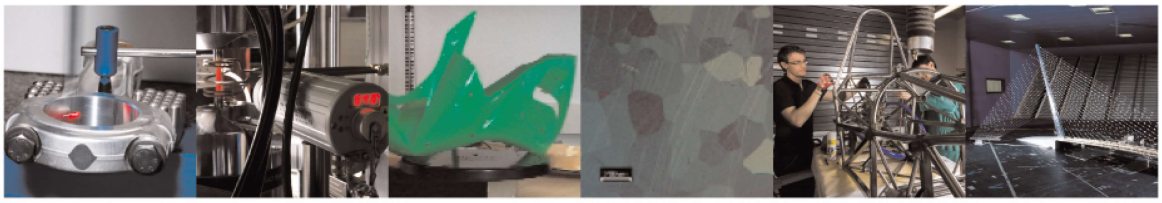

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Robust model-based control of multistage manufacturing processes

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We present a novel method that utilizes in-process measurements of product quality and models that relate those measurements with the underlying manufacturing process parameters to drive down the product quality errors via strategic adjustments of the controllable process parameters. Uniqueness of the new method is its robustness to inevitable inaccuracies in the underlying models, as well as the absence of traditional, but restrictive assumptions of Gaussianity and independence of measurement and process noise terms. The new approach was demonstrated using models and data from a laboratory-scale machining process and a lithography overlay process from a modern semiconductor manufacturing plant.

Model based control of quality in multistage manufacturing processes, inaccurate knowledge of noise characteristics, robust control

1. Introduction

Since the seminal paper [1], significant research efforts were dedicated to process control based on explicit models of the flow of product quality errors from one manufacturing operation to another in a multistage manufacturing processes (MMP). These so-called Stream of Variation (SoV) models which established analytical connections between manufacturing process parameters and errors in product quality were used for identification of process-level sources of product quality errors, selection of the most informative measurements of product quality, as well as manufacturing systems analysis and design in a wide array of MMPs, including autobody assembly, machining of prismatic parts, sheet metal rolling and semiconductor manufacturing [2]-[5]. Most recently, the research in model-based process control focused on exploiting the analogies between SoV models and traditional control theory to facilitate active on-line control of outgoing product quality through automatic adjustment of controllable MMP parameters based on the information from distributed, in-process measurements within an MMP [4]-[6].

Nevertheless, almost all prior research on model-based process control assumed that the underlying SoV model was perfectly known. On the other hand, weather the model is pursued using first-principle physics based approaches, as in [4], or data-driven paradigm, as in [5], there will be inherent uncertainties in the estimates of model parameters and noise characteristics. A notable exception can be found in [7], where parametric uncertainties in the SoV model parameters were modelled as normally distributed random variables with zero means and known variances. Nevertheless, though [7] did not assume perfect knowledge of model parameters, the authors assumed Gaussianity and perfect knowledge of the random variables describing the model parameters, thus essentially still relying on Gaussian and Bayesian statistics. More recently, in [8], the problem of stochastic SoV model-based multistage process control was addressed in a way that delivered robustness to inaccurate knowledge of variance characteristics of the modelling noise terms. Nevertheless, structural model parameters were still assumed to be perfectly known, while noise terms were still modelled as normal, independent, identically distributed (NIID) random vectors.

Besides the need to fully incorporate model-parametric uncertainties into SoV-model based MMP control approaches, let us also note that in highly sophisticated and safety critical MMPs, such as those we encounter in semiconductor or pharmaceutical manufacturing, control laws may be required to absolutely guaranty the system performance in spite of model parametric uncertainties and noise characteristics. This basically disqualifies Bayesian stochastic approaches, as well as normality and independence assumptions, which were in the foundations of [4]-[8]. Hence, there is a great need for a robust method for automatic control of quality in an MMP, with the capability to bypass the need for perfect knowledge of model parameters, as well as the assumptions of normality, independence and known characteristics of the noise terms in the model. The goal of the paper at hand is to fill the abovementioned gap.

