Nonlinear iterative learning control with applications to lithographic machinery

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Abstract

An experimental demonstration is given of (nonlinear) iterative learning control applied to a reticle stage of a lithographic wafer scanner. To limit the presence of noise in the learned forces, a nonlinear amplitude-dependent learning gain is proposed. With this gain, high-amplitude signal contents is separated from low-amplitude noise, the former being compensated by the learning algorithm. Contrary to the underlying linear design, the continuously varying trade-off between high-gain convergence rates and low-gain noise transmission demonstrates a significant improvement of the nonlinear design in achieving performance.

Keywords: Iterative learning control; Feedforward control; Lifted system approach; Lithographic machinery; Lyapunov theory; Nonlinear control

1. Introduction

In the past decades, the fabrication of integrated circuits has greatly benefited from improved lithographic technologies. Herein the control design of a reticle stage containing the patterns needed for illumination and a wafer stage containing the wafers to be illuminated is of major importance. In terms of feedback control, both reticle and wafer stages are controlled using PID-based control schemes on a single-input single-output basis. To obtain nano-scale position accuracy within less than milliseconds of settling time, the main part of the control effort, however, is induced by feedforward control.

In terms of feedforward, this paper considers iterative learning control (ILC) as a means to obtain zero settling times on a reticle stage in scanning direction; see, for example, Bien and Xu (1998), Moore and Xu (2000), Norrlöf (2000), and Xu and Tan (2003) for a thorough treatment of ILC, its design methods, and fields of usage. Roughly speaking, ILC refers to the iterative process of finding the learned commands needed to improve performance under repetitive motion using information from previous executions of such motion. In the lithographic field, the application of ILC is not new, see for example Rotariu, Ellenbroek, and Steinbuch (2003), Rotariu, Dijkstra, and Steinbuch (2004), Dijkstra (2004), but application on an industrial scale is not often seen. The main contribution of this paper, however, is the introduction of a nonlinear learning gain to continuously balance the trade-off between noise transmission/amplification and error convergence rates as a means to surpass linear control performance; all linear ILC techniques suffer to a certain extent from noise amplification—recurring disturbances are attenuated, nonrecurring are amplified; in this context, see Moore (1999) and Tayebi and Islam (2006). Under nonlinear learning, signal contents beyond a pre-defined threshold level is subjected to nonlinear weighting: larger signal levels correspond to larger learning gains. Below this level signals like small noises induce a zero learning gain and as such are excluded from the learning process.

Stability of the discrete-time nonlinear learning control is derived on the basis of Lyapunov theory, see also French...
and Rogers (2000) and Yakubovich, Leonov, and Gelig (2004), the latter for a recent contribution to this field. Herein a distinction is made between the nonperturbed case with no external inputs like noises and the perturbed case having such inputs. In both cases exponential convergence of the learning scheme is derived as long as the servo errors during subsequent iterations contain elements that exceed the pre-defined threshold level. Performance is expressed in terms of convergence as well as time-domain (settling) behavior. By adapting learning gains, rates of convergence are obtained at which the underlying linear learning schemes become unstable. In fact, nonlinear learning is shown to combine fast convergence with robust stability, see de Roover (1996), Gunnarsson and Norrlöf (2001), and Tousain and Van de Meché (2001) for linear approaches based on optimal control with a similar aim. Zero settling is demonstrated on an industrial reticle stage module. By itself, this significantly contributes in optimizing wafer throughput and, therefore, helps improving general performance of lithographic machinery.

The paper is organized as follows. First, the modelling, dynamics and control of a reticle stage are considered. Second, the ILC scheme is proposed including the introduction of the nonlinear gain filter and a motivation for nonlinear learning. Third, a Lyapunov-based stability and performance analysis is conducted with special focus on convergence and robustness properties. Fourth, an experimental demonstration in time-domain is given towards zero settling times on a reticle stage of an industrial wafer scanner. This paper is concluded with a summary of the main findings regarding nonlinear learning in the context of lithographic machinery.

2. Modelling, dynamics, and control of a reticle stage

In the manufacturing of integrated circuits (ICs) wafer scanners provide the means to achieve both position accuracy, resolution within 70 nm, and production speed: over hundred wafers an hour each wafer containing over hundred ICs. During the scanning process light from a laser passes a reticle through a lens and onto a silicon wafer. Both reticle and wafer are part of two separate motion controlled sub-systems: the reticle stage and the wafer stage. For reasons of presentation, further discussion is limited to the reticle stage module. However, there is no fundamental reason to exclude the presented results from being applied to the wafer stage module, see, for example, Dijkstra and Bosgra (2002) for an approach in this direction.

