Estimating structural deformations for inferential control: a disturbance observer approach

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Abstract: Increasingly stringent requirements for motion systems lead to a situation where the positioning performance can often not be measured directly and therefore has to be estimated. A typical example is a wafer stage, where the performance is desired at the point-of-exposure on the wafer but the sensors are located at the edge of the wafer stage. Increasingly stringent performance requirements necessitate taking structural deformations, caused by actuation or disturbance forces, into account. The aim of this paper is to develop a disturbance observer approach including an observer relevant model identification approach and to experimentally validate this approach on a prototype motion system. The experimental results confirm that the proposed disturbance observer approach leads to an improved estimation of the unmeasured performance variables.

1. INTRODUCTION

The quality in precision manufacturing is determined by the positioning accuracy of certain critical components, e.g., the print-head in printing systems, or the point-of-exposure on a wafer in photolithography (Oomen et al., 2015). The positions of these components are often not directly measured in real-time, either due to practical limitations or cost considerations. Therefore, they have to be inferred from measurements that are not collocated with the performance variables.

Increasingly stringent accuracy and throughput requirements lead to a situation where the flexible structural behavior becomes relevant in the relation between the measured variables and the performance variables. Regarding accuracy, the desire to produce products with smaller features directly makes such internal deformations relevant. Regarding throughput, increased accelerations necessitate either a more light-weight system design or higher actuation forces, which both lead to more significant flexible dynamic behavior (Oomen et al., 2014).

In traditional motion control, it is often justified by the lower accuracy and speed requirements to neglect the internal deformations. Using this rigid-body approximation, a static, linear mapping between the sensor outputs and the performance variables can be derived, leading to a significant simplification of the control problem. It is envisaged that for next-generation motion systems the structural flexibilities have to be taken into account, leading to a dynamic relation between the sensor variables and the performance variables. In addition, this dynamic relation is position dependent, leading to a highly non-trivial inferential control problem.

In inferential control, the effect of exogenous disturbances on the performance location can often not be directly reconstructed from the sensor outputs. Therefore, estimating the influence of such disturbances is a key aspect in improving the inferential performance. Examples of common exogenous disturbances include friction forces, disturbances caused by linked bodies such as the cable schlepp (Hoogerkamp et al., 2014), immersion hood disturbances in immersion lithography (Kocsis et al., 2006), and parasitic commutation forces (Compter, 2004). These disturbances can often be regarded as low-frequent force disturbances. These low-frequent disturbances cause the mechanical structures to deform due to their finite stiffness. These deformations can cause serious degradation of product quality, similar to the deformations induced by reference signals (Boerlage et al., 2006). In this paper, an approach is investigated to explicitly take the influence of such low-frequent disturbances into account. The main challenges in this approach include:

(1) the dynamic relation between the sensor outputs and the unmeasured performance variables,
(2) the presence of unknown, low-frequent, disturbance forces.

Recently, in Oomen et al. (2015), an inferential motion control framework is proposed to address the dynamical relation between sensor outputs and performance variables. The used criterion in this framework involves the $\mathcal{H}_\infty$ norm. With the $\mathcal{H}_\infty$ approach, the worst-case cost for all systems within a model set is optimized. This worst-case cost involves both the worst-case frequency content and the worst-case input direction (Skogestad and Postlethwaite, 2005, Section 5.1). For the considered applications however, prior knowledge regarding the location, direction, and frequency characteristics of the disturbances is avail-

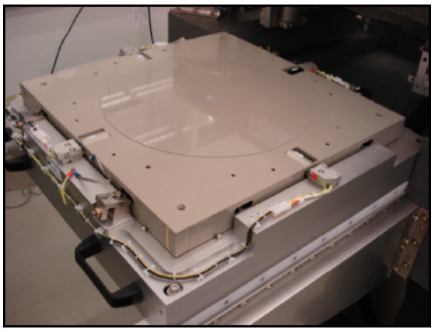

Fig. 1. The experimental setup: a prototype wafer stage.

