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Performance Analysis of a Model-Free Predictor for Delay Compensation in Networked Systems ⋆

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Abstract: One important challenge with networked systems is that communication delays can significantly deteriorate system performance. This paper considers a model-free predictor framework to compensate for communication delays and improve networked system performance, where the term "model-free" indicates that the predictor does not need to know the dynamic equations governing the system. Stability analysis of this predictor is available in the literature; however, ensuring stability does not guarantee a good performance. Understanding when the predictor can perform well and what its limitations are is critical, but the performance characteristics of the predictor are unknown. Hence, this paper aims to fill this gap by providing a predictor performance analysis for constant time delays. First, a frequency-domain analysis is performed for the predictor and the relationship between the predictor design parameter, time delay, and steady-state performance is revealed. Fundamental limitations of the predictor at higher frequencies are laid out. Next, this analysis is confirmed on a case study. The case study further allows for testing the transient performance of the predictor in closed-loop with the networked system, and shows that the predictor holds significant potential to alleviate the negative impact of communication delays, even if its higher frequency performance may be limited.

Keywords: model-free predictors, time delay systems, networked systems

1. INTRODUCTION

Networked systems are systems that are coupled through information exchange over a communication channel. Example applications include tele-operation, network control, and networked hardware-in-the-loop simulation systems.

Typically, the communication channel introduces delays, which could deteriorate the system performance significantly and could even destabilize the system. The literature presents many techniques to address this challenge. Some of these techniques leverage the system models. For example, in the tele-operation literature, model predictive control has been applied to time delay systems to predict future commands with maximized tracking performance (Bemporad, 1998). Methods to predict operator inputs have been developed (Smith and Jensfelt, 2010). The network control system literature describes many techniques to handle both deterministic (Lian et al., 2002; Montestruque and Antsaklis, 2003) and stochastic network delays (Nilsson, 1998; Goktas, 2000; Liu et al., 2007; Wang et al., 2010). When system models are not available, other methods can be used. For example, researchers from the tele-operation field designed a PD-type predictor in the form of prediction of observation (Kawada and Namerikawa, 2008) and extended it to a state predictor based on solution trajectories of the dynamics (Yoshida et al., 2008). The passivity approach guarantees stability without requiring knowledge about system dynamics (Anderson and Spong, 1989); however, this guarantee comes at the expense of performance (Lawrence, 1993). Networked hardware-in-the-loop simulation literature presents learning-based methods to ensure a high-fidelity integration with no or minimal knowledge about the system (Ersal et al., 2013, 2014; Ge et al., 2014). However, these methods are more suitable in an experimental setting, where experiments can be repeated under controlled environments.

Recently, a predictor was developed that does not require repeated experiments or system models (Tandon et al., 2013). This model-free predictor allows for making predictions regardless of the direction of the communication and hence can be applied bilaterally. The relationship between the design parameter of this predictor and time delay has been established to ensure a stable predictor for constant delays (Tandon et al., 2013). However, a stable predictor is not guaranteed to lead to a good performance, and the performance characteristics of this predictor has not yet been studied. This is a critical research question to address, if

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a systematic way to design the predictor is desired and its performance limitations is to be understood.

Thus, this paper considers the model-free predictor framework originally conceived in (Tandon et al., 2013) and performs a frequency-domain study as a first step to understand the performance characteristics of the predictor. Specifically, this analysis reveals the relationship between the design parameter of the predictor, time delay, and steady-state performance. This helps establish the fundamental performance limitations of the predictor beyond a certain frequency determined by the time delay. Then, a case study is performed to validate this analysis and further study the transient performance of the predictor. The case study also demonstrates that the predictor can perform well in transient even when its high-frequency steady-state performance is very limited.

The rest of the paper is organized as follows. Section 2 presents the problem formulation using a generic networked system framework and summarizes the technique considered in this paper, including the existing stability analysis result. The frequency domain analysis on the steady-state performance of the predictor is performed in Section 3. In Section 4, the predictor is applied to a networked motor-gear-shaft system to evaluate its transient performance. Conclusions are given in Section 5.

2. PROBLEM FORMULATION AND BACKGROUND

Consider the generic networked system with communication delay as shown in Fig. 1. System 1 and System 2 are the two remote systems that are coupled over the network, where the network is considered as a pure, constant delay. If the delay from System 1 to System 2 and from System 2 to System 1 are denoted with t_{d1} and t_{d2}, respectively, then there is a total delay of $t_{d1} + t_{d2}$ between System 1 sending out a signal to and receiving the response from System 2. This delay distorts the system dynamics and reduces performance. It may even cause instability.