Having two key modules, the long-stroke for fast positioning and the short-stroke for achieving position accuracy, see Fig. 1, the reticle stage mainly performs repetitive (scanning) motion in the indicated y-direction. Scanning refers to motion under constant velocity (typically 2.4 ms⁻¹) at which the process of wafer exposure takes place. It is performed in both the positive and negative direction within an effective stroke of 0.3 m. The short-stroke module—the long-stroke merely follows the short-stroke and as such is less relevant in the context of this paper—contains the reticle, a quartz object with a pattern of transparent and nontransparent regions; its terminology stems from retina being a light sensitive layer in the eyeball. It is controlled in six degrees-of-freedom on a single-input–single-output basis, see van de Wal, van Baars, Sperling, and Bosgra (2002) for a multi-input multi-output approach.

A simplified representation of the position tracking control scheme of the short-stroke reticle stage module in scanning direction is depicted in Fig. 2. On the basis of a reference signal $r$, an error signal $e_y$ is constructed using the relation $e_y = r - y$ with $y$ the position of the considered electro-mechanics given by $P$. The error signal $e_y$ is fed into a controller $C$ after which two signals are added: $f_{ff}$ representing a simplified (inertial) feedforward signal based on $s$ the Laplace variable) of a simplified position tracking control scheme for the short-stroke reticle stage module in scanning direction.

![Fig. 1. Long-stroke (left) and short-stroke (right) reticle stage modules of an industrial wafer scanner: (a) long-stroke reticle stage module, (b) short-stroke reticle stage module.](image)

![Fig. 2. Block-diagram representation (with $s$ the Laplace variable) of a simplified position tracking control scheme for the short-stroke reticle stage module in scanning direction.](image)
on the estimated module’s mass \( m \) and \( f_{\text{ilc}} \) representing a learned force.

The controller \( C \) is based on a series connection of a PID-filter extended with loop-shaping filters. A continuous-time model in frequency–domain representation is given by the transfer function
\[
C(s) = \text{PID}(s)L\text{P}(s)N_1(s)N_2(s),
\]
with
\[
\text{PID}(s) = \frac{k_p(s^2 + \omega_d s + \omega_n \omega_d)}{\omega_d s},
\]
\( \omega_1 \approx 5.02 \times 10^2 \text{ rad s}^{-1} \) the cut-off frequency of the integral action, \( \omega_d \approx 8.86 \times 10^2 \text{ rad s}^{-1} \) the cut-off frequency of the differential action, and \( k_p = 1.48 \times 10^7 \text{ Nm}^{-1} \) the loop gain,
\[
\text{LP}(s) = \frac{\omega_p^2}{s^2 + 2\beta \omega_p s + \omega_p^2},
\]
\( \omega_p \approx 1.57 \times 10^4 \text{ rad s}^{-1} \) the cut-off frequency of a second-order low-pass filter, \( \beta \approx 0.7 \) its dimensionless damping coefficient,
\[
N_1(s) = \frac{s^2 + 2\beta_1 \omega_n s + \omega_n^2}{s^2 + 2\beta_2 \omega_n s + \omega_n^2},
\]
\( \omega_n,1 \approx 3.49 \times 10^3 \text{ rad s}^{-1} \) the cut-off frequency of a first notch filter, \( \beta_1 = 0.01 \) the dimensionless damping coefficient of the numerator, and \( \beta_2 = 0.05 \) the dimensionless damping coefficient of the denominator,
\[
N_2(s) = \left( \frac{\omega_n,3}{\omega_n,2} \right)^2 \cdot \frac{s^2 + 2\beta_3 \omega_n,2 s + \omega_n,2^2}{s^2 + 2\beta_4 \omega_n,3 s + \omega_n,3^2},
\]
\( \omega_n,2 \approx 1.32 \times 10^4 \text{ rad s}^{-1} \) and \( \omega_n,3 \approx 5.65 \times 10^4 \text{ rad s}^{-1} \) both cut-off frequencies of a second notch filter, \( \beta_3 = 0.01 \) the dimensionless damping coefficient of the numerator, and \( \beta_4 = 0.27 \) the dimensionless damping coefficient of the denominator. Given a sampling frequency of \( f_s = 5 \text{ kHz} \), a discrete-time version of this controller is considered for implementation.

The short-stroke electro-mechanics are represented by the following model:
\[
P(s) = \frac{1}{ms^2} \exp(-s/f_s),
\]
i.e., a double integrator-based plant with \( m \approx 13 \text{ kg} \) in series connection with a one-sample time delay. The validity of this model is shown in Fig. 3 which shows both measured and simulated frequency response functions.