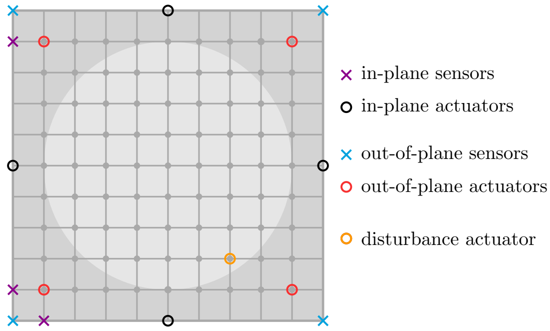

Fig. 2. Schematic top view of the experimental setup.

able. In this paper, it is aimed to develop an inferential motion control framework that utilizes this prior knowledge of the disturbances acting on the system to achieve an improved estimation and control of the unmeasured performance variables.

An alternative approach is to explicitly model and estimate the disturbances and their influence through the use of disturbance observers, as in e.g., Johnson (1971), Profeta et al. (1990a), and Schrijver and van Dijk (2002). For a recent overview on disturbance observer based control see Li et al. (2014) This approach shows promising results for the suppression of several types of disturbances in multiple applications, such as torque disturbances in target tracking systems (Profeta et al., 1990a) and cable schlepp disturbances in wafer stages (Hoogerkamp et al., 2014).

Although important work on disturbance observers and inferential control has been done, at present an inferential control framework that explicitly addresses exogenous disturbances is not available. An essential part in such a framework, is the design of an observer. The aim of the present paper is a disturbance observer framework for inferential control, including

(1) the observer design for estimating the unmeasured performance variables in the presence of disturbances,
(2) the identification of observer relevant, low-order, standard plant models.

In e.g. Schrijver and van Dijk (2002) or Profeta et al. (1990b), the disturbances are considered as unknown superpositions of known deterministic signals and most often as (piece-wise) constants. In Profeta et al. (1990a), the possibility of a stochastic disturbance is mentioned but not yet explicitly quantified and taken into account in the observer design. In this paper, the stochastic nature of the disturbance is considered to be an essential aspect of the system description and integral to the observer design. An optimal approach is proposed to design observers in the presence of such stochastic disturbances.

The ability to accurately model the relevant system dynamics is essential to successful observer design. To obtain a suitable model, a frequency domain system identification approach is developed. This approach is specifically tailored to emphasize the relevant dynamics such that they are accurately identified and included in the model. For the proposed approach this means placing emphasis on the low-frequent region and the inclusion of the compliant dynamics in the system model.

This paper includes the following contributions:

C.1 A disturbance observer design approach for inferential control problems.
C.2 An identification approach to obtain low order models, containing the dynamics relevant for the observer.
C.3 An experimental validation of the proposed approach on a prototype wafer stage setup.

In the next section, the experimental setup is introduced and the observer design problem is formulated. In Section 3, the relevant system and disturbance dynamics are analyzed. In Section 4, the proposed observer structure and design approach are presented. In Section 5, the identification problem is considered and an observer relevant system identification procedure is applied to the experimental setup to obtain two low order models. In Section 6, the validation experiments are presented. In Section 7, the conclusions of this research are presented, as well as an outlook on ongoing research.

2. SETUP AND PROBLEM FORMULATION

In this section, the prototype wafer stage setup is introduced on which the experiments are performed. Also, the observer design problem is formulated for the considered inferential control problem with exogenous disturbances.

2.1 Experimental setup

The considered experimental setup is a prototype wafer stage, which is depicted in Figure 1 and designed to facilitate research on next generation motion control. Therefore, this stage is purposely designed to be lightweight with pronounced flexible dynamical behavior. In addition, the stage is designed to have a re-configurable input/output configuration, enabling the addition of extra sensors and actuators at various points in the setup. Furthermore, the wafer stage is designed to be able to hold a future 450 mm wafer and thus has a dimension of $600 \times 600 \times 60$ mm. As a result, this prototype system reflects the physical dimensions of an industrial wafer stage much better compared to, e.g., the two degrees of freedom prototype-system in Oomen et al. (2015).

A schematic top view of the setup is shown in Figure 2. This overview shows the actuator and sensor locations for the system as considered in this research, distinguishing between the in-plane ($x-$ and $y-$direction) and out-of-plane directions. Only the out-of-plane direction is considered in the present paper.

2.2 Problem formulation

The problem that is investigated in this paper involves two main aspects. First, the inferential performance aspect is considered, which is relevant because the performance variables are not directly related to the sensor outputs. Second, the exogenous disturbances and their consequences for the inferential performance are investigated. The considered observer design problem, involving both these aspects, is formulated at the end of this section.