To alleviate the negative impact of communication delay, a predictor-based framework as illustrated in Fig. 2 is considered. The site of System 1 contains a predictor for System 2 that aims to predict the non-delayed response of System 2. Instead of interacting with System 2 directly over the network, System 1 interacts with System 2 indirectly through its predictor and without delay. The System 2 Predictor receives the information about System 2 with the delay t_{d2}. Ensuring that the System 2 Predictor can track the outputs of System 2 satisfactorily despite the delay is the problem of interest. A similar predictor structure applies to the site of System 2, as well.

Assume that System 1 and System 2 are both nonlinear systems of the form:

$$\dot{x}_f(t) = f(x_f(t)) + g(x_f(t))u_f(t) \tag{1}$$

where $x_f(t)$ and $u_f(t)$ are the states and inputs of the system, and $f(\cdot)$ and $g(\cdot)$ are nonlinear functions. The

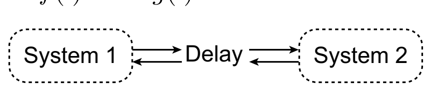


Fig. 1. A generic networked system with communication delay

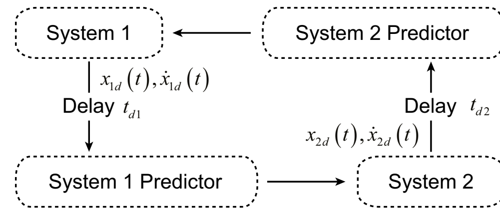


Fig. 2. Predictor-based framework applied to two systems separated by a pure delay

subscript f is introduced to distinguish the full state vector $x_f(t)$ from the state vector $x_d(t)$, $x_d \subseteq x_f$, that contains only the states related to the calculation of the coupling signals; i.e., the signals that are communicated over the network to establish the coupling between the remote systems. Note that when the predictors are introduced (Fig. 2), $x_d(t)$ and its derivative $\dot{x}_d(t)$ are communicated over the network instead of the coupling signals, and the predictors are used to estimate the non-delayed coupling signals according to the following dynamic equations (Tandon et al., 2013):

$$\begin{aligned} \dot{x}(t) &= \dot{x}_d(t - t_d) - \lambda(x(t - t_d) - x_d(t - t_d)) \\ y(t) &= h(x(t)) \end{aligned} \tag{2}$$

where t_d denotes the communication delay, and $x_d(t - t_d)$ and $\dot{x}_d(t - t_d)$ are the delayed state and state derivative vectors from the remote system that are considered as the inputs of the predictor. $x(t)$ is the state vector of the predictor itself. $y(t)$ is the output equation of the predictor, which yields an estimate of the non-delayed response of the remote system. λ is the only design parameter introduced in the predictor. Assuming $h(\cdot)$ is perfectly known, the goal of the predictor is to drive its states, $x(t)$, as close as possible to the coupling-related states of the remote system, $x_d(t)$. Note that no knowledge about the system dynamics is used in the predictor; i.e., neither $f(\cdot)$, nor $g(\cdot)$ appears in (2).

The stability analysis of this predictor was also addressed in (Tandon et al., 2013) for constant delays. The conclusion of that analysis is that asymptotic stability of the predictor is guaranteed for constant delays if and only if the following relationship holds:

$$0 \le \lambda < \frac{\pi}{2t_d} \tag{3}$$

3. FREQUENCY DOMAIN ANALYSIS

The stability criterion (3) is useful to choose a λ for a given time delay, t_d, such that the predictor is stable. However, it does not provide any insight into the performance of the predictor. Therefore, this section provides a frequency-domain analysis for a steady-state performance evaluation of the predictor.