Below 30 Hz, a poor measurement quality induces a poor correspondence between actual process and model; all measurements are done under closed-loop conditions. Beyond 2 kHz, higher-order dynamics no longer justify the model assumptions.

The feedback controlled dynamics in scanning direction are characterized by the open-loop frequency response functions such as depicted in Fig. 4. Both measured and simulated, it can be seen that a bandwidth is obtained of 230 Hz along with a phase margin of 49° and a gain margin of -4.5 dB. This leads to the conclusion that the closed-loop system is robustly stable.

In opposition to stability, closed-loop performance is largely obtained under feedforward control. But the feedforward forces—\( f_{\text{ff}} \) in Fig. 2—are obtained via a model-based (and therefore approximative) relation rather than the actual inverse process relation. To compensate for this approximation, learning is introduced. Through learning, the forces \( f_{\text{ilc}} \) are derived, needed to counteract the remaining (and recurring) part in the servo error \( e_y \).
The latter being the result of repeated reticle stage scanning motion.

3. A nonlinear ILC

Introduced in the early eighties ILC aims at improved servo performance by reducing the recurrent part of the servo error under repetitive motion, see Moore (1998) and Bristow, Tharayil, and Alleyne (2006) for an overview. Herein the error signals obtained at past iterations are reduced at current iterations by applying updated learned forces. This is done via an estimated inverse process relation which can be obtained in time-domain from finite impulse response modelling and which in this case is referred to as the lifted system description (Bamieh, Boyd, Francis, & Tannenbaum, 1991; Phan & Longman, 1988). In this section, first, a nonlinear learning scheme is presented in such a lifted system description, second, a motivation is given for incorporating nonlinearity in this scheme, and third, update laws are presented needed to study its stability.

In the lifted system description, the nonlinear learning scheme is represented in block diagram representation in Fig. 5. A key role is given to the closed-loop process sensitivity matrix $S_p \in \mathbb{R}^{n \times n}$ (with $n > 0$ a positive number of samples), or

\[
S_p = \begin{bmatrix}
    h_1 & 0 & \ldots & 0 \\
    h_2 & h_1 & \ldots & 0 \\
    \vdots & \vdots & \ddots & \vdots \\
    h_n & h_{n-1} & \ldots & h_1
\end{bmatrix}
\]  

Fig. 5. Block-diagram representation in trial-domain of the nonlinear iterative learning control of the short-stroke reticle stage in scanning direction.

which has a Toeplitz structure with $h_1, h_2, \ldots, h_n$ the Markov parameters; $h_1$ represents the first error response sample to a unitary force impulse. This matrix acts as a filter operation on the $n$-sample colon of learned control forces $f_{ilc}(k) \in \mathbb{R}^{n \times 1}$ (with $k \in \mathbb{Z}^+$ expressing the $k$th iteration or trial) and aims at counteracting the effect of disturbances $d(k) \in \mathbb{R}^{n \times 1}$ on the error colon $e_y(k) \in \mathbb{R}^{n \times 1}$. $S_p$ is closely related to the process sensitivity function, i.e., the transfer between the closed-loop error $e_y$ and the reference input $r$, see also Fig. 2. The disturbances are modelled by a trial-independent part which is assumed to contain random entries taken from a uniform distribution along with a trial-dependent part containing the trial-invariant mismatch in feedforward compensation between the model and the actual short-stroke reticle stage process; note that $d(k)$ acts through the closed-loop sensitivity matrix $S \in \mathbb{R}^{n \times n}$ which has a similar Toeplitz structure as $S_p$ and which is related to the sensitivity function, i.e., the transfer between the closed-loop error $e_y$ and the reference input $r$, see also Fig. 2. The closed-loop process sensitivity matrix $S_p$ is preceded by a memory loop where $z^{-1}$ expresses a one-trial time delay and $I \in \mathbb{R}^{n \times n}$ represents a unitary