Inferential performance To facilitate the exposition, the focus in this paper is on the specific wafer stage application. The proposed approach can however be directly generalized to more diverse applications and performance objectives.

In a wafer scanner, a pattern is sequentially projected onto hundreds of separate dies on a wafer. In the positioning control of a wafer stage, the performance variables are the position and orientation of the die, or section on the wafer that is currently being exposed.

It is not possible to directly measure the position of points on the wafer, typically the sensors are located at the edges of the wafer table. This is schematically depicted in Fig. 3. The performance variables are denoted with z and the sensed variables are denoted with y. The goal of the wafer motion control is to minimize the positioning error at the performance location, i.e., to minimize

$$e_z(t) = r_z(t) - z(t), \tag{1}$$

where $r_z(t)$ denotes the desired reference value for the performance variable $z(t)$.

In the specification and analysis of the wafer positioning performance, a further distinction is made between low and high frequency errors, which determine the overlay accuracy and the feature blur respectively. These distinct errors are typically quantified by the moving average (MA) and the moving standard deviation (MSD) respectively:

$$\mathrm{MA}_z = \frac{1}{T}\int_{-T/2}^{T/2} e_z(t)\,\mathrm{d}t\,, \tag{2}$$

$$\mathrm{MSD}_z = \sqrt{\frac{1}{T}\int_{-T/2}^{T/2} (e_z(t) - \mathrm{MA}_z)^2\,\mathrm{d}t}\,. \tag{3}$$

The overlay performance, which is an important specification for the market position, directly improves with a decreasing Moving Average error. This in turn emphasizes the low-frequent tracking error e_z in (1) due to the low-pass characteristic of the MA.

Traditionally, the wafer stage is assumed to be rigid, i.e., the deformation of the wafer stage due to its structural flexibility is neglected. Using this approximation, the performance variables can be directly estimated from the measured outputs using a static linear mapping, through

$$\hat{z}_{\mathrm{RB}}(t) = T\,y(t). \tag{4}$$

This transformation matrix $T \in \mathbb{R}^{n_z \times n_y}$, relates the output signals $y(t)$ to the performance variables $z(t)$.

This estimation based on rigid body models, is accurate if the structural deformations are negligible and, in addition, in the absence of significant measurement noise on the outputs y. In this case, the control problem straightforwardly

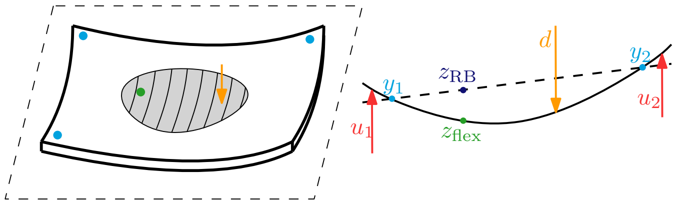

Fig. 3. Schematic deformed wafer-stage (left) and cross section (right), showing non-collocated performance location z (green), sensors y (cyan), disturbance d (orange), actuators u (red) and rigid body estimation $\hat{z}_{\mathrm{RB}}$ (dark blue).

reduces to the usual servo control problem of minimizing the output error, i.e.,

$$e_y(t) = r_y(t) - y(t). \tag{5}$$

If the structural flexibilities are significant, then such a transformation cannot be used to estimate the performance variables z with sufficient accuracy. This is exemplified in Fig. 3 where the performance location is depicted in green while the rigid body estimation of this location is depicted in dark blue. In this case, the performance variables can not be directly reconstructed from the sensor outputs, as in (4). In this case, a dynamic estimator enables accurate estimation of the performance variables z from the current and past sampled values of the outputs y and the controlled inputs u, i.e.,

$$\hat{z}(k) = f(y(k), y(k-1), \ldots, u(k), u(k-1), \ldots). \tag{6}$$

Once such an estimator for z is available, traditional control approaches can again be used. The control performance is directly determined by the accuracy of this estimate. Hence, obtaining a good estimator is essential for the inferential performance.

Exogenous disturbances In addition to the inferential performance aspect, exogenous disturbance forces also play an important role in the performance of motion systems. Indeed, when a disturbance force acts on the system, the important moving average error can become too large leading to overlay problems. Examples of such disturbances are cable schlepp, immersion hood disturbances, and electromagnetic cross-talk disturbances.

