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DOI
10.1016/j.ifacol.2023.10.1078

Publication date
2023

Document Version
Final published version

Published in
IFAC-PapersOnLine

Citation (APA)
Poot, M., van Hulst, J., Yan, K. W., Kostic, D., Portegies, J., & Oomen, T. (2023). Feedforward Control in the Presence of Input Nonlinearities: With Application to a Wirebonder. *IFAC-PapersOnLine*, *56*(2), 1895-1900. https://doi.org/10.1016/j.ifacol.2023.10.1078

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IFAC PapersOnLine 56-2 (2023) 1895–1900

Feedforward Control in the Presence of Input Nonlinearities: With Application to a Wirebonder ⋆

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Abstract: The increasing demands on throughput and accuracy of semiconductor manufacturing equipment necessitates accurate feedforward motion control that includes compensation of input nonlinearities. The aim of this paper is to develop a data-driven feedforward approach consisting of a Wiener feedforward, i.e., linear parameterization with an output nonlinearity, to achieve high tracking accuracy and task flexibility for a class of Hammerstein systems. The developed approach exploits iterative learning control to learn a feedforward signal from data that minimizes the error and utilizes a control-relevant cost function to learn the parameters of a Wiener feedforward parameterization. Experimental validation on a wirebonder shows that the developed approach enables high tracking accuracy and task flexibility.

Keywords: Iterative and repetitive learning control, Identification and control methods, Nonlinear system identification, Data-driven control, Learning for control.

1. INTRODUCTION

The increasing demands on throughput and accuracy of semiconductor manufacturing equipment necessitates accurate feedforward motion control (Fleming and Leang, 2014). An example of such a semiconductor manufacturing machine is a wirebonder, which bonds small wires between the integrated circuit and a die with micrometer precision. Besides the stringent requirements on high manufacturing throughput and micrometer accuracy, flexibility in the motion tasks need to be attained (Boeren et al., 2016), posing challenges on feedforward control. Moreover, nonlinear effects, such as input nonlinearities, changing environments, and machine-to-machine differences pose challenges for the control methodology. Data-driven feedforward tuning methods are envisaged to deal with these requirements and challenges through machine-specific calibration procedures and compensation of nonlinear effects.

Data-based feedforward tuning methods, such as iterative learning control (ILC), enable learning of feedforward signals to achieve high motion accuracy. In ILC, feedforward signals are iteratively learned from data using a linear model of the system for repeating motion tasks, enabling compensation of repetitive disturbances, including repetitive nonlinear effects. To achieve task flexibility, i.e., changes in the motion task, basis functions are introduced, see, e.g., (van de Wijdeven and Bosgra, 2010). In ILC with basis functions (ILC BF), the feedforward signal is parameterized by basis functions as a function of the motion task, enabling task flexibility. These basis functions constitutes the approximate inverse model of the system, necessitating proper selection of these to obtain high tracking accuracy and task flexibility. In (van der Meulen et al., 2008), polynomial functions of the motion tasks are included, resulting in a linear parameterization of the feedforward signal and allowing inclusion of nonlinear basis functions, e.g., Coulomb friction. In (Poot et al., 2021), the linear parameterization is extended with a high-order noncausal FIR parameterization while maintaining the possibility of prescribing nonlinear basis functions, enabling higher tracking performance. In (Bolder and Oomen, 2015), the FIR parameterization is extended to a rational parameterization, allowing better representation of the inverse system by learning both poles and zeros of the feedforward filter. These learning methods enable high performance for systems that are approximated well by a linear system.

To achieve high performance for nonlinear systems, extensions are necessary as linear parameterization are often insufficient to describe the nonlinear dynamics, which is particular the case for systems with input nonlinearities, e.g., magnetic saturation in linear actuators (Polinder, 2002). These types of systems often exhibit predominantly linear dynamics with a static input nonlinearity, i.e., these systems can be accurately described by Hammerstein systems. A variety of model structures are developed for Wiener and Hammerstein systems, including polynomials

⋆ This work is supported by ASMPT, Beuningen, The Netherlands.