2. Methods

Following numerous papers in the realm of model-based process control [2], let us assume that the SoV model of the flow of quality errors in an MMP follows the linear time-varying state space form

$$\boldsymbol{x}(i) = \mathbf{A}(i)\boldsymbol{x}(i-1) + \mathbf{B}_{\mathrm{c}}(i)\boldsymbol{u}_c(i) + \mathbf{B}_{\mathrm{E}}(i)\boldsymbol{u}_E(i) + \boldsymbol{w}(i),$$
$$\boldsymbol{y}(i) = \mathbf{C}(i)\boldsymbol{x}(i) + \mathbf{D}_{\mathrm{c}}(i)\boldsymbol{u}_c(i) + \mathbf{D}_{\mathrm{E}}(i)\boldsymbol{u}_E(i) + \boldsymbol{v}(i),$$
$$\boldsymbol{x}(0) = 0;\ i = 1,2\cdots,N \qquad (1)$$

where i denotes the operation index, N is the total number of operations in the MMP, the state vector $\boldsymbol{x}(i)$ consists of errors in the parameters that describe the workpiece after it is processed in operation i, output vector $\boldsymbol{y}(i)$ contains errors in product quality measured after operation i, $\boldsymbol{u}_c(i)$ denotes the vector of controllable process parameters that can be automatically actuated in operation i, $\boldsymbol{u}_E(i)$ is the vector of uncontrollable process parameters at operation i, while $\boldsymbol{w}(i)$ and $\boldsymbol{v}(i)$ denote the vectors of plant and measurement noise terms, respectively.

Just to give the reader a physical sense of various terms in the model (1), let us note that in the case of machining of prismatic parts, the state vector $\boldsymbol{x}(i)$ consists of errors in the orientations and positions of planar features, as well as orientations, positions and diameters of cylindrical features of the workpiece [9], while in the case of lithography overlay, the state vector consists of misalignment errors in control points of the wafer corresponding to layer i and the reference layer [4].

The problem of SoV model-based process control comes down to utilizing the measurements obtained up to any given operation k, history of past control actions, if available, as well as model (1) to strategically set controllable process parameters $\boldsymbol{u}_c(k)$ in operation k in such a way that the outgoing quality errors $\boldsymbol{y}(k)$ are minimized in some sense. Let us now assume the following for each operation $i \in \{1,2,\ldots,N\}$.