These disturbance forces are typically not collocated with the actuator, sensor, and performance locations, see also Hong and Bernstein (1998). This means there is a distinct dynamical relation between the disturbances and the performance variables and sensor outputs. To be able to detect and mitigate the effects of these disturbances, their influence on both the sensor outputs and the performance variables should be included in the system model.

Observer design problem The considered observer design problem is the problem of determining a dynamic system, as in (6), that is able to accurately reconstruct the unmeasured performance variables, z, and the unknown disturbance forces, d, from the known actuation signals, u, and measured sensor outputs.

The goal of the observer design problem is to minimize the estimation error of the point of interest position in the presence of a localized quasi-static force disturbance in a wafer stage. This error is given by

$$e_{\hat{z}}(k) = z(t_k) - \hat{z}(k)\,. \tag{7}$$

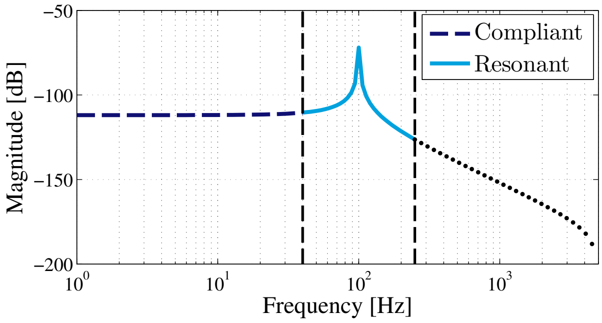

Fig. 4. Compliant and resonant behavior of a flexible mode.

To achieve this, a model of the system dynamics is made. Based on this model the observer is synthesized. To model the system dynamics, it is first investigated what behavior is expected of the system and what dynamics should be included in the wafer stage model and the disturbance model. Considering this desired model class, the proposed observer design approach is outlined in Section 4. Finally, a model of the experimental setup is identified and the designed observer is tested experimentally.

3. SYSTEM ANALYSIS

In this section, it is investigated what dynamical behavior is expected for the wafer stage system. This is investigated to determine what dynamics should be included in the system model as well as in the disturbance model.

3.1 Wafer stage dynamics

Wafer stages are high precision motion systems that are designed to exhibit highly reproducible and linear dynamic behavior. The models used in this paper are therefore all linear and time invariant (LTI). Due to the emphasis on low frequent (MA) performance and considering the dominant disturbance sources to be low-frequent, the model is aimed to be especially accurate at low frequencies. Therefore, the rigid body behavior of the systems needs to be modeled accurately. In addition to the rigid body behavior, the low-frequent contributions of the flexible modes of the system needs to be modeled. This low-frequent contribution is also known as the compliant contribution, see also Boerlage et al. (2006). Lastly, the resonant behavior of some dominant flexible modes might have to be included in the model, this largely depends on the frequency range in which the observer will be used. The distinction between the compliant and resonant contributions of a flexible mode is shown in Figure 4.

Mechanical structures such as a wafer stage can in first principle be modeled as a continuum, leading to an infinite number of flexible modes (Gawronski, 1998), i.e.,

$$P(\omega) = \sum_{i=1}^{\infty} \frac{(c_{mqi} + j\omega c_{mvi})\, b_{mi}}{\omega_i^2 - \omega^2 + 2j\zeta_i\omega_i\omega}\,. \qquad (8)$$

All of these flexible modes have a compliant contribution in the low-frequent region. To accurately approximate this behavior using low-order models, the sum of the compliant contributions of all flexible modes can be considered as a single lumped contribution. This lumped compliance can be included in the model as a constant term, or if such a direct feed-through term is undesired, low pass filters can be used to obtain a strictly-proper model.

The low-order models considered in this paper therefore include a model of the rigid body behavior of the system, the lumped compliance and possibly the first few resonant modes.

3.2 Disturbance characteristics

In this research, the immersion hood disturbance is considered, which typically is one of the dominant disturbances. In immersion lithography, the air gap between the final lens and the wafer is replaced by purified water, enhancing the achievable resolution of the lithography tool. The immersion hood, which contains the water under the lens, exerts an unknown force on the wafer causing it to deform. The proposed approach directly generalizes to other disturbances.

The force exerted on the wafer stage by the immersion hood is modeled as a stochastic process with predominantly low-frequent contributions, due to slow movement over the wafer. Hence, it can be modeled as a dynamical system driven by white noise, i.e.,

$$d(t) = H\, e(t), \qquad (9)$$

where the noise process, H, has a low-pass characteristic and e is zero mean white noise. In this paper, the noise process is modeled as an integrator, with possible non-zero initial condition. The resulting disturbance can be interpreted as a random-walk disturbance, also known as Brownian noise.