10.1016/j.ifacol.2023.10.1078

(Giri et al., 2002) and piecewise-linear parameterizations (Giri and Bai, 2010, Chapter 6). Identification of these type of systems is generally based on input and output data (Giri and Bai, 2010) and the optimization schemes are often focused towards model accuracy such that the model prediction error is minimized, which not necessarily have to result in the a minimizing the tracking error for feedforward control.

Although high tracking accuracy is enabled by ILC, it lacks the ability to compensate for nonlinearities in the input when incorporating a linear parameterization for task flexibility. Moreover, data-driven Hammerstein system identification methods enable identification of a parameterized nonlinear system, but these are not geared towards reducing the tracking error in feedforward control.

The aim of this paper is to develop a data-driven feedforward tuning approach consisting of a Wiener feedforward, i.e., linear parameterization with an output nonlinearity, to achieve high tracking accuracy and task flexibility for a class of Hammerstein systems. The developed approach exploits ILC to learn a feedforward signal from data that minimizes the error and utilizes a control-relevant cost function to learn the parameters of a Wiener feedforward parameterization.

This research extends pre-existing research of (van Hulst et al., 2022) with experimental validation on a commercial wirebonder and an analysis on the cost landscape of the nonlinear optimization problem. See (van Hulst et al., 2022) for comparison of the developed approach with traditional system identification methods.

This paper is structured as follows. In Section 2, the problem is formulated. In Section 3, the developed approach is introduced. In Section 4, the experimental validation is presented. Lastly, in Section 5, the conclusions are given.

Notation. Systems are assumed to be discrete-time (DT), linear, time-invariant (LTI), single-input, single-output (SISO) and are denoted by $\underline{H}(z)$ with complex indeterminate z. Signals are tacitly assumed of length $N \in \mathbb{Z}^+$. The output $y(k)$ of the response of $\underline{H}(z)$ to input u is $y(k) = \sum_{l=-\infty}^{\infty} h(l)u(k-l)$, where $h(l)$ is the impulse response of the system $\underline{H}(z)$. Assuming $u(k) = 0$ for $k < 0$ and $k > N-1$, the response can be cast into a finite-time convolution as

$$\underbrace{\begin{bmatrix} y[0] \\ y[1] \\ \vdots \\ y[N-1] \end{bmatrix}}_{y} = \underbrace{\begin{bmatrix} h(0) & h(-1) & \cdots & h(1-N) \\ h(1) & h(0) & \cdots & h(2-N) \\ \vdots & \vdots & \ddots & \vdots \\ h(N-1) & h(N-2) & \cdots & h(0) \end{bmatrix}}_{H} \underbrace{\begin{bmatrix} u[0] \\ u[1] \\ \vdots \\ u[N-1] \end{bmatrix}}_{u}, \quad (1)$$

with $u, y \in \mathbb{R}^N$ the input and output, respectively, and $H \in \mathbb{R}^{N\times N}$ the convolution matrix corresponding to $\underline{H}(z)$. The i-th element of a vector x is denoted by $x[i]$. The weighted 2-norm of the vector $x \in \mathbb{R}^n$ with positive semi-definite weighting matrix $W \in \mathbb{R}^{n\times n}$ is denoted by $\|x\|_W = \sqrt{x^\top W x}$.

2. PROBLEM FORMULATION

In this section, the problem is formulated. First, the control setting is described. Second, the pre-existing approach and its shortcomings are highlighted. At last, the problem is stated and the requirements for the solution are formalized.

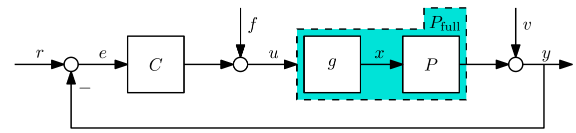

Fig. 1. Closed-loop control scheme with plant P_{full} that is described by a Hammerstein system, feedback controller C, and feedforward signal f.

2.1 Control setting

Consider the control scheme depicted in Figure 1, where P_{full} is assumed to be a nonlinear Hammerstein system consisting of a static input nonlinearity g with intermediate output x and LTI dynamics P. Moreover, the output is assumed to be subjected to output noise $v \in \mathbb{R}^N$. The plant P_{full} is controlled by DT and LTI feedback controller C and the closed-loop system is assumed to be stable.