- Structural matrices of the model (1) can be represented as
$$\mathbf{A}(i) = \mathbf{A}_{Nom}(i) + \Delta\mathbf{A}(i);\ \mathbf{B}_{\mathrm{c}}(i) = \mathbf{B}_{\mathrm{c}_{Nom}}(i) + \Delta\mathbf{B}_{\mathrm{c}}(i)$$
$$\mathbf{B}_{\mathrm{E}}(i) = \mathbf{B}_{\mathrm{E}_{Nom}}(i) + \Delta\mathbf{B}_{\mathrm{E}}(i);\ \mathbf{C}(i) = \mathbf{C}_{Nom}(i) + \Delta\mathbf{C}(i)$$
$$\mathbf{D}_{\mathrm{c}}(i) = \mathbf{D}_{\mathrm{c}_{Nom}}(i) + \Delta\mathbf{D}_{\mathrm{c}}(i);\ \mathbf{D}_{\mathrm{E}}(i) = \mathbf{D}_{\mathrm{E}_{Nom}}(i) + \Delta\mathbf{D}_{\mathrm{E}}(i)$$
where $\mathbf{A}_{Nom}(i)$, $\mathbf{B}_{\mathrm{c}_{Nom}}(i)$, $\mathbf{B}_{\mathrm{E}_{Nom}}(i)$, $\mathbf{C}_{Nom}(i)$, $\mathbf{D}_{\mathrm{c}_{Nom}}(i)$ and $\mathbf{D}_{\mathrm{E}_{Nom}}(i)$ denote the corresponding nominal matrices, while $\Delta\mathbf{A}(i)$, $\Delta\mathbf{B}_{\mathrm{c}}(i)$, $\Delta\mathbf{B}_{\mathrm{E}}(i)$, $\Delta\mathbf{C}(i)$, $\Delta\mathbf{D}_{\mathrm{c}}(i)$ and $\Delta\mathbf{D}_{\mathrm{E}}(i)$ respectively denote the uncertainties in those matrices, describing one's lack of knowledge about model parameters.
- All entries $[\Delta * (i)]_{k_1,k_2}$ in the uncertainty matrices Δ are assumed to be unknown, but residing within known bounds, i.e.
$$\left|[\Delta * (i)]_{k_1,k_2}\right| \le \varepsilon_{k_1,k_2}^{\Delta*(i)} \qquad (2)$$
where $\varepsilon_{k_1,k_2}^{\Delta*(i)}$ are all known.
- All entries $[\boldsymbol{w}(i)]_j$, $[\boldsymbol{v}(i)]_l$ and $[\boldsymbol{u}_E(i)]_m$ in vectors $\boldsymbol{w}(i)$, $\boldsymbol{v}(i)$ and $\boldsymbol{u}_E(i)$ are unknown but lie within some known bounds, i.e.
$$\left|[\boldsymbol{w}(i)]_j\right| \le \varepsilon_j^{\boldsymbol{w}(i)};\ |[\boldsymbol{v}(i)]_l| \le \varepsilon_l^{\boldsymbol{v}(i)};\ |[\boldsymbol{u}_E(i)]_m| \le \varepsilon_m^{\boldsymbol{u}_E(i)} \qquad (3)$$
where all ε bounds are known.
- The vector of controllable process parameters is modeled as
$$\boldsymbol{u}_c(i) = \overline{\boldsymbol{u}}_c(i) + \overline{\boldsymbol{b}}(i) + \boldsymbol{\eta}(i)$$
where $\overline{\boldsymbol{u}}_c(i)$ is the vector of user-commanded values for $\boldsymbol{u}_c(i)$, $\overline{\boldsymbol{b}}(i)$ denotes the estimated bias vector associated with controllable parameters $\boldsymbol{u}_c(i)$, and $\boldsymbol{\eta}(i)$ denotes uncertainties associated with the execution of desired controllable process parameters $\overline{\boldsymbol{u}}_c(i)$ and the estimate of the bias vector $\overline{\boldsymbol{b}}(i)$.
- All components $[\boldsymbol{\eta}(i)]_p$ in the vector $\boldsymbol{\eta}(i)$ satisfy
$$\left|[\boldsymbol{\eta}(i)]_p\right| \le \varepsilon_p^{\boldsymbol{\eta}(i)} \qquad (4)$$
where bounds $\varepsilon_p^{\boldsymbol{\eta}(i)}$ are known.

Let us now note that, unlike what we see in the previous work, the assumptions above incorporate uncertainties in the model parameters and do not assume anything regarding the distribution form or independence of the terms characterizing the noise and actuation uncertainties. Instead, all uncertainties in the model are only assumed to be bounded within known bounds and nothing else. As for the last two assumptions describing the behavior of controllable process parameters, the bias vectors are used to describe longer term product-to-product or run-to-run (R2R) changes in the controllable parameters, usually caused by wear out **Errore. L'origine riferimento non è stata trovata.** or temperature induced offsets in machining and assembly systems **Errore. L'origine riferimento non è stata trovata.**, or material build-up and equipment aging induced changes in semiconductor manufacturing [12]. These bias terms are usually tracked and compensated for using various types of R2R controllers, which themselves are not perfect. Imperfections of such bias-modelling approaches, as well as actuator noise associated with the controllable process parameters $\boldsymbol{u}_c(i)$ are captured in the uncertainty terms $\boldsymbol{\eta}(i)$, which again are not modelled via any specific distribution, but rather as an unknown parameter residing within some known bounds. Of course, if no R2R controller exists in the system of interest, the bias terms can be completely omitted and the vector of controllable parameters $\boldsymbol{u}_c(i)$ could then comprise of only the vector of commanded values $\overline{\boldsymbol{u}}_c(i)$ and the associated uncertainties $\boldsymbol{\eta}(i)$ that are bounded within some known (but perhaps wider) bounds.