Fig. 4. Open-loop frequency response functions in Bode representation of the controlled short-stroke reticle stage dynamics in scanning direction.
matrix. Both memory loop and nonlinear gain operation
\[ L(e_i(k)) = Lφ(e_i(k)) \]
form the core of the learning scheme; without loss of generality, it should be noted that standard (robustness) Q-filters, see for example Tomizuka, Tsao, and Chew (1989), are excluded from presentation. \( L \in \mathbb{R}^{n \times n} \)
represents the linear gain part and is given by
\[ L = (S_p \Sigma_p + λI)^{-1}S_p^T, \]  
(8)
with tuning parameter \( λ > 0 \), see Ghosh and Paden (2002). Σ is chosen as small as possible (without causing stability problems) such that \( L \) approximates the inverse process sensitivity matrix \( S_p \). The nonlinear gain part is given by
\[ \Phi(e_i(k)) \in \mathbb{R}^{n \times n}, \]
\[ \Phi(e_i(k)) = \text{diag}(\phi(e_i(k))[1]), \]
\[ \phi(e_i(k))[2], \ldots, \phi(e_i(k)[n])) \geq 0, \]  
(9)
with
\[ φ(x) = \begin{cases} 
1 - \frac{δ}{|x|} & \text{if } |x| > δ, \\
0 & \text{if } |x| \leq δ. 
\end{cases} \]  
(10)
Accordingly all entries in \( e_i(k) \) that are bounded in absolute value by a threshold level \( δ \geq 0 \) are assumed to be noise contributions and as such are not subjected to learning; see also Fig. 6. Contributions which in absolute value exceed this level are subjected to learning but in a nonproportional sense. It should be mentioned that the choice for variable gains is exemplary and not restrictive regarding other choices.

A motivation for the application of the proposed learning strategy is depicted in Fig. 7. It shows the results of a linear learning control \( (\Phi = I) \) applied at the short-stroke reticle stage module in scanning direction for three different tuning parameter values: \( λ \in \{10^{-16}, 10^{-15}, 10^{-14}\} \). For \( λ = 10^{-16} \) (this induces the largest learning gain) it can be seen that the induced 2-norm of the error colon \( e_i(k) \) quickly reduces in the initial trials but then appears unstable. Similarly \( λ = 10^{-15} \) induces unstable behavior which is expressed after a larger number of trials. Only for \( λ = 10^{-14} \) (this induces the smallest learning gain) the design appears stable at the considered trial interval. To avoid the expression of unstable behavior, observe that an initial large learning gain—inducing fast initial error convergence—should be reduced along the iteration process. This is the purpose of the nonlinear learning control such as demonstrated by the curve denoted with \( Φ = Φ(e_i(k)) \), see (9) with \( δ = 5 \) nm.

For \( λ = 10^{-15} \), the nonlinear learning control combines fast initial error convergence under ‘large-gain’ learning with sufficient robustness against model uncertainty—during further trials—under ‘small-gain’ learning.

Stability of the learning scheme in Fig. 5 can be studied using the following update laws:
\[ f_{ik}(k+1) = (I - L(e_i(k))S_p) f_{ik}(k) + L(e_i(k))Sd(k), \]
\[ k \in \mathbb{Z}, \]  
(11)
in terms of learned forces, and
\[ e_i(k+1) = (I - S_pL(e_i(k)))e_i(k) + Sd(k+1) - Sd(k), \]
\[ k \in \mathbb{Z}, \]  
(12)
in terms of errors. Given the properties of \( Φ(e_i(k)) \) and \( d(k) \), it will be shown that stability of both update laws boils down to satisfying \( ||LS_p||_2 = ||S_pL||_2 \leq 1 \) with \( ||L||_2 \) the induced matrix norm. That is, stability is determined by the underlying linear filter properties and cannot be deteriorated by the introduction of the nonlinear weighting \( Φ(e_i(k)) \), a result which is derived on the basis of Lyapunov theory.

4. Lyapunov stability

Lyapunov stability of the nonlinear learning control given by (11) and (12) is assessed either in the absence of input, the nonperturbed case, or in the presence of a uniformly bounded input representing noises, the perturbed case. In both cases, the same Lyapunov function candidate is used to guarantee stability. In fact, stability of the perturbed case is based on the results obtained with the nonperturbed case. Under perturbation, upper- and lower bound estimates are derived on the number of iterations needed to converge to a ball of fixed radius about zero error whereas variable robustness margins (induced by the nonlinear learning gains) are discussed.

The considered Lyapunov function candidate is given by
\[ V(k) = (e_i(k) - Sd(k))^T(e_i(k) - Sd(k)) > 0, \]
\[ k \in \mathbb{Z}. \]  
(13)
This function is positive definite for any \( ||e_i(k)||_{\mathbb{R}} \geq B \) where \( ||e_i(k)||_{\mathbb{R}} \) represents the smallest element in \( e_i(k) \) that exceeds (in absolute value) the bound \( B = e_1 δ \). \( δ \) approximates the threshold level \( δ \), see (10), because \( e_1 \) can be chosen arbitrarily close to one. Substitution of (12) in (13) gives the following incremental change:
\[ V(k+1) - V(k) = -e_i^T(k)A(e_i(k))e_i(k) \]
\[ -e_i^T(k)A^T(e_i(k))e_i(k) \]
\[ + e_i^T(k)A^T(e_i(k))A(e_i(k))e_i(k) \]
\[ + 2d^T(k)S^T A(e_i(k))e_i(k), \]
\[ k \in \mathbb{Z}, \]  
(14)
\[ \text{The induced 2-norm for matrices is given by } \|X\|_2 = \sqrt{\max\{\text{eig}[X^TX]\}}. \]
with \( A(e_i(k)) = S_pL(e_i(k)) \) satisfying
\[
0 \leq x^TA(e_i(k))x \leq x^TSP_Lx \quad \forall \|x\| > 0, \; k \in \mathbb{Z}^+.
\] (15)