The goal is to design f such that accurate tracking of the reference is obtained. Assume that P_{full} is linear, i.e., $x = u$, then, from Figure 1, the error is derived as

$$e = Sr - SP_{\text{full}}f - Sv, \quad (2)$$

where $S := (1+P_{\text{full}}C)^{-1}$ is the sensitivity. To obtain task flexibility it is necessary to design f as a function of r, as described next.

2.2 Problem of pre-existing approach

To obtain task flexibility, the feedforward signal is now an explicit function of the reference signal r. Often, the feedforward signal is parameterized by so called basis functions,

$$f = F(\theta)r \quad (3)$$

where $F(\theta)$ is the convolution matrix representation of a parameterized feedforward filter $\underline{F}(\theta, z)$ with parameters θ. The parameters θ can be learned from data with pre-existing solutions such as ILC with basis functions, see, e.g., (van de Wijdeven and Bosgra, 2010). This solution is able to cope with closed-loop noise and learns the parameters θ from that minimize the tracking error for a certain motion task.

By substituting (3) in (2), the error can be expressed as

$$e = Sr - SP_{\text{full}}F(\theta)r - Sv, \quad (4)$$

from which can be observed that the reference-induced error are eliminated for any motion task r when $F = P_{\text{full}}^{-1}$. In the case that P_{full} is linear, F can be designed as a linear LTI system to achieve this. However, in case P_{full} is a nonlinear Hammerstein system, reference induced errors are introduced and no task flexibility is obtained for linear parameterizations of F.

2.3 Problem formulation

The objective in this paper is to design f as a function of r such that reference-induced errors are eliminated for linear systems P with a static input nonlinearity, i.e., the Hammerstein system $P_{\text{full}} = P(g(u))$. The problem is that a linear feedforward parameterization using ILC

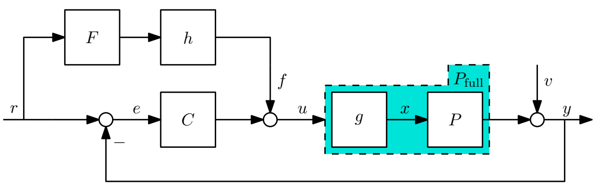

Fig. 2. Proposed closed-loop control scheme with plant P_{full} that is described by a Hammerstein system, feedback controller C, and Wiener feedforward $f = h(Fr)$.

BF is unable to compensate for the input nonlinearity, resulting in low performance and no task flexibility. Data-driven Hammerstein system identification methods enable learning of a system parameterization that is task flexible but these are not geared towards reducing the tracking error in feedforward control as these use input-output data (Giri and Bai, 2010) instead of a relevant motion task, i.e., control-relevant.

The requirements for the solution of the problem are summarized:

R1. High tracking accuracy defined by zero reference-induced error, i.e., $e \approx -Sv$.
R2. Flexibility with respect to the motion task.
R3. Feedforward parameterization as function of r.
R4. Data-driven tuning of the parameters.
R5. Control-relevant optimization that minimizes the error.

In the next section, the developed approach that is a solution to the problem is presented.

3. APPROACH

The developed approach consists of a Wiener parameterization of the feedforward with a data-driven optimization using ILC. First, the feedforward parameterization is presented. Second, the aspects regarding data generation using ILC is elaborated upon. Third, the control-relevant optimization problem is defined.

3.1 Wiener feedforward parameterization

Consider Figure 2 where the Wiener feedforward $f = h(Fr)$, consisting of a linear system $F(\theta)$ with parameters θ and a static output nonlinearity $h(\phi)$ with parameters ϕ. Note that for brevity the parameters θ, ϕ are often omitted. The key idea in the proposed solution is to design h and F such that the error is minimized for any reference r. The error can be derived from the figure and is given by

$$e = r - Pg\big(Ce + h(Fr)\big). \tag{5}$$

Zero reference-induced error for any reference r is obtained for $Pg\big(h(Fr)\big) = r$ and is satisfied if $h = g^{-1}$ and $F = P^{-1}$. Recall from (4) that $F \approx P^{-1}$ can often be achieved with pre-existing linear parameterizations, such as basis functions (van de Wijdeven and Bosgra, 2010). Moreover, in case the inverse input nonlinearity is described by $h(\phi)$ with, e.g., a polynomial function (Giri et al., 2002), that approximates g^{-1}, the requirements R1., R2., and R3. can be satisfied.