At any operation k, the control problem now comes down to utilizing upstream measurements of quality errors $\boldsymbol{y}(i), i = 1,2,\ldots,k-1$ and, if available, estimates of the bias terms $\overline{\boldsymbol{b}}(i), i = 1,2,\ldots,k$ to determine the command vector $\widehat{\boldsymbol{u}}_C(k)$ for controllable parameters in operation k that will minimize some weighted sum of squared errors in product quality measured in that operation, *for the worst case scenario regarding all the model uncertainties*. More formally, following robust control formalism [10], we pursue

$$\widehat{\boldsymbol{u}}_C(k) = \underset{\overline{\boldsymbol{u}}_C(k)}{\operatorname{argmin}} \quad \max_{\substack{\Delta*(i),\boldsymbol{u}_E(i),\boldsymbol{\eta}(i),\boldsymbol{w}(i),\boldsymbol{v}(i)\\ i=1,2,\ldots,k}} \boldsymbol{y}^{\mathrm{T}}(k)\boldsymbol{\Sigma}\,\boldsymbol{y}(k)$$
$$\text{Subject to: model (1) for } i = 1,2,\ldots,k$$
$$\text{constraints (2)-(4) for } i = 1,2,\ldots,k \qquad (5)$$

where $\boldsymbol{\Sigma}$ is a diagonal matrix of weights. Eq. (5) describes a large and complex optimization problem involving hundreds of decision variables and constraints, even for an MMP as simple as the one described in [9]. to solve it, let us follow [11] and respectively denote with $\boldsymbol{\phi}_{ub}$ and $\boldsymbol{\phi}_{lb}$ the upper and lower bounds on the uncertain parameters in (5), rendering (5) in the form

$$\widehat{\boldsymbol{u}}_C(k) = \underset{\overline{\boldsymbol{u}}_C(k)}{\operatorname{argmin}} \ \max_{\boldsymbol{\phi}} \ \mathrm{J}(k)$$
$$\text{Subject to: model (1) for } i = 1,2,\ldots,k$$
$$\boldsymbol{\phi}_{lb} \le \boldsymbol{\phi} \le \boldsymbol{\phi}_{ub} \qquad (6)$$

Let us now define the function $f_0(\boldsymbol{\phi}_k) = \min_{\boldsymbol{\phi}_k} -\mathrm{J}(k)$, and let $f_1(\boldsymbol{\phi}_k), \ldots, f_m(\boldsymbol{\phi}_k)$ and $\sigma_1, \ldots, \sigma_m$ be defined to represent each row of the constraints $\boldsymbol{\phi} \le \boldsymbol{\phi}_{ub}$ and $-\boldsymbol{\phi} \le -\boldsymbol{\phi}_{lb}$ as $[f_1(\boldsymbol{\phi}_k) \ldots f_m(\boldsymbol{\phi}_k)]^T \le [\sigma_1 \ldots \sigma_m]^T$. Further, based on these functions and variables, let us consider a function

$$\psi(\sigma_0) = \left\{\min_{\boldsymbol{\phi}_k} \max_{0\le i\le m} \left(\frac{f_i(\boldsymbol{\phi}_k)}{\sigma_i}\right)\right\} - 1 \qquad (7)$$

The inner maximization in (6) can then be solved by finding the root of $\psi(\sigma_0)$ [11], transforming (6) into a much simpler and computationally feasible unconstrained optimization problem

$$\widehat{\boldsymbol{u}}_C(k) = -\underset{\overline{\boldsymbol{u}}_C(k)}{argmax} \quad root\big(\psi(\sigma_0)\big) \qquad (8)$$

3. Results

The newly proposed control method is evaluated using SoV models describing the flow of product quality errors in a cylinder head machining process used by a US car manufacturer, and a lithography overlay process in a modern semiconductor fab.

3.1. Robust control of a Machining Process

The robust model-based process control algorithm introduced in this paper was tested in control of dimensional errors in machining of the automotive cylinder head shown in Figure 1. The process is described in Table 1, while details of the SoV model of the flow of dimensional errors in this process can be found in [9]. Measurements of all features machined after setup 2 are assumed to be available, while fixture parameters in setup 3 are assumed to be controllable. Measurements available after setup 2 and, if available, information about the tooling bias in setup 3 are then used to adapt controllable parameters in setup 3 to minimize the squared distance between the Slot (S) and Joint Face (JF) planes.