In a wafer scanner, the immersion hood moves over the wafer, leading to a position dependent disturbance force. The position of this disturbance force is known. In this research the disturbance location is fixed. Incorporating this position dependence is a topic of ongoing research.

4. OBSERVER DESIGN APPROACH

In this section the proposed observer structure is introduced, including the general approach for the design of these observers.

4.1 Observer structure

In this section it is assumed that a low order, proper model, accurately describing the low-frequent behavior of the system, as described in section 3.1, is available. In state space form, this model is given by,

$$\tilde{P}: \begin{bmatrix} \dot{\tilde{x}} \\ \hline \tilde{y} \\ \tilde{z} \end{bmatrix} = \left[\begin{array}{c|cc} \tilde{A} & \tilde{B}_u & \tilde{B}_d \\ \hline \tilde{C}_y & \tilde{D}_{yu} & \tilde{D}_{yd} \\ \tilde{C}_z & \tilde{D}_{zu} & \tilde{D}_{zd} \end{array}\right] \begin{bmatrix} \tilde{x} \\ \hline u \\ d \end{bmatrix}, \qquad (10)$$

where the state vector x contains both the states associated with the rigid body dynamics as well as the states associated with the modeled flexible dynamics. This model describes the behavior of the full standard plant, i.e., the transfers from both the actuator inputs u and the disturbances d to the sensor outputs y and the performance variables z.

In linear system theory, the observer structure that is often used is the Luenberger observer (Luenberger, 1966). In this observer, the system output and the estimated system output from the observer are subtracted from one another and multiplied by a matrix L, often called the observer gain. The system equations for such an observer are given by

$$\mathcal{O}:\begin{bmatrix}\dot{\hat{x}}\\ \hat{z}\end{bmatrix}=\left[\begin{array}{c|cc}\tilde{A}-L\tilde{C}_y & \tilde{B}_u-L\tilde{D}_{yu} & L\\ \hline \tilde{C}_z & \tilde{D}_{zu} & 0\end{array}\right]\begin{bmatrix}\hat{x}\\ u\\ y\end{bmatrix}. \quad (11)$$

Given this observer structure, the remaining task is to synthesize a suitable observer gain matrix L.

In the synthesis of an observer gain matrix, a number of things need to be taken into account. First of, the observer should be stable, meaning that the matrix $\tilde{A}-L\tilde{C}_y$ should be Hurwitz. Furthermore, a trade-off has to be made in the observer gain between amplification of measurement noise and the suppression of state disturbances. A popular method of synthesizing a suitable observer gain matrix is the Kalman filter method (Kalman and Bucy, 1961). This method produces the optimal observer gain for a system that is described exactly by the observer model as in (10) and where the state disturbances d and the measurement noises v are white zero-mean Gaussian noise sources with known (co-)variances.

The assumptions on which the Kalman filter method is based make it ill suited for the considered observer problem. This is mainly due to the fact that the dominant state disturbances in the considered system are not white noise disturbances. It is possible however to augment the observer model with a dynamical model for the disturbances enabling the problem to be recast in such a way that the Kalman filter method can be applied effectively. This is explained further in the following section.

4.2 Augmented observer design

A dynamical model that describes the disturbance characteristics is added to the system description to be able incorporate the low-frequent behavior of the dominant disturbance sources in the observer design. In this case, the disturbances are modeled as integrators driven by white noise.

The augmented observer model can be described by the following equations

$$\tilde{P}_a:\begin{bmatrix}\dot{\tilde{x}}\\ \dot{\tilde{x}}_a\\ \hline \tilde{y}\\ \tilde{z}\end{bmatrix}=\left[\begin{array}{cc|cc}\tilde{A} & \tilde{B}_d\tilde{C}_a & \tilde{B}_u & \tilde{B}_d\tilde{D}_a\\ 0 & \tilde{A}_a & 0 & \tilde{B}_a\\ \hline \tilde{C}_y & \tilde{D}_{yd}\tilde{C}_a & \tilde{D}_{yu} & \tilde{D}_{yd}\tilde{D}_a\\ \tilde{C}_z & \tilde{D}_{zd}\tilde{C}_a & \tilde{D}_{zu} & \tilde{D}_{zd}\tilde{D}_a\end{array}\right]\begin{bmatrix}\tilde{x}\\ \tilde{x}_d\\ \hline u\\ d^*\end{bmatrix} \quad (12)$$

here d^* is the white noise driving disturbance of the disturbance model and the augmented states $\tilde{x}_a$ are added to model the behavior of the disturbance forces acting on the system.