3.2 Data generation using iterative learning control

To learn the parameters θ of $F(\theta)$ and ϕ of $h(\phi)$ using data, ILC is exploited to generate the data.

The idea in norm-optimal ILC (NOILC) is to learn f that compensates for repetitive disturbances in a trial-to-trial fashion using a cost criteria. Temporarily assume that P_{full} is linear, i.e., $u = x$ and $P_{\mathrm{full}} = P$, from Figure 1, the error of (2) in a noiseless situation can be written as

$$e_j = Sr_j - SPf_j, \tag{6}$$

where j denotes the trial index.

By increasing the index j to $j+1$, and assuming a trial-invariant reference, i.e., $r = r_j = r_{j+1}$, the error propagation from trial j to $j+1$ can be derived by subtraction, resulting in

$$\hat{e}_{j+1} = e_j - \widehat{SP}(f_{j+1} - f_j), \tag{7}$$

where $\hat{e}_{j+1}$ is the predicted error of the next iteration and $\widehat{SP}$ a model of the real system SP. The objective in ILC is to minimize $\hat{e}_{j+1}$ based on measurements e_j and f_j, and the model $\widehat{SP}$.

To minimize the tracking error of the next trial $\hat{e}_{j+1}$, the following optimization for ILC is defined

$$f_{j+1}^{\mathrm{NOILC}} = \operatorname*{argmin}_{f_j+1} \|e_j - \widehat{SP}(f_{j+1} - f_j)\|_{W_e}^2 + \|f_{j+1}\|_{W_f}^2, \tag{8}$$

where $W_e \succ 0$ and $W_f \succeq 0$. The solution is computed analytically and is given by

$$\begin{aligned} f_{j+1}^{\mathrm{NOILC}} &= Le_j + Qf_j, \\ L &= R^{-1}\widehat{SP}^{\top} W_e, \\ Q &= R^{-1}\big(\widehat{SP}^{\top} W_e \widehat{SP}\big), \\ R &= \widehat{SP}^{\top} W_e \widehat{SP} + W_f. \end{aligned} \tag{9}$$

Monotonic convergence with respect to $\| \ f_j \ \|_2$ of the solution can be guaranteed by selecting $W_f \succ 0$ and is often necessary in case of model-mismatch (Bolder et al., 2014). Note that bias is introduced if W_f is increased, as this results in non-zero error. Moreover, due to closed-loop noise, bias might be introduced. At last, note that basis functions ILC is obtained when selecting $f = \Psi(r)\theta$ and results in a convex optimization problem with an analytic solution, see, e.g., (van de Wijdeven and Bosgra, 2010).

The key idea of learning f^{NOILC} using ILC is that ILC can compensate for any repetitive disturbances, including those arising from input nonlinearities. Using (9), f^{NOILC} can be learned in a few iterations for a repeating reference r to minimize the tracking error despite nonlinearities.

Next, the developed approach regarding learning the Wiener parameterization from this data is explained.

3.3 Optimization problem

The key idea in the developed approach is to fit the Wiener parameterization $h(F(\theta)r, \phi)$ on the converged f^{NOILC}, as the latter is designed to minimize the tracking error in the presence of input nonlinearities.

To optimize the parameters θ and ϕ from the data, the following control-relevant cost function is defined

$$\mathcal{K}(\theta,\phi) := \|\widehat{SP}\big(f^{\text{NOILC}} - h(F(\theta)r,\phi)\big)\|^2, \tag{10}$$

where $\widehat{SP}$ is introduced to make the cost function control-relevant as it relates the feedforward signal to its contribution to the error, see (Aarnoudse et al., 2021). The optimal parameters can be computed using

$$\{\theta^{\text{opt}},\phi^{\text{opt}}\} = \underset{\{\theta,\phi\}}{\operatorname{argmin}}\, \mathcal{K}(\theta,\phi), \tag{11}$$

which is a nonconvex optimization problem. Hence, a solver is necessary that avoids local minima, see Section 4.4 for an analysis on the optimization problem.