We randomly generated 100 trajectories of bias terms using 2nd order Kalman filter (KF) processes and within each of those simulations, we utilized a 1st order KF based R2R method [12] to track those bias terms. For each of the trajectories, the parametric uncertainties Δ were assumed to be within 1%, 5%, 10% and 20% of the corresponding nominal values. Concurrently, increasing levels of uncertainty were assumed on the plant and sensor noise terms, as well as the actuator uncertainty and uncontrollable process parameters, thus simulating situations with progressively less accurate model knowledge. All uncertainties and random parameters were simulated using various distributions and we report here only the results obtained using uniform distributions within the uncertainty bounds, though similar observations could be made for all simulations we performed (this is not surprising because, once again, unlike the past research, the approach proposed here does not depend on any distribution assumptions).

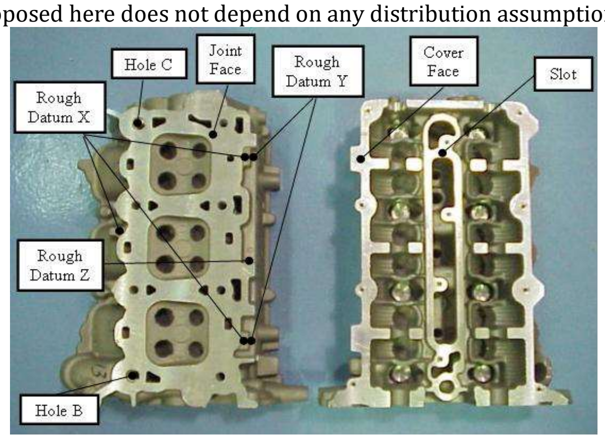

Figure 1. Automotive cylinder head machined in the process used to evaluate the newly proposed robust control approach.

Table 1 Process plan for machining process considered in Sec. 3.1.

	Locating surfaces	Operations
Setup 1	Primary: Raw Datum X_1, X_2 and X_3 Secondary: Raw Datum Y_1 and Y_2 Tertiary: Raw Datum Z_1	1. Mill the Cover Face CF.
Setup 2	Primary: Machined Cover Face CF Secondary: Raw Datum Y_1 and Y_2 Tertiary: Raw Datum Z_1	2. Mill the Joint Face J. 3. Drill the Hole B. 4. Drill the Hole C.
Setup 3	Primary: Machined Joint Face J Secondary: Machined Hole B Tertiary: Machined Hole C	5. Mill the Slot S.

For each of the uncertainty levels, the newly proposed controller (labeled as *Robust multistage controller*) was compared to the traditional KF-based R2R approach that just sets control commands to act opposite of the KF-based estimates of the bias term [12] (labeled as *KF R2R controller*), as well as the approach from [4], which combines the R2R bias estimates with a stochastic model-based controller that assumes NIID nature of all random terms, as well as perfect knowledge of all parameters (labeled as *KF R2R + stochastic multistage controller*). Figure 2 shows the distributions of worst-case outcomes for the distance between the JF and S planes, as observed over all simulations. It is clear that the newly proposed controller outperforms the controllers, with benefits increasing with increasing model uncertainties. Similar observations can be made from Figure 3, which shows the average controller performance obtained from the same simulations.

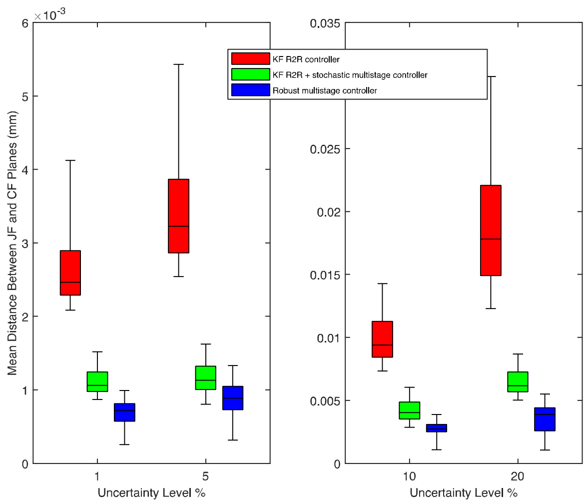

Figure 2. Box and whisker plots depicting distributions of the worst observed distance between the JF and S planes, as observed from the simulations containing increasing model uncertainties.