Consider Fig. 3, where the state tracking error between the predictor state and remote system state is given by

$$\tilde{x}(t) = x_d(t) - x(t) \tag{4}$$

Ideally, the state tracking error should be zero to completely eliminate the delay effect. Substituting (2) into the time derivative of (4), the following results can be derived:

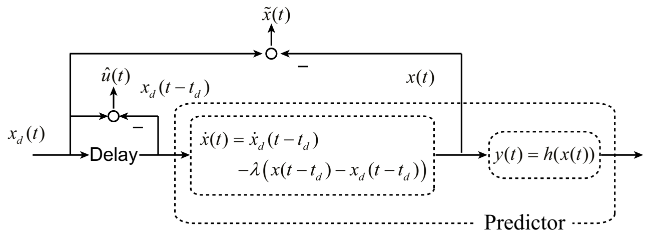


Fig. 3. Analyzing performance of predictor

$$\begin{aligned}\dot{\tilde{x}}(t) &= -\dot{x}(t) + \dot{x}_d(t) \\ &= -\dot{x}_d(t-t_d) + \lambda(x(t-t_d) - x_d(t-t_d)) + \dot{x}_d(t) \\ &= -\dot{x}_d(t-t_d) - \lambda\tilde{x}(t-t_d) + \dot{x}_d(t) \\ &= -\lambda\tilde{x}(t-t_d) + \frac{d}{dt}\hat{u}(t)\end{aligned} \tag{5}$$

where $\hat{u}(t)$ is the coupling error over the communication channel and is defined as:

$$\hat{u}(t) \triangleq x_d(t) - x_d(t-t_d) \tag{6}$$

Then, the following transfer function from the input $\hat{u}(t)$ to the output $\tilde{x}(t)$ can be obtained:

$$\frac{\tilde{X}(s)}{\hat{U}(s)} = \frac{s}{s + \lambda e^{-t_d s}} \tag{7}$$

A good choice of the design parameter, λ, should not only guarantee the predictor's stability, but also minimize $\tilde{x}(t)$. From a frequency-domain perspective, the gain of the transfer function (7) should be be less than one at all frequencies where it is desired to attenuate the coupling error, $\hat{u}$. If $|\tilde{X}(s)/\hat{U}(s)| > 1$ at a given frequency, then the coupling error at that frequency is amplified, which could lead to a bad predictor performance even if the predictor is stable.

The Bode plots of (7) for various values of t_d and λ are shown in Fig. 4 and 5. All $\{\lambda, t_d\}$ pairs shown satisfy the stability criterion (3). A number of observations can be made in these figures regarding the performance characteristics of the predictor. First, Fig. 4 illustrates that the state tracking performance is better at low frequencies for larger λ values. However, it is not always the case that larger λ gives better state tracking. Namely, within the range of about 90 rad/s to 200 rad/s, small λ values may be a better choice for this example delay value, since larger λ values lead to an overshoot above 0dB in the magnitude plot. Furthermore, at higher frequencies, the predictor is less effective in terms of attenuating the state tracking error, since the magnitude remains close to 0dB regardless of the λ value chosen, i.e., $|\tilde{X}(s)/\hat{U}(s)| \approx 1$. Finally, Fig. 5 shows that it is more difficult for the proposed predictor to be effective as the delay, t_d, becomes larger, since the frequency range corresponding to a magnitude smaller than 0dB becomes smaller as delay increases.

Thus, (7) establishes the relationship between the steady-state performance of the predictor, its design parameter, λ, and the time delay, t_d. Hence, this analysis is important to understand some fundamental, frequency-domain performance characteristics of the predictor. It is still unknown, however, how the predictor will perform in transient when introduced into a system as shown in Fig. 2. This motivates the case study in the next section.