The reference used in NOILC should be a concatenation of typical relevant reference to make the cost function relevant for control. Moreover, for an accurate estimation of the Wiener feedforward parameters, the reference should be persistently exciting with respect to the input nonlinearity. At last, the frequency content of the reference should be in the range where P^{-1} is approximated well by $F(\theta)$.

Since f^{NOILC} can be learned from data, the developed approach satisfies R4. Moreover, the weighting $\widehat{SP}$ in the cost function enables a control-relevant optimization problem as it satisfying requirement R5.

To summarize, by parameterizing the feedforward signal using a Wiener parameterization as a function of r and learning the parameters using data from ILC, the requirements formulated in Section 2 can be satisfied. Next, the developed approach is validated on an experimental setup.

4. EXPERIMENTAL VALIDATION

In this section the proposed method is validated on a wirebonder and compared to the pre-existing linear feedforward method of ILC BF. First, the experimental setup is explained. Second, the modeling aspects of the developed approach are discussed. Third, aspects regarding data generation are mentioned. Fourth, the optimization problem is analyzed. At last, the results and comparisons are presented.

4.1 Wirebonder experimental setup

The experimental setup is a commercial wirebonder by ASMPT, depicted in Figure 3, that consists of a stacked xyz-stage of which only the x-stage is considered. The actuator in this machine subjected to magnetic saturation, resulting in a nonlinear relationship between the applied current of the actuator and the resulting force. Moreover, the dynamics of the machine can be approximated well by a linear system. Hence, it is expected that the system can be modeled accurately by a Hammerstein system description.

4.2 Wiener feedforward parameterization

The developed approach models the feedforward signal using a parametric Wiener parameterization. Hereto, it is assumed that the linear part of the Wiener representation can describe the linear dynamics of P. The system is expected to be approximated well by a rigid-body feedforward parameterization compensating effects due to moving a mass with friction. The feedforward parameterization is given by

$$\underline{F}(\theta,z) = \frac{1-z^{-1}}{T_s}\theta_1 + \frac{(1-z^{-1})^2}{T_s^2}\theta_2, \tag{12}$$

where θ_1 and θ_2 correspond to, respectively, velocity and acceleration feedforward parameters.

Fig. 3. Commercial wirebonder from ASM Pacific Technology consisting of a stacked xyz-stage of which only the x-stage is considered and subjected to nonlinear current saturation due to magnetic saturation.

The input nonlinearity describes the magnetic saturation that takes place in the actuator (Polinder, 2002). Magnetic saturation causes the force of the actuator to drop-off as the input current in the motor increases and can be modeled with

$$g(u) = I_{\max}\cdot\tanh\Big(\frac{u}{I_{\max}}\Big), \tag{13}$$

where $I_{\max}$ is the current saturation parameter (Na et al., 2018). The inverse input nonlinearity compensating this nonlinear behavior is the inverse of (13) with rigid-body feedforward, and is given by

$$f = h(F(\theta)r,\phi) = \phi\cdot\operatorname{atanh}\Big(\frac{F(\theta)r}{\phi}\Big), \tag{14}$$

where ϕ models the current saturation parameter $I_{\max}$.

4.3 Data generation

In order to generate relevant data for the developed approach, a relevant reference is performed and the feedforward compensating all repetitive disturbances is learned using NOILC. A reference is used that consists of a sequence of 5 quintic-polynomial reference profiles with varying maximum accelerations. These varying maximum accelerations ensure that different levels of saturation take place in the actuator, making the reference persistently excited. The motion distance is kept short to avoid any excitation of position dependency. The reference position and acceleration are depicted in Figure 4.