For the nonperturbed system, i.e., with \( d(k) = 0 \), this incremental change is negative definite by satisfying two conditions: \( \|A(e_i(k))\|_2 \leq 1 \), and \( |e_i(k)|_{\mathcal{A}} \geq \mathcal{B} \). The first condition implies
\[
\|A^T(e_i(k))A(e_i(k))\|_2 \leq \|A^T(e_i(k))\|_2 \leq \|A(e_i(k))\|_2
\]
(16)
and therefore relates to the upper bound
\[
V(k + 1) - V(k) \leq -\varepsilon_3 \|e_i(k)\|^2 \quad \forall \|e_i(k)\|_{\mathcal{A}} \geq \mathcal{B}, \; k \in \mathbb{Z}^+,
\] (17)
The second condition assures that \( \|A(e_i(k))\|_2 > 0 \), because it implies the existence of at least one element \( e_i(k) \) in \( S_p(k,i\ldots n f_{ik}(k) \in \mathbb{R}^{1 \times 1} \) in \( e_i(k) \) that exceeds the threshold level \( \Delta \). Under these conditions, (17) can be written as
\[
V(k + 1) - V(k) \leq -\varepsilon_3 \|e_i(k)\|^2 \quad \forall \|e_i(k)\|_{\mathcal{A}} \geq \mathcal{B}, \; k \in \mathbb{Z}^+,
\] (18)
with \( \varepsilon_3 > 0 \), see the appendix. Substitution of \( V(k) = \|e_i(k)\|^2 = \|S_p f_{ik}(k)\|^2 \) gives
\[
\|S_p f_{ik}(k)\| \leq \sqrt{(1 - \varepsilon_3)k^{-1}} \|S_p f_{ik}(1)\| \quad \forall \|e_i(k)\|_{\mathcal{A}} \geq \mathcal{B}, \; k \in \mathbb{Z}^+,
\] (19)
or
\[
\|e_i(k)\| \leq \sqrt{(1 - \varepsilon_3)k^{-1}} \|e_i(1)\| \quad \forall \|e_i(k)\|_{\mathcal{A}} \geq \mathcal{B}, \; k \in \mathbb{Z}^+,
\] (20)
demonstrating convergence of the nonperturbed system.

For the perturbed system (with \( V'(k) = \|e_i(k) - Sd(k)\|^2 = \|S_p f_{ik}(k)\|^2 \) where \( \|Sd(k)\| > 0 \) and \( Sd(k) \) is assumed to satisfy the uniform bound \( \|Sd(k)\|_{\mathcal{A}} \leq \Delta / 2 \) for each element \( i \) contained in \( Sd() \)), it follows (using (18)) that
\[
V(k + 1) - V(k) \leq -\varepsilon_3 \left( 1 - \frac{1}{\varepsilon_3} \right) \|e_i(k)\|^2 - \frac{\varepsilon_3}{\varepsilon_1} \|e_i(k)\|^2
\]
\[
+ \delta_1 |e_i(k)|_{\mathcal{A}} + \cdots + |e_i(k)|_{\mathcal{A}} \quad \forall \|e_i(k)\|_{\mathcal{A}} \geq \mathcal{B}, \; k \in \mathbb{Z}^+,
\] (21)
where \( |e_i(k)|_{\mathcal{A}} \) represents the \( j \)th element (\( j + 1 \leq n \)) contained in \( e_i(k) \) for which holds \( |e_i(k)\|_{\mathcal{A}} \geq \cdots \geq |e_i(k)\|_{\mathcal{A}} \) with \( j \in \mathbb{Z}^+ \). Herein \( |e_i(k)|_{\mathcal{A}} \geq |Sd(k)|_{\mathcal{A}} \) for all \( i \) satisfying \( |e_i(k)\|_{\mathcal{A}} \geq |e_i(k)\|_{\mathcal{A}} \). Since
\[
\frac{3}{2} \|e_i(k)\|^2 \leq \frac{3}{2} |e_i(k)|_{\mathcal{A}} \geq \max \|S_p f_{ik}(k)\|
\]
(22)
it also follows that
\[
V(k + 1) - V(k) \leq -\varepsilon_3 \left( 1 - \frac{1}{\varepsilon_3} \right) \|e_i(k)\|^2
\]
\[
\|e_i(k)\|_{\mathcal{A}} \geq \mathcal{B}, \; k \in \mathbb{Z}^+.
\] (23)
This gives the following convergence property:
\[
\|S_p f_{ik}(k)\| \leq \sqrt{(1 - \varepsilon_3)k^{-1}} \|S_p f_{ik}(1)\| \quad \forall \|e_i(k)\|_{\mathcal{A}} \geq \mathcal{B}, \; k \in \mathbb{Z}^+.
\] (24)
Using (22) together with the fact that
\[
\frac{1}{2\sqrt{n}} \|e_i(k)\| \leq \frac{1}{2} |e_i(k)|_{\mathcal{A}} \leq \max \|S_p f_{ik}(k)\|
\]
(25)
it is derived that
\[
\|e_i(k)\| \leq 3n \sqrt{(1 - \varepsilon_3)k^{-1}} \|e_i(1)\| \quad \forall \|e_i(k)\|_{\mathcal{A}} \geq \mathcal{B}, \; k \in \mathbb{Z}^+.
\] (26)
thus showing convergence for the perturbed system. Regarding the previous analysis, three remarks are of particular interest.