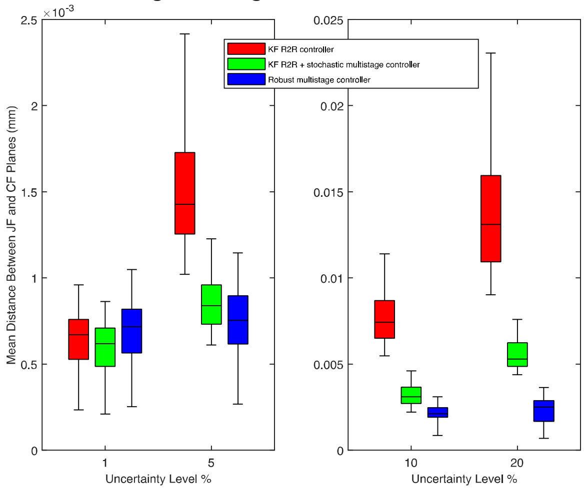

Figure 3. Box and whisker plots depicting distributions of the average of distances between the JF and S planes, as observed from the simulations containing increasing model uncertainties.

3.2. Robust control of Lithography Overlay Errors

The newly introduced process control was also evaluated in the control of overlay and stack up overlay errors in a 4-layer lithography process utilized in a major 300mm semiconductor factory. Overlay depicts alignment deviations between markers produced in strategic locations across a semiconductor wafer in order to control alignment of patterns in two neighboring layers of a microelectronic product. whose fabrication ultimately leads to production of microelectronic circuits. Similarly, stack-up overlay errors depict accumulation of overlay errors between non-neighboring layers and are defined as a vectorial sum of overlay errors between those two layers [4]. One must maintain angstrom level overlay accuracies over all of the marker points (100s of them), which are dispersed over a 300mm diameter wafer. It is therefore no surprise that controlling overlay and stack up overlay errors is the heart of the semiconductor fabrication process, demanding strictest guarantees of controller performance.

Overlay errors and process control data from 30 consecutive wafers were used to build the layer-level overlay error models and combine them into a multistage model describing the progression of stack-up overlay errors in the form (1), as well as to estimate the distributions of process and measurement noise terms. More details about the modeling procedure and the process can be found in [13], though numerous details had to be withheld even there due to the highly proprietary nature of the data and process. Control bias terms evaluated based on those first 30 wafers were used to initiate the R2R controller in the form of a 1st order KF, after which measurement and control data from the next 60 wafers were used to determine the trajectories of process bias terms, as well as the distributions of the bias/actuator uncertainties.

It was assumed that for each layer, measurements of its overlay errors, as well as stack-up overlay errors between that layer and the substrate (layer 0). Please note that in order not to reveal the highly proprietary relative importance of pattern layers in the process, this does not depict the actual measurements that were taken and that it is easy to consider some other weighted combinations of the overlay and stack-up overlay errors.

The newly proposed controller was then again compared to the KF R2R controller, as well as to the purely Bayesian controller from [4]. As in the machining case study, structural model uncertainties Δ were assumed to be within 1%, 5%, 10% and 20% of the corresponding nominal parameters. Concurrently, uncertainty bounds on the plant and sensor noise terms, as well as the actuator uncertainty and uncontrollable process parameters were scaled up by the same percentages, relative to the bounds observed in the data. All uncertainties and random parameters were simulated using various distributions and, again, we report only the results obtained using uniform distributions within the uncertainty bounds, though similar observations were made for all simulations we performed. Figure 4 and 5 respectively illustrate the distributions of worst-case outcomes and average outcomes for the resulting objective function for all 4 layers, as observed over all simulations. Again, it is clear that the newly proposed controller outperforms the other controllers, with benefits increasing with increasing levels of model uncertainties.