Next, the NOILC algorithm is setup with $W_e = I$ and a nonzero value for W_f is necessary for convergence of

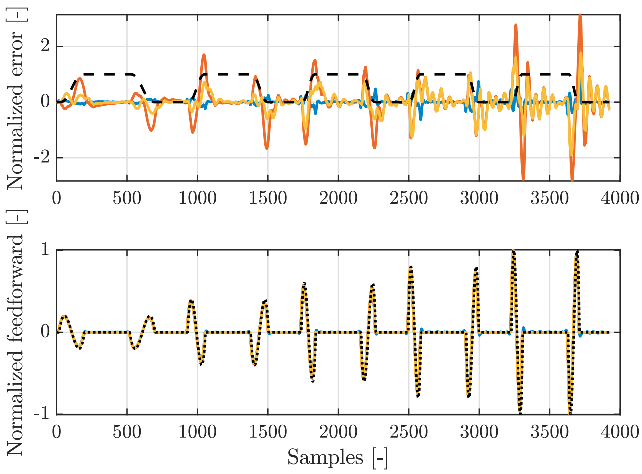

Fig. 4. Normalized time-domain error and feedforward signal of NOILC (—), pre-existing case without compensation (—), the developed approach (—), with the scaled reference position (- -) and acceleration (·····). Clearly, the feedforward is dominated by acceleration feedforward and ILC BF with nonlinear compensation achieves lower error compared to the ILC BF without nonlinear compensation.

NOILC due to model-mismatch. Note that this creates some bias in the cost function, hence, the resulting NOILC feedforward signal results in nonzero error but no major drawbacks are expected due to this. The NOILC algorithm is applied to this reference for 15 iterations, allowing sufficient iterations for convergence.

The time-domain error and feedforward signals of NOILC, including the scaled reference, are denoted in Figure 4. Clearly, the NOILC signals resembles the shape of the reference acceleration profile, confirming the assumption that the system is dominated by rigid-body feedforward.

4.4 Optimization analysis

The cost function of (10) can be evaluated using the generated data and the proposed Wiener feedforward parameterization. Using a particle swarm optimization scheme, the minimum is found. The resulting normalized parameters are $\phi = 1.89$ and $\theta_2 = 1.03$, θ_1 is omitted as this parameter is less relevant. The saturation curve for the current-force relationship in the actuator for the optimal value is shown in Figure 5, showing clear saturation of the force at high currents.

Figure 6 shows the cost function landscape, where the value of the velocity parameter is fixed at the optimal value. The cost function landscape is nonlinear and has a global minimum. Note that there exist a clear valley around the global optimum, indicating that a low cost can be obtained for different current saturation parameters for different mass parameters. Which is beneficial if relearning of the mass parameter is possible after fixing the current saturation parameter. For low values of the current saturation, i.e., a very strong compensation of the saturation, the cost increases rapidly. If the compensation is too strong, a lower mass parameter is expected as less linear feedforward force is necessary, which is clear form

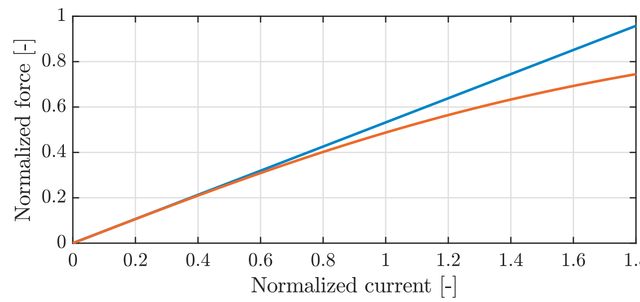

Fig. 5. Normalized current-force relationships for the pre-existing linear feedforward case (—) and the saturation curve described by (13) with the optimal parameter $\phi = 1.89$ (—). The figure is normalized with respect to the maximum current in the NOILC signal and the linear force relationship.

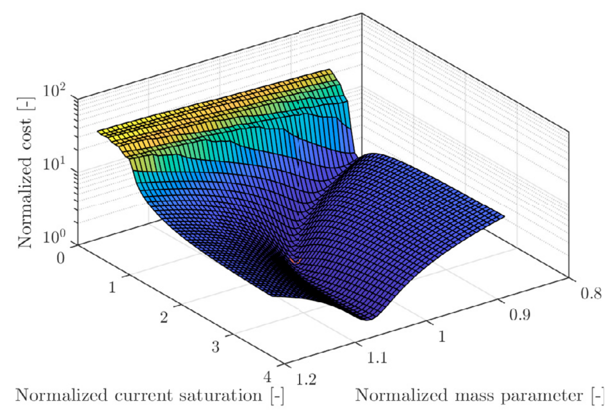

Fig. 6. The normalized cost function landscape fixed for the optimal value of velocity parameter as a function of current saturation and mass parameter where the optimum value is denoted by (×). The cost function has one clear optimum,

the curvature of the valley towards lower mass values for lower current saturation parameters.