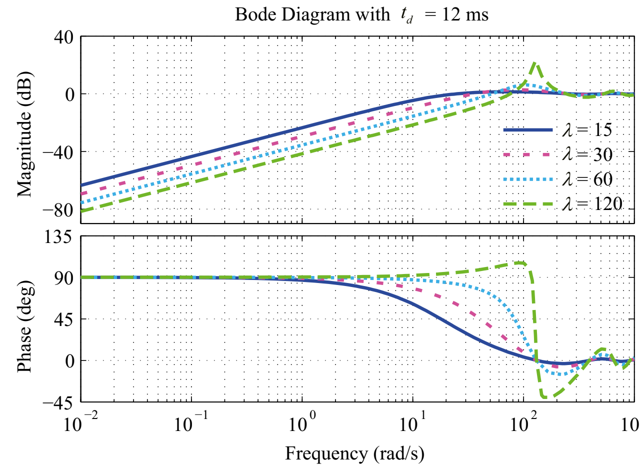


Fig. 4. Bode plot of (7) with $t_d = 12$ms for various λ values

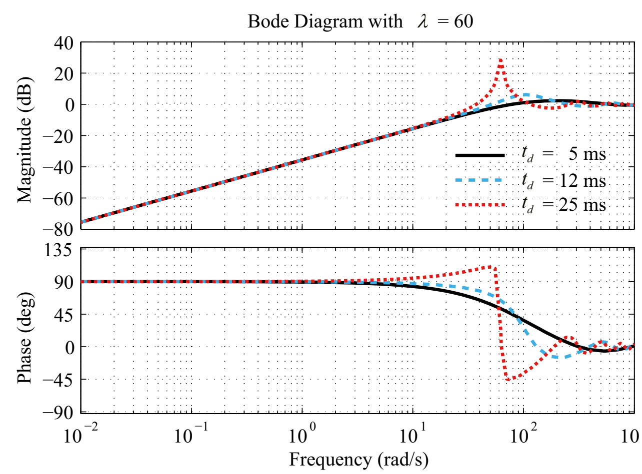


Fig. 5. Bode plot of (7) with $\lambda = 60$ for various t_d values

4. CASE STUDY

A case study is performed in this section to validate the analysis above and also gain some insight into the transient performance of the predictor.

Consider the example system shown in Fig. 6. This example simulates a networked motor-shaft-gear system, where System 1 includes a DC motor, a pair of gears, two shafts and two bearings. A motor voltage, E, is given to drive the DC motor, which rotates the motor shaft connected to a gear pair. The output shaft gives a shaft torque. Bearings are mounted on both shafts; therefore, viscous dampings R_{v1} and R_{v2} are introduced for the motor shaft and the output shaft, respectively. The compliance of the motor shaft is neglected, whereas the compliance of the output shaft is taken into account. System 2 consists of a gear pair, a shaft, a fly wheel and two bearings. The input is the shaft torque from System 1, which drives the gear pair. The gear pair drives the shaft, which is connected to a fly wheel. There are two bearings, with viscous frictions R_v and R_{v4}, at both ends of this shaft. There is viscous damping, R_{v3}, along with the gear pair. System 1 needs shaft speed, ω_s, from the remote site and System 2 needs shaft torque, T_s, from the remote site. The communication delay between the systems is $t_d = 12$ ms. The output of interest of the entire system is the difference of the angular

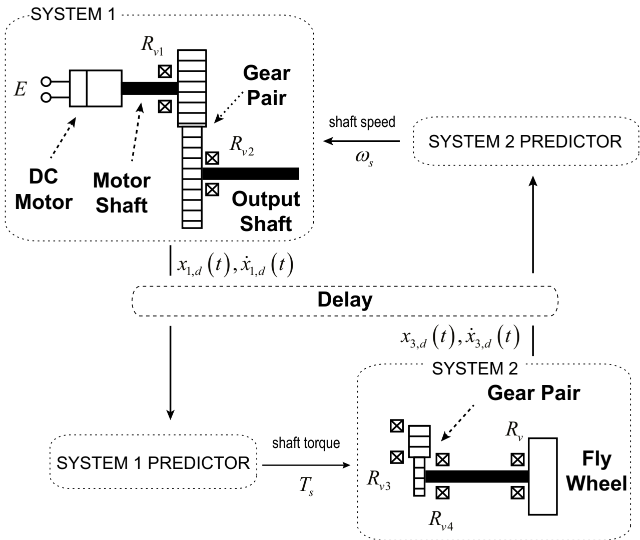


Fig. 6. Networked motor-shaft-gear system with constant communication delay

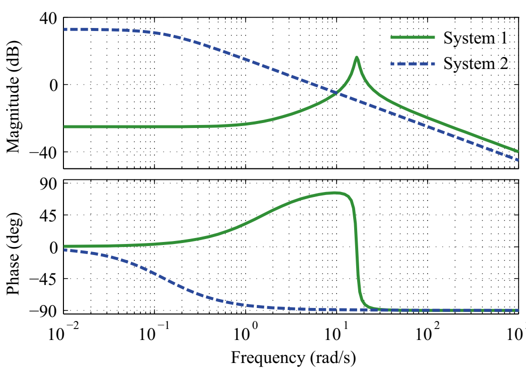


Fig. 7. Bode plot of System 1 (from ω_s to $y_{1,d}$) and System 2 (from T_s to $y_{2,d}$)

displacement of the two ends of the output shaft in System 1, $\Delta\theta$. The dynamics of the individual systems are given as:

