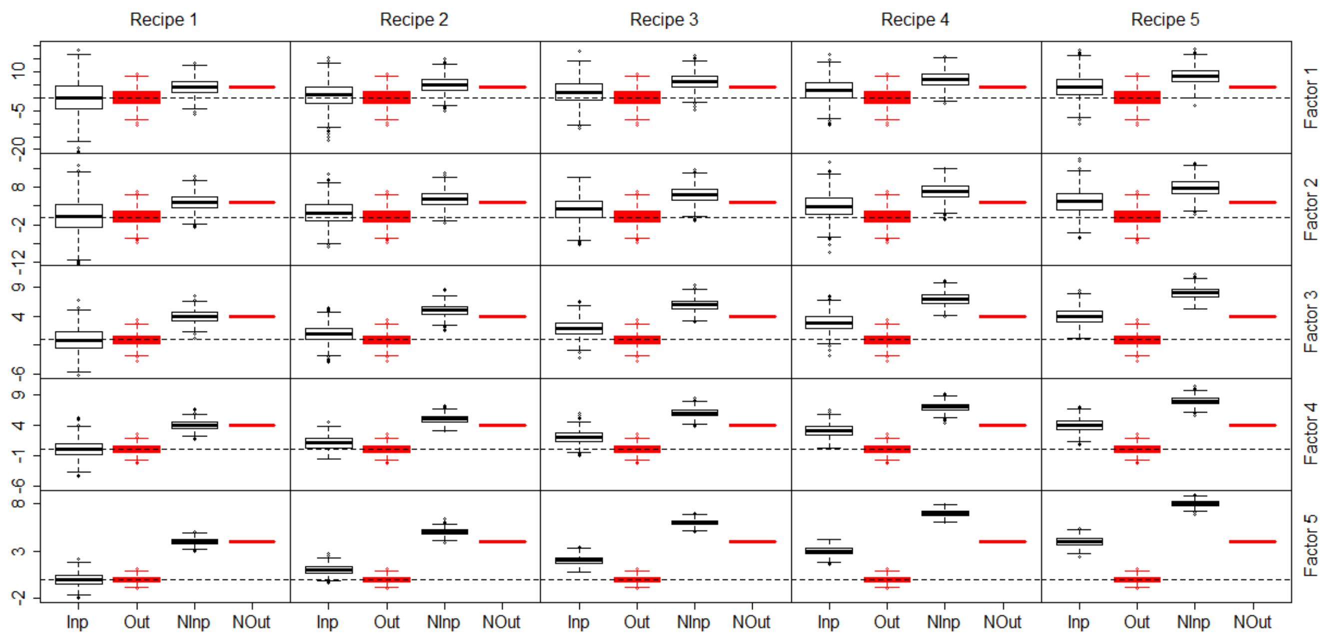

Fig. 6. Simulation results of estimated input (white) and output (red) of five process variables for minimax treated-EWMA controller vs. simple non-threaded-EWMA controller for recipes 1-5, when "Inp" and "Out" refer to input and output of model with communication protocol and "NInp" and "NOut" address to the input and output of simple controller. Horizontal dash lines show the target value, T.

V. EMPIRICAL STUDY

The empirical data in [31] is used for performance evaluation of a major semiconductor manufacturer in Taiwan, including four recipes connected to the reticle of the scanner for 4600 runs or 184 lots. Among ten overlay factors in [47], asym-

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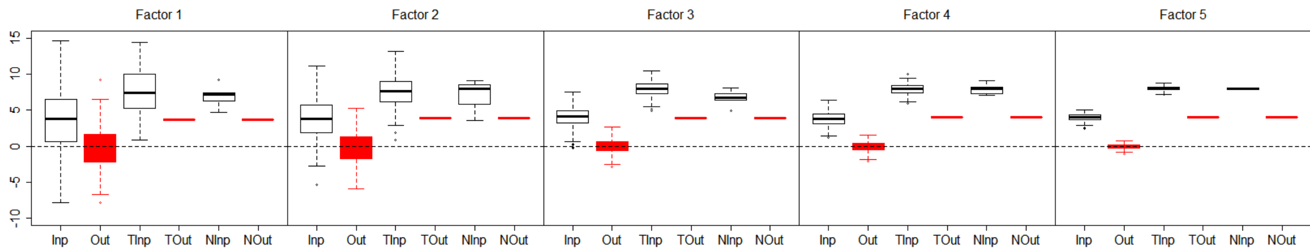

Fig. 7. Simulation results of estimated input (white) and output (red) of five process variables for minimax treated-EWMA controller vs. simple threaded-EWMA and simple non-threaded-EWMA controller for a low frequency recipe, when "Inp" and "Out" refer to input and output of model with communication protocol, 'TInp" and "TOut" address to the input and output of treated-EWMA controller, and 'NInp" and "NOut" address to the input and output of simple non-treated-EWMA controller. Horizontal dash lines show the target value, T.

metric rotation and asymmetric magnification have not been controlled in this fab. The $\omega = 0.3$ as the fixed discount factor used for feedback control in this fab. The target value of each overlay factor and total overlay errors was zeroed.