4.5 Results

The nonlinear compensation of the current saturation with the optimized parameters is applied in the feedforward scheme. A comparison between the pre-existing approach, namely ILC BF without the nonlinear compensation, and the developed approach where the nonlinear compensation is learned and applied in ILC BF scheme where only θ is relearned but ϕ is fixed on the optimal value. The results are compared in Figure 4. Clearly, the tracking error of the developed approach is significantly lower than the pre-existing method that does not have nonlinear compensation. Moreover, the performance seems to be more consistent as the error increases for higher reference accelerations.

The performance regarding extrapolation is validated by performing individual references with varying motion distances and maximum accelerations. The estimated mass parameters for the pre-existing method without nonlinear compensation and the developed approach are depicted in Figure 7. The learned mass parameter increases for

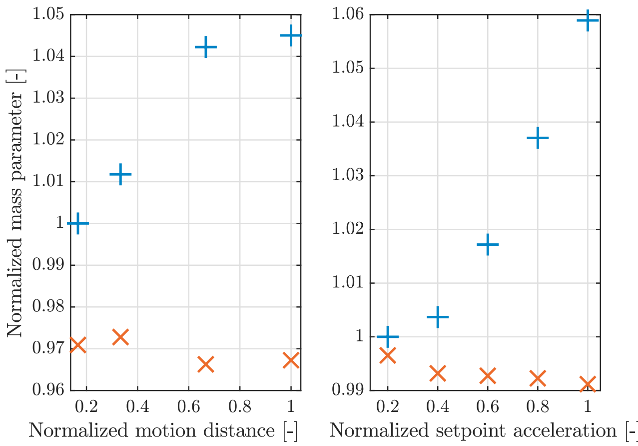

Fig. 7. Normalized mass parameter tuned per individual reference with varying motion distances (left) and varying setpoint acceleration (right) using the pre-existing linear feedforward without compensation (+) and the developed approach with nonlinear compensation (×), normalized with respect to the first value of the pre-existing approach. The variation in the mass parameter is significantly reduced with the developed framework compared to pre-existing linear feedforward case, indicating extrapolation capabilities using the developed framework.

increased setpoint acceleration if no compensation is applied, which is expected as the mass parameter could try to counteract the saturation effect by increasing the input current of the actuator. Moreover, the pre-existing approach has a 5 percent variation, while the mass parameter of the developed approach varies significantly less for varying motion distances. The results in Figure 7 strongly suggest that the developed approach is able to achieve task flexibility as the mass parameter only shows minor variation with respect to the different references.

Note that mass parameter still varies slightly in Figure 7 for different references, which can be explained by the fact that the NOILC signal is unable to achieve zero error as there is bias in the cost function due to $W_f \neq 0$ or by inevitable model-mismatch in the parametric model of the saturation effect.

5. CONCLUSION

This paper proposes a data-driven tuning method of a Wiener feedforward for a class of nonlinear Hammerstein systems that achieves high tracking accuracy and task flexibility. The developed method employs a Wiener parameterization for the feedforward and the feedforward parameters are optimized based on a control-relevant cost function and data generated by ILC. The developed approach is experimentally validated on a wirebonder and shows that the mass parameter for varying maximum accelerations and varying motion distances is significantly more consistent than the pre-existing linear feedforward approach, indicating task flexibility. The cost landscape is analyzed and shows a clear global minimum.

Future research focuses on extending the feedforward to compensate for other unmodeled nonlinear effects, such as, position dependent effects, cogging, etc.

6. ACKNOWLEDGMENT

The authors would like to thank Robin van Es for his contributions to this research.

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