First, it should be noted that the Lyapunov function $V(k)$ in (13) becomes positive semi-definite for $|e_r(k)|_d \leq \delta$. Any further decrease of $V(k)$ is then initiated by those noise contributions contained in $d(k)$ that lift the remaining recurring contributions contained in $e_r(k)$ beyond the threshold level $\delta$. A process that is continued until $e_r(k)$ no longer contains recurring contributions that exceed $\delta/2$, in which case the nonlinear learning gain matrix becomes $L(e_r(k)) = 0$, and which subsequently gives $f_{ik}(k + 1) - f_{ik}(k) = 0$ and $e_r(k + 1) - e_r(k) = Sd(k + 1) - Sd(k)$. This shows that the learned forces are fully converged whereas the one-trial difference in error merely contains contributions that do not exceed $\delta$.

Second, the stability result (26) can be related to upper- and lower bound estimates on the number of iterations needed to enter a ball of radius $\beta$ about zero error, thus to converge arbitrarily close to the threshold level $\delta$. This is because the error $|e_r(k)|_d$ is enclosed by a constant and two functions that decrease exponentially, see Fig. 8 for a graphical interpretation. As a result, any finite $|e_r(1)|$ with $|e_r(1)|_d > \beta$ crosses $|e_r(k)|_d = \beta$ in a finite number of iterations $k = m \geq 1$ with $m \in \mathbb{Z}^+$ an upper bound estimate. A lower bound can be found at $k = l$ where $l \in \mathbb{Z}^+$ represents the minimum number of iterations after which $|e_r(k)|_d/\sqrt{n}$ crosses $\beta$.

Third, stability is obtained under the assumption that $\|S_pL\|_2 \leq 1$. So the nonlinear learning control is bounded-input bounded-output stable as long as the eigenvalues of $S_pL$ are located in the interior of the unitary circle, see Fig. 9. The nonlinear gains induce a variable robustness margin relative to these eigenvalues. Namely elements in $e_r(k)$ that do not significantly exceed the threshold level $\delta$ (these elements are considered as noise contributions) impose large margins, because

$$\Phi(e_r(k)) \rightarrow 0 \quad \text{and} \quad \|A(e_r(k))\|_2 \rightarrow 0, \ k \in \mathbb{Z}^+. \quad (27)$$

For elements in $e_r(k)$ that sufficiently exceed the threshold level $\delta$ and as such contain relevant signal contents, these margins diminish

$$\Phi(e_r(k)) \rightarrow I \quad \text{and} \quad \|A(e_r(k))\|_2 \rightarrow \|S_pL\|_2, \ k \in \mathbb{Z}^+. \quad (28)$$

At this point in the analysis, let us return to the reticle stage system and study the effect of the stability properties in achieving performance.

5. Performance assessment on a short-stroke reticle stage

Performance of the nonlinear learning control applied to a short-stroke reticle stage module (see Section 2) is assessed as follows. Prior to learning, the performance-limiting effect of settling times is addressed. This is accompanied by a short analysis on recurring versus nonrecurring signal contributions, the latter providing an estimate for the threshold level used in the variable learning gain operation. Similarly an impulse response analysis is conducted which provides the basis for computing learned forces. After learning, the nonlinear design demonstrates the ability of achieving zero settling times while avoiding the unnecessary injection of noise through the learned forces. Convergence of both the learned forces as well as the servo errors is demonstrated along with the learning gain variation across the considered trial interval, the latter being characteristic of the nonlinear learning design.