This augmented observer model now does admit the same assumptions on the disturbances and measurement noise as the Kalman filter method, which can therefore be used to obtain a suitable observer gain matrix L.

The observer gain can be obtained by solving the following Ricatti equation for X:

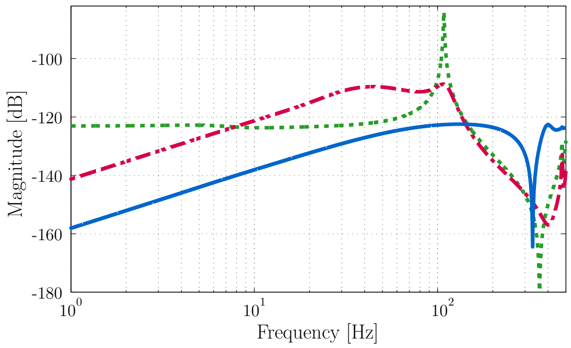

Fig. 5. Comparison of high and low gain observer. Shows the response from disturbance d to $e_{\hat{z}} = z - \hat{z}$ for the rigid body estimation (green, dotted), low gain observer (red, dash dotted) and high gain observer (blue, solid).

$$0 = XA^T + AX - X\tilde{C}_y^T R^{-1}\tilde{C}_y X + \underbrace{\tilde{B}_d Q \tilde{B}_d^T}_{Q_n}, \quad (13)$$

the observer gain is then given by,

$$L = XC_y^T R^{-1}. \quad (14)$$

Here a choice is made to model all process (or state) disturbances as disturbance forces d instead of modeling additional direct state disturbances in the system, i.e. by having $Q_n = \tilde{B}_d Q \tilde{B}_d^T + Q_s$.

In (13), R is the co-variance matrix of the measurement noise. To achieve the optimal observer performance, this covariance, as well as the covariance of the disturbances Q, or equivalently the full state covariance matrix Q_n, should be obtained from measurements. However, in this paper the goal is not to obtain the best performing observer but to showcase the viability of the proposed approach and the key mechanisms behind it. Therefore, it is assumed here that the measurement noises on the different sensors are all uncorrelated and of equal intensity, i.e., $R = rI$. Furthermore, the scaling factor r is considered a design variable. This factor can be used to tune the observer gain, where low r leads to a high observer gain and high r leads to a lower observer gain. A higher gain observer has a better response to the disturbances at the expense of more measurement noise amplification.

In Fig. 5, a comparison is shown between a high and low gain observer, showing the response from disturbance d to $e_{\hat{z}} = z - \hat{z}$. This figure clearly shows that the high gain observer leads to much better low-frequent disturbance rejection than both the rigid body estimation and the low gain observer. The frequency range in which disturbances are rejected is also improved for the high gain observer. For the considered case, the modeled force disturbances are expected to be most important cause for errors at the performance location, and due to the use of high quality sensors, the measurement noise is relatively small, so a high gain observer is preferred.

5. SYSTEM IDENTIFICATION APPROACH

To obtain a low-order model of the system, a frequency domain system identification procedure is used. Both the non-parametric identification of the systems frequency response and the parametric modeling procedures are specifically tailored to enhance the model accuracy in the low-

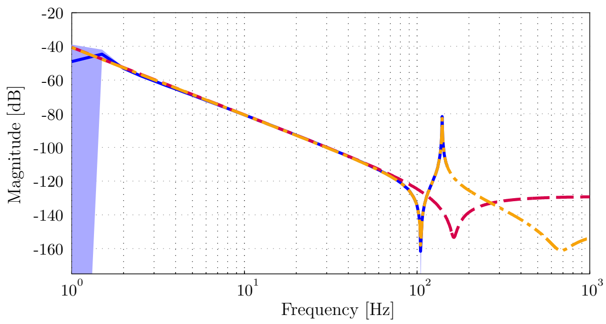

Fig. 6. Identification results for the (1, 1) element, showing the identified FRF (blue, solid) with 95% confidence bound (light blue) and two identified models: one with the resonance (orange, dash dotted) and one without the resonance (red, dashed).

frequent region, which is where the considered disturbance force is most significant and where performance requirements are most stringent.