The estimated value of $\hat{\mathbf{u}}_t$ and $\hat{\mathbf{Q}}_t$ from proposed minimax EWMA controller is compared with the actual values from empirical data to calculate the performance improvement. Table III summarizes the improvement of Range (10) and RMSE (11) for each overlay factor between the proposed model and the original control setting in the fab. The result shows how the error compensated by using the proposed minimax threaded-EWMA controller for each recipe when there is sufficient historical information in RMS for supporting minimax decision.

$$\text{Range} = \max_{t,i} \widehat{Q}_{t,i} - \min_{t} \widehat{Q}_{t,i} \tag{10}$$

$$RMSE = \sqrt{\frac{1}{t} \sum_{k=1}^{t} \frac{\sum_i \left(\widehat{\mathbf{Q}}_k - T \right)^2}{i}} \tag{11}$$

VI. Conclusion and Discussion

This paper introduced a multi-hop communication system for monitoring the overlay error during the photolithography process and estimating the parameters of controller based on minimax optimization strategy. The approach has been tested through the simulation study on different conditions (number of recipes and disturbance density). For all the given situations, the proposed design almost has an advantage compared to simple threaded-EWMA and non-threaded-EWMA controllers disconnected from RMS. In addition, the empirical data validated the excellent performance of proposed approach in comparison with EWMA controller as a benchmark in the industry.

In contrast, the proposed communication system engaged in minimax optimization only needs to connect to a database management system, making real-time processing possible. For making this approach works in real time, an important assumption is that the historical information from the database management system support the optimal solution for the controller for each recipe. For applying this condition, the EWMA is extended to a dynamic threaded EWMA to address the mixed-effect, and R2R controller is optimized by minimax optimization algorithm.

To apply the minimax strategy, each component (recipe) for high-mixed model has been considered as a self-interested agent. Then, the Nash equilibrium optimization technique has been considered to update the controller using the minimax optimization algorithm.

In summary, some further remarks and future research topics are listed as follows:

A. The Path for Misalignment Compensation

The proposed model in this paper could be extended to a more comprehensive situation in the lithography process such as:

1) Extend the proposed model to the multiple-input-multiple-output (MIMO) or multi-input single-output (MISO) structures.
2) Develop game-theoretical approaches for the model affected by the metrology delay.
3) Develop the model for the multi-layer lithography process.
4) Extend the high-mixed model to higher mixture-system (i.e., mixtures of recipes, products, and tools).

B. The Path for Game Theory in Semiconductor Manufacturing

The different aspects of game theory for decision making could be applied in the semiconductor industry to facilitate the system performance evaluation and analysis such as:

1) The theoretical-game approach in this study estimated the best decision for updating the parameter setting of the control system. To improve this model and to attain a static strategy, the behavior of each recipe can be predicted by intelligent behavioral game theory. The behavioral game theory can optimize the utility function. Therefore, the system will support convergence and stability after several runs.
2) Due to the high complexity of the fabrication process, process engineers generally prefer the fixed parameter setting for the controller and update the setting if and only if any out of control case happens. The situation of out of control can be formulated with bargaining game theory when the ask is higher than the bid.

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TABLE III. SUMMARY OF EMPIRICAL DATA

Overlay Factors	**Recipe (number of lot)**							
	A (154)		**B (25)**		**C (3)**		**D (2)**	
	RMSE	*Range*	*RMSE*	*Range*	*RMSE*	*Range*	*RMSE*	*Range*
Wafer rotation	37.4	91.8	66.7	80.7	53.1	-74.3	-34.8	-59.3
Non-orthogonality	85.9	99.1	24.8	-112.3	56.6	-108.1	27.5	-142.4
Scaling along the X axis	74.9	96.3	75.6	49.3	77.7	-10.2	87.3	87.4
Scaling along the Y axis	93.2	99.6	92.5	83.7	93.3	72.4	86.7	77.64
Translation along the X axis	88.6	99.7	95.9	88.8	92.6	86.8	70.3	39
Translation along the Y axis	89.3	98.1	84.1	30.2	90.2	59.8	80.5	73
Reticle rotation	15.4	80.1	86.7	56.9	91.9	61.3	32.8	27.5
Isotropic magnification	21.8	92.2	89	54.4	84.1	82.8	4.5	0.5

C. The Path for intelligent production in Semiconductor Manufacturing

1) Intelligence decision making in semiconductor industry usually is based on data driven technology [48]. However, the data is not valid for a long period and has a short expiration time due to high-complexity in this industry. Learning based decision making [49], or dynamic models [50] could enhance the validation of decisions in longer periods.

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2019.2957145, IEEE Transactions on Industrial Informatics

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