System 1:

$$\begin{bmatrix} \dot{x}_{1,d} \\ \dot{x}_{2,f} \end{bmatrix} = \begin{bmatrix} 0 & 500 \\ -0.56 & -1.5 \end{bmatrix} \begin{bmatrix} x_{1,d} \\ x_{2,f} \end{bmatrix} + \begin{bmatrix} 0 & -1 \\ 0.00074 & 0 \end{bmatrix} \begin{bmatrix} E \\ \omega_s \end{bmatrix}$$

$$y_{1,d} = T_s = 10x_{1,d} \tag{8}$$

System 2:

$$\begin{aligned} \dot{x}_{3,d} &= -0.13x_{3,d} + 0.28T_s \\ y_{2,d} &= \omega_s = 20x_{3,d} \end{aligned} \tag{9}$$

The Bode plots of System 1 and System 2 are shown in Fig. 7. Both systems act like low-pass filters.

The coupling-related states for System 1 and System 2 are $x_{1,d}$ and $x_{3,d}$, respectively. With the coupling signal output equations for System 1 and System 2 known, the equations for the two predictors are given by:

System 1 Predictor:

$$\begin{aligned} \dot{x}_1(t) &= \dot{x}_{1,d}(t - t_d) - \lambda(x_1(t - t_d) - x_{1,d}(t - t_d)) \\ y_1(t) &= 10x_1(t) \end{aligned} \tag{10}$$

	ω (rad/s)	1	10	30	100	400
p	$\lambda = 0$	8.2	10.5	11.3	8.3	8.2
p_n	$\lambda = 15$	26.6%	26.6%	27.7%	26.7%	26.6%
	$\lambda = 30$	7.8%	8.1%	9.0%	7.8%	7.8%
	$\lambda = 60$	3.3%	3.6%	4.2%	3.3%	3.3%
	$\lambda = 120$	1.6%	1.7%	2.0%	1.6%	1.6%

Table 1. Performance metrics for different λ values and excitation frequencies over a simulation time window of 80s; a smaller metric value indicates better performance.

System 2 Predictor:

$$\begin{aligned} \dot{x}_3(t) &= \dot{x}_{3,d}(t - t_d) - \lambda(x_3(t - t_d) - x_{3,d}(t - t_d)) \\ y_2(t) &= 20x_3(t) \end{aligned} \tag{11}$$

Note that the same λ is used in this case study in both predictors only for simplicity. In general, different values can be used.

To characterize the time-domain performance of the predictors, the 2-norm of the differences between the simulation results with predictors and the simulation results for the ideal case (i.e., when there is no communication delay) is used. To characterize the performance improvement relative to the case when predictors are not used, a normalized version of the performance metric is also considered, where normalization is done with respect to the 2-norm of the simulation results for the delayed case without predictors. Mathematically, the performance metric p and its normalized version p_n are given as:

$$p = ||r - r_i||_2, \; p_n = \frac{||r - r_i||_2}{||r_d - r_i||_2} \tag{12}$$

where r is the simulation output trajectory vector (in this case, r is $\Delta\theta$) with subscripts i and d standing for the ideal and delayed cases without predictors, respectively. Best performance is achieved when $p = p_n = 0$; i.e., when the impact of delay is completely attenuated. $p_n > 1$ would mean that the predictors worsen the performance, and $p_n < 1$ would mean that the predictors improve the performance compared to the case when predictors are not used.

The simulation is run for 80s using a sinusoidal voltage input $E = 50sin(\omega t) + 50$ volts and zero initial conditions. Performance metrics p_n and p for various ω and λ values are summarized in Table 1. Note that all λ values yield stable predictors according to (3). $\lambda = 0$ corresponds to the case when predictors are not used. The predictors are effective at all excitation frequencies tested and, in general, a larger λ value corresponds to better predictor performance in terms of attenuating the effect of delay as can be seen by the smaller p_n values. Two specific ω values will be discussed further to aid with the comparison between the frequency-domain analysis of Section 3 and the time-domain simulation results.

When ω is 1rad/s, the output of interest, $\Delta\theta$, for the ideal case (no delay), delayed case, and delayed case with predictors ($\lambda = 15$ and $\lambda = 120$) is shown in Fig. 8 for the first 9s. With delay introduced into the system, the output of interest deviates significantly from the ideal case. When predictors are added into the system, the delay effect is reduced, with a larger λ value leading to a better performance.