5.1 Non-parametric identification

As a first step in frequency domain system identification, it is common to identify the non-parametric frequency response function (FRF) of the system Pintelon and Schoukens (2012).

FRF measurements are performed using random phase multisines in a closed loop setup. In these measurements, one direction (one actuator) is perturbed with the identification signal in each separate experiment, simplifying the full MIMO identification procedure to multiple SIMO measurements. The excitation signals in all these measurements are designed such that only frequencies in the low frequent region (1-150 Hz) are excited. Additionally a linear weighting is applied to the amplitude of the excited frequencies such that extra emphasis is placed on the lower end of the spectrum. In the subsequent parametric identification step this FRF is used to accurately fit system models which match the low frequent behavior of the FRF.

5.2 Parametric identification

The parametric identification procedures attempts to fit the low-order models, as described in Section 3.1, to the obtained FRF. Two models are fitted to this data, the first one includes only the rigid body behavior of the system and the compliance, i.e.,

$$P_1(s) = \frac{1}{s^2} M_{\text{inv}} + D\,, \tag{15}$$

with D, $M_{\text{inv}} \in \mathbb{R}^{n_y \times n_u}$. The second model also includes the first resonant mode of the system. This second model is included to both see whether including the resonant dynamics in the observer model influences the performance of the observer well below the first resonance frequency, and to see how well the proposed framework can be applied beyond the low-frequent quasi-static region.

In the fitting procedure, extra weighting is applied to the low frequent region to ensure that the model is accurate in this region. The fitted models, as well as the identified FRF can be seen in Fig. 6. This figure clearly shows that both models accurately described the low-frequent behavior of the system, and the second model also accurately describes the first resonance, which is visible between 100–140 Hz. The first model is unable to accurately describe this behavior due to the lower model order.

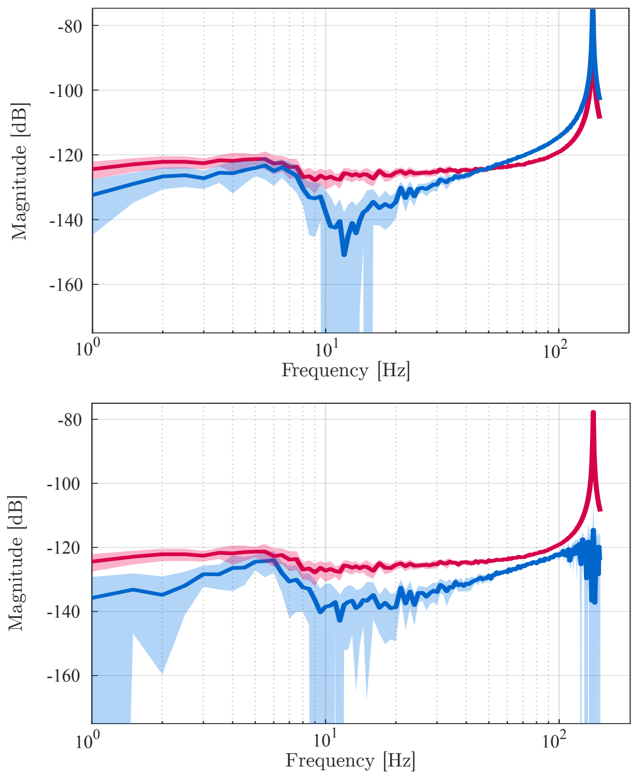

Fig. 7. Observed frequency response from d to $e_{\hat{z}} = z - \hat{z}$ and 95% confidence bounds for the rigid body estimation (red) and the proposed observers (blue) using the identified models without resonance (top) and with the resonance (bottom).

6. EXPERIMENTAL VALIDATION

In this section, the results are shown for a number of validation experiments that were performed on the prototype light weight wafer stage system described in section 2.1. These include a number of time domain experiments as well as a frequency domain overview of the expected performance of the designed point-of-interest observers.

In Fig. 7, the overall frequency domain performance of the proposed observers is shown. In the low frequent range both the observers show an improvement over the rigid body estimation. In the higher frequent region, from 40 Hz onward, the observer based on the model that does not include the first resonance shows a deteriorated performance with respect to the rigid body estimation. The observer based on the model that does include this first resonance shows a clear improvement in this region.