In lithographic machinery, settling times are an important measure to quantify performance in terms of wafer throughput. For the considered short-stroke reticle stage module, the effect of settling behavior is shown in Fig. 10. Given a representative nonsmooth acceleration profile, which—in scaled form—is depicted in the upper part of the figure, the servo error signal in scanning direction shows large excursions during the nonsmooth changes of this acceleration profile. In the interval where performance should be achieved—in between the acceleration hubs—this induces an undesired (settling) time needed for the error to become sufficiently small and subsequently delays the process of wafer exposure. This is the indicated interval. The reproducibility of the settling phenomenon is shown in the lower part of the figure. By comparing 20
separately measured error traces obtained under equal reference input, it can be seen that a residual error remains of about $\pm 5 \text{ nm}$. As a result, the nonrecurring part of the servo error signal does not obstruct a potential improvement in error reduction when dealing with the recurring part ($\pm 50 \text{ nm}$) through learning.

An essential feature of the learning control is the process sensitivity matrix $S_p$, see Fig. 5, which is based on impulse response measurement. For the considered reticle stage module, an impulse response analysis is shown in Fig. 11 where an averaged response is obtained by subjecting the controlled dynamics to a $100 \text{ N}$ force impulse and subsequently computing the mean of 50 individual responses. By comparing the level of the averaged response ($\approx 13 \text{ nm/N}$) in the left part with the nonrecurring parts of each of the individual responses, this is the right part of the figure, it is concluded that the measurements combine a good signal-to-noise ratio with an accurate description of the dynamics involved.

Based on impulse response analysis, the nonlinear learning control is applied to the reticle stage system with the aim of achieving zero settling times without transmitting too much noise through the learned forces. The result of this is shown in Fig. 12. For the nonlinear filter setting with $\delta = 5 \text{ nm}$ (this setting is based on the nonrecurring error contributions in the lower part of Fig. 10), it can be seen that the servo error in scanning direction (black) after hundred trials roughly remains below the threshold level $\delta$. By itself, this gives a significant improvement in servo performance in comparison with the error before learning (gray). Practically speaking, the settling behavior in the indicated interval reduces to zero. Herein the amplification of noises through learning is kept small, especially in the interval where performance should be achieved, i.e., in between the acceleration hubs. This is expressed by the noiseless learned forces in the lower part of the figure which tend to zero at those error contributions that remain below the threshold level during the iteration process.

Convergence of both the learned forces and the servo errors is shown in Fig. 13. For two different designs with tuning parameter $\lambda \in \{10^{-15}, 10^{-14}\}$ it can be seen that both the learned forces (left part) and the servo errors (right part) convergence. In this evaluation either the induced 2-norm (upper part) or the induced $\infty$-norm (lower part) are considered. For the learned forces, it can be seen that the
system is not fully converged at the end of the trial interval. In terms of servo errors, it can be seen that this convergence is nonmonotonic; see also Moore, Chen, and Bahl (2005) for a monotonic convergence approach. For the induced $1$-norm, this is not surprising given the fact that convergence in (26) is based on a weighted sum of the entire error colon $e_y(k)$ instead of a single maximum absolute value, see also Fig. 8. For the induced 2-norm, it is concluded that there is room for nonmonotonicity given the fact that (26) gives an upper-bound on convergence.

The effectiveness of the nonlinear learning control mainly relates to the usage of variable gains. The degree of variability of these gains is shown in Fig. 14. By depicting the largest singular value using the previously considered measured data along the trial interval, it can be seen that the learning gains decrease for an increased number of trials (or decreased values of the servo error $k e_y(k)$). Fig. 14 also shows the largest singular values of the linear part of the learning gain matrix $L(e_y(k))$, see the dotted lines. These fixed values act as upper bounds on the

Fig. 12. Time-series measurement of the servo error signals in scanning direction before (gray) and after (black) learning (100 trials) along with the learned force signal; $\lambda = 10^{-15}$ and $\delta = 5$ nm.

Fig. 13. Time-series measurement demonstrating (nonmonotonic) convergence of both the learned forces and the servo errors in scanning direction; $\lambda \in \{10^{-15}, 10^{-14}\}$ and $\delta = 5$ nm.
attainable gains. In achieving performance, see Fig. 7, it can be seen that the nonlinear learning control realizes quick initial error reduction under large learning gains but, at the same time, creates robustness along later trials by residing to smaller learning gains.