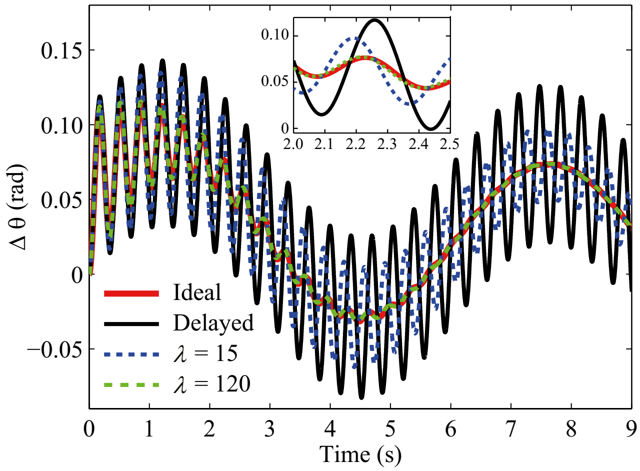


Fig. 8. Output of interest for $\omega = 1$ rad/s

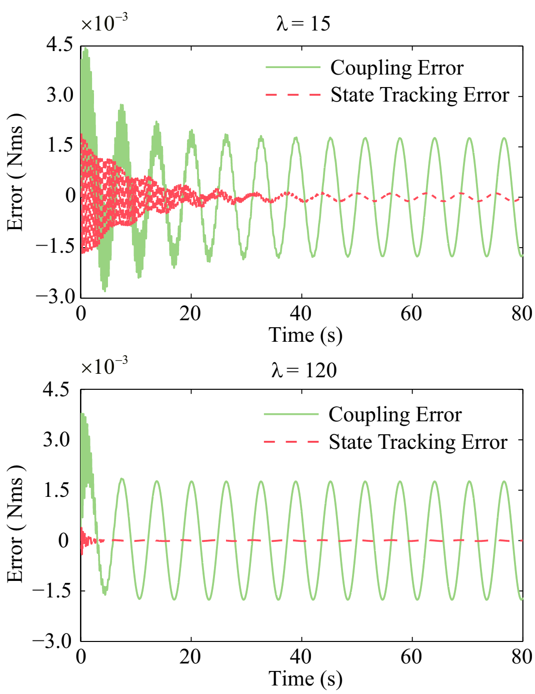
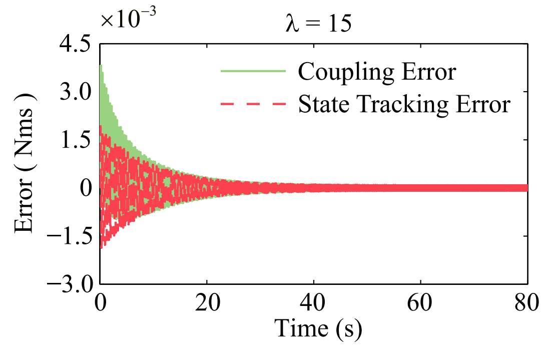


Fig. 9. System 2 predictor performance for $\omega = 1$ rad/s

The state tracking error for the System 2 Predictor is shown in Fig. 9 for two λ values. Note that for different λ values, the coupling errors may be different. Fig. 9 shows that with the larger λ value, the predictor gives a faster state tracking response, and the ratio of the magnitude of state tracking error to the magnitude of coupling error becomes smaller in steady state, which is consistent with the frequency domain analysis in Section 3.

The same analysis also showed, however, that at higher frequencies the predictors would be less effective in terms of reducing the coupling error. Nevertheless, in this case study, p_n is reduced as effectively even when ω is larger. Here, the results obtained with $\omega = 100$ rad/s will be used as an example to explain the reason behind this observation.

For this particular frequency, according to Fig. 4, using $\lambda = 15$ does not make much difference in the coupling error, whereas $\lambda = 120$ yields a steady-state performance that is even worse than the case without any predictors. Indeed, the coupling and state tracking errors shown in Fig. 10 confirm this analysis. In steady state, the amplitude of the coupling and state tracking errors are almost the same for $\lambda = 15$, and state tracking error is worse than the coupling error for $\lambda = 120$. The reason why the predictors are still effective in terms of p_n is because of the combination of two facts. The first fact is that p_n captures the transient response, as well. The transient response does not only include the excitation frequency itself, but also the lower frequencies, where the predictors are effective. The second fact is the low-pass-filter nature of the systems, which places more emphasis on the lower frequency performance and attenuates the higher frequency signals. Thus, even though the performance of the predictors is very limited at higher frequencies, even amplifying the coupling errors for certain λ values, this reduced performance does not have a significant impact on the system response. Fig. 11 shows the output of interest for $\omega = 100$ rad/s for the first 9s of the simulation to highlight the transient performance of the predictors.