In Fig. 8 the results for a number of time domain experiments are shown. These are results for the observer that does include the first resonance. The experimental results clearly show that both statically and dynamically in a broad frequency range, the estimation performance for the performance variables is significantly improved. Furthermore, it can also be seen that the applied disturbance force is also estimated accurately for the static case and the slower (10 Hz) dynamic disturbance. The estimation for the high frequent (140 Hz) disturbance is less accurate.

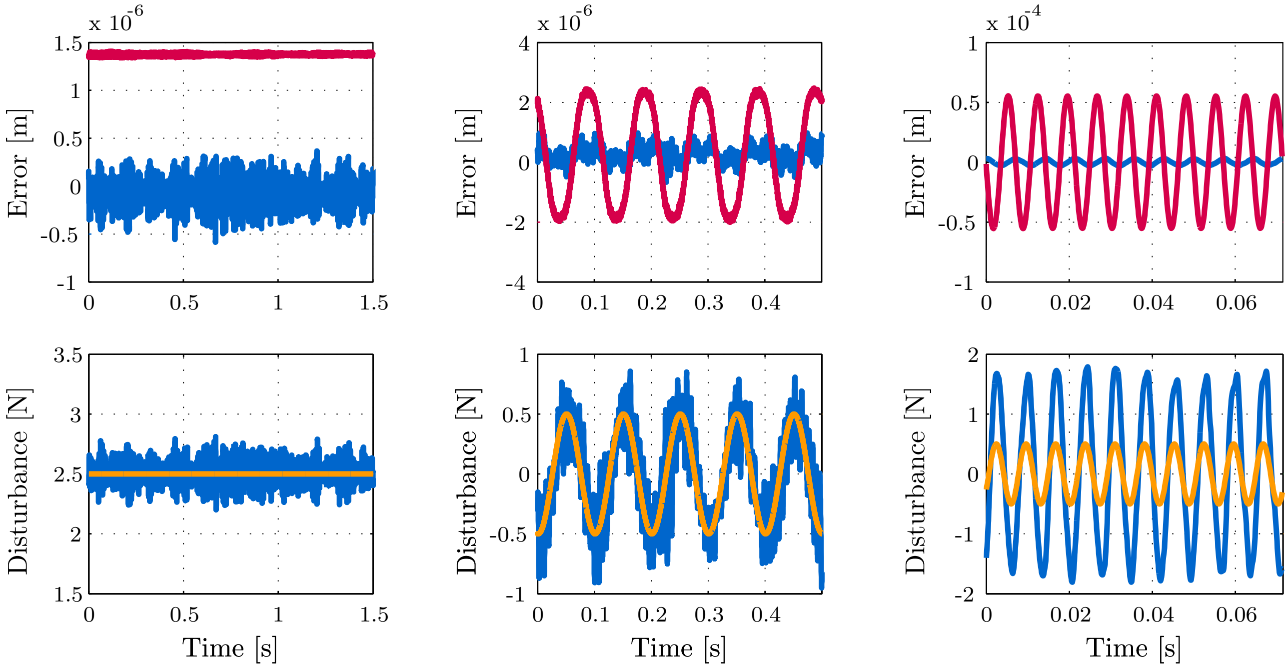

Fig. 8. Results of time domain experiments, showing the response to a constant (left), 10Hz (middle) and 140Hz (right) disturbance. The top plots show $e_{\hat{z}} = z - \hat{z}$ for the rigid body estimation (red) and the designed high gain observer (blue), bottom shows the applied disturbance (orange) as well as the disturbance as estimated by the observer (blue).

7. CONCLUSIONS AND OUTLOOK

In this paper, a flexible observer structure is introduced which can be used in combination with well-established, optimal observer gain synthesis techniques. Furthermore, a frequency domain system identification procedure is proposed and used to obtain a low-order system model. This procedure is tailored to obtain models which are specifically accurate in the frequency range where the observer performance is most relevant, which for this paper is the low-frequent region. It is shown experimentally that these observers can be used effectively to significantly improve the estimation of unmeasured performance variables.

A next step in this research is to use the improved estimates for the performance variables to close the control loop to enhance the system performance at the performance location. Another important addition is to incorporate the variable position of the disturbances. This requires the development of position-dependent models for mechanical structure which is also an important topic of ongoing research.

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