6. Conclusions

To improve performance of lithographic machinery in terms of wafer throughput, this paper aims at zero settling times under nonlinear learning control. Having a variable learning gain, the fixed trade-off between error convergence rates and noise transmission/amplification such as present in linear learning schemes is avoided. As a result fast convergence can be combined with limited noise amplification. This is because the error is quickly reduced (under high gain) towards a pre-defined threshold level. Below this level, signals are no longer subjected to learning (the gain becomes zero) and, therefore, can neither be transmitted nor amplified through the learned forces.

Stability of the nonlinear learning control is studied using Lyapunov analysis. With a single Lyapunov function candidate both the nonperturbed case (with no external inputs) as well as the perturbed case (with external inputs containing uniformly bounded noises) are shown to possess convergence properties. This relates to upper- and lower bounds on the number of trials needed to convergence to a fixed error level, but also to additional robustness to model uncertainty induced by the variable learning gains.

The nonlinear learning scheme demonstrates the ability of achieving zero settling times on an industrial short-stroke reticle stage module; the error signals in the settling region can no longer be distinguished from the remaining signals below the pre-defined threshold level. Learning therefore gives a significant improvement in performance as compared to the current PID-based feedback/feedforward control design. For both the learned forces and the servo error signals (nonmonotonic) convergence is demonstrated on a limited trial interval. The corresponding learning gain variation provides the basis for having a quick initial error reduction under large learning gains combined with sufficient robustness properties at further trials under smaller gains.

Appendix A

The validity of (18) is constructed as follows. For any element $e_r(k)(i) = -S_p[i, 1 \ldots n]f_{ik}(k) \in \mathbb{R}^{1 \times 1}$ in $e_r(k)$ that exceeds $\beta = \varepsilon_1 \delta$, it can be verified (at the lower bound, $|e_r(k)(i)| = \varepsilon_1 \delta$) that

$$-\phi(e_r(k)(i))e_r(k)(i) + S_p[i, 1 \ldots n]e_r(k) \\
= \frac{\delta}{\varepsilon_1} e_r(k) L_1[n, i] S_p[i, 1 \ldots n] e_r(k)$$

$$\geq -e_r(k) L_1[n, i] S_p[i, 1 \ldots n] e_r(k)$$

$$\geq -e_r(k) \Lambda e_r(k)$$

$\forall |e_r(k)|_2 \geq \beta$, $k \in \mathbb{Z}^+$. (29)

Herein the matrix $\{L[n, i] S_p[i, 1 \ldots n]\}$ can be decomposed via

$$L[n, i] S_p[i, 1 \ldots n] = (S_p^T S_p + \lambda I)^{-1} S_p^T[i, 1 \ldots n] S_p[i, 1 \ldots n]$$

with $\Lambda \in \mathbb{R}^{n \times n}$ and $\Lambda^* \in \mathbb{R}^{n \times n}$ the eigenvalue matrices. Moreover for a positive constant $\varepsilon_2 = 1/\langle\langle S_p^T S_p\rangle_2 + \lambda\rangle > 0$, it holds true that

$$x^T S_p^T S_p x \leq \|S_p^T S_p\|_2^2 x^T x = \left(\frac{1}{\varepsilon_2} - \varepsilon_2\right) x^T x$$

$\forall \|x\| > 0$, (31)

which gives

$$x^T (S_p^T S_p + \lambda I)^{-1} x \geq \varepsilon_2 x^T x$$

$\forall \|x\| > 0$. (32)

Substitution of (30) in (32) shows that

$$\varepsilon_2 x^T \Xi^T \Lambda^* \Xi x \leq \varepsilon_2 x^T S_p^T[i, 1 \ldots n] S_p[i, 1 \ldots n] x$$

$$\leq x^T L[n, i] S_p[i, 1 \ldots n] x$$

$\forall \|x\| > 0$. (33)

which substituted in (29) gives

$$-e_r(k)(i) \Lambda e_r(k)$$

$$\leq -\left(\frac{\delta}{\varepsilon_1} \varepsilon_2 e_r(k) S_p^T[i, 1 \ldots n] S_p[i, 1 \ldots n] e_r(k)$$

$$\leq -\varepsilon_3 |e_r(k)|_2^2$$

$\forall |e_r(k)|_2 \geq \beta$, $k \in \mathbb{Z}^+$. (34)
Herein the positive constant $0 < \epsilon_3 < 1$ is defined as

$$\epsilon_3 = \frac{\epsilon_1 - 1}{\epsilon_1} \left[ \frac{\rho_{\min}}{\| S_p^T S_p \|_2 + \epsilon} \right]_{0 < \cdots < 1}, \quad (35)$$

with $\rho_{\min}$ being the smallest nonzero eigenvalue of $S_p^T S_p$.

References