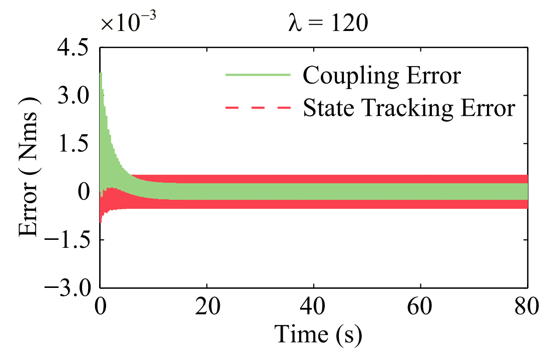


Fig. 10. System 2 predictor performance for $\omega = 100$ rad/s

Fig. 12 shows the coupling error trajectory for $\omega = 100$ rad/s when the predictors are not used. Note that without the predictors the convergence speed to steady state is much slower compared to Fig. 10. Fig. 10 also shows that a higher λ value gives a faster response, even though it leads to a higher steady-state error. Hence, depending on the frequency, there may be a trade-off between faster transient response and lower steady-state error.

This case study illustrates that even though the frequency-domain analysis in Section 3 points out a limited steady-state performance of the predictors at higher frequencies, the predictors may still be helpful, especially if those

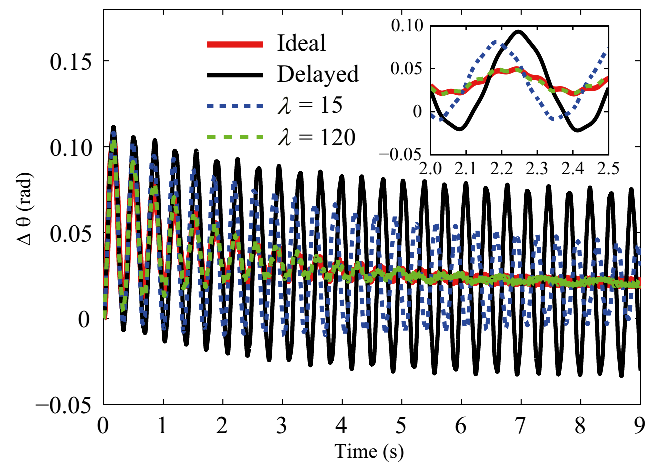


Fig. 11. Output of interest for $\omega = 100$ rad/s

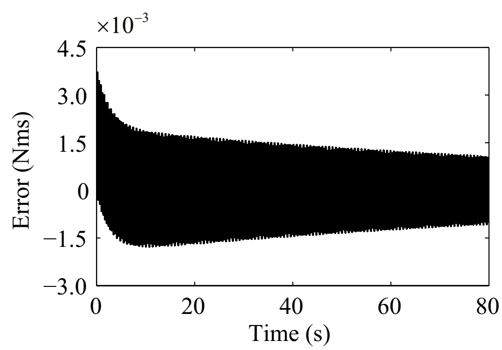


Fig. 12. Coupling error for $\omega = 100$ rad/s when predictors are not used

higher frequencies are beyond the system's bandwidth and the transient response is of interest.

5. CONCLUSION

A frequency-domain performance analysis is provided for a model-free predictor framework to compensate for communication delays in networked systems. A networked motor-gear-shaft system has been used as an example to further study the time-domain performance of the framework in simulation. The analysis provides insight into the relationship between the steady-state performance of the predictor, its design parameter, and time-delays, and thus lays out its fundamental performance characteristics. The case study confirms this analysis, but also illustrates the time-domain, transient performance of the predictor. The main conclusion is that the predictor has significant potential to attenuate the negative impact of delays, especially if the systems exhibit a low-pass-filter type behavior that puts more emphasis on the performance at lower frequencies and thus makes the performance limitations of the predictor at higher frequencies less consequential. These results encourage further research to fully develop and understand this predictor framework. Performance under stochastic delays is of particular interest. Future work also needs to focus on closed-loop stability, as the stability of the predictor does not automatically guarantee closed-loop stability.

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