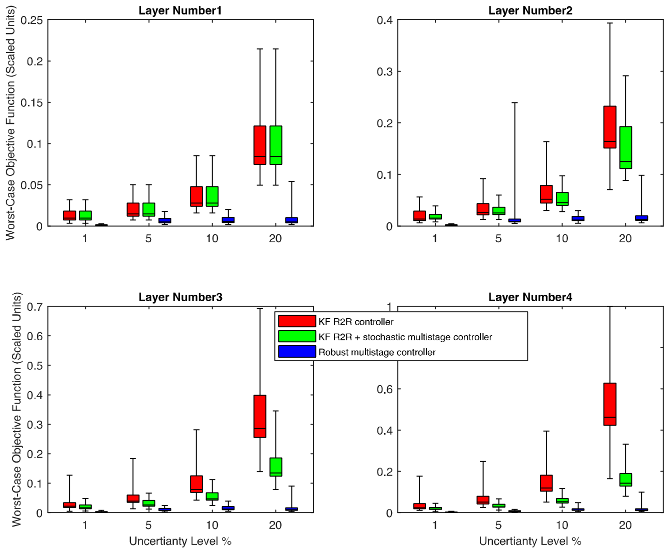

Figure 4. Box and whisker plots depicting distributions of the worst observed objective function values (sum of the scaled norm of the overlay and stack up overlay errors) for each of the 4 layers, as observed from the simulations containing increasing model uncertainties.

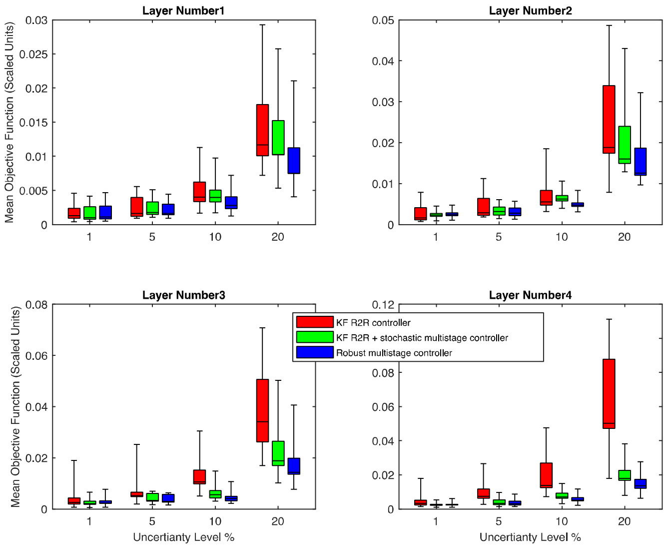

Figure 5. Box and whisker plots depicting distributions of the average observed objective function values (sum of the scaled norm of the overlay and stack up overlay errors) for each of the 4 layers, as observed from the simulations containing increasing model uncertainties.

5. Conclusions and future work

In this paper, we describe a new method for robust model-based control of quality in MMPs. The method utilizes models of the flow of quality errors in a manufacturing system, without the need to perfectly know the model parameters, nor any assumptions regarding the distributions or independence of noise terms in the model. Instead, all model parameters and noise terms are assumed to be unknown, but within certain known bounds, while the control task is formulated as a min-max optimization problem that optimizes the worst-case controller performance regarding all model uncertainties. Performance of the newly proposed method for control of quality in MMPs was evaluated using a series of simulations based on the models describing the flow of dimensional errors in an automotive cylinder head machining process, as well as overlay errors in a lithography process utilized by a modern 300mm semiconductor fab. The results illustrate clear benefits of the novel controller over the traditional R2R approaches and the purely Bayesian stochastic controllers, with benefits becoming more pronounced when with increasing uncertainties in the underlying error flow models.

As for future work, formulating a control law that is fully robust to model parametric uncertainties and noise characteristics was perhaps the key element that prevented model-based process control algorithms to gain wider acceptance in industry. Hence, research presented in this paper enables immediate industrial implementation that can now be pursued. As for further research extensions, one could link the research presented in this paper with the general problem of manufacturing systems design by exploring possibilities to strategically select measurements and controllable tooling capabilities that maximize one's ability to deliver robust control performance.

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