A Comparison Study on Observer-based Force Control of Series Elastic Actuators

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***Abstract*—This paper presents a comparison study for the robust force control of series elastic actuators (SEAs). In most robotics systems, SEAs are used as an essential actuation method due to the benefits such as lower reflected inertia and safety. However, the robustness to the modeling uncertainties and external disturbances is still a study material for researchers. It is known that when model-based control methods are used with disturbance observers, high precision tracking results can be obtained. Therefore, in this study, model predictive control and model-based feedforward control methods are investigated in different scenarios and simulation results are provided for comparison.**

***Index Terms*—Series Elastic Actuator, robustness, force control**

I. Introduction

Precision and safety are important concerns in robotic applications; especially, when the humans coexist within the workspace. Such systems, including exoskeletons, humanoids, collaborative industrial robots, require special actuators due to the need for high force output, safety and dependability. These requirements compelled researchers to adopt a new approach to the design of actuators. Pratt and Williamson proposed SEAs, the concept of reducing the stiffness of the actuator [2]. Desired superiorities of the SEAs over conventional rigid actuators are lower reflected inertia, high force fidelity and safety [2], [3].

Numerous studies were conducted so far to achieve high fidelity force control of SEAs. Compared to conventional actuators, the control problem of a SEA can be difficult due to the elastic element placed between the motor and link side of the actuator, as it makes SEAs physically compliant [3]. This elastic component may introduce oscillation to the link side, and also sensitivity to disturbances is higher than the conventional rigid actuators [3]. Therefore robust control algorithms become necessary to overcome these problems.

A SEA suffers from not only collocated but also non-collocated disturbances. Therefore, its robust control problem is very complicated. [3]. To this end, observer-based control methods are believed to be capable of suppressing the disturbances acting on the spring and the link side to ensure robustness [20].

In order to address fine torque tracking, Pratt and Williamson implemented a classical PID controller with feedforward loop [2]. A simple PD controller was studied by Tomei with feedforward term which intents to suppress disturbances of modeling uncertainties [11]. However, it is argued that the controller performance suffered from slow response and the method ignores the external disturbances which are highly important in SEAs [3]. Numerous researchers in the literature implemented and investigated disturbance observers (DOB) to achieve robustness against both external disturbances and modeling errors [3], [12]–[14], [16].

Oh and Kong proposed a novel force controller which has a feedback control, feedforward control and a DOB. They applied a DOB to the deflection and fed back deflection with a conventional PID controller [1]. They design a higher order system in the frequency domain. Which may be counter-intuitive to tune. To tackle tuning problem Sariyildiz proposed a robust controller design in state space [15].

Model predictive control (MPC) was proposed by Cutler and Remaker [17] and widely used in process control industry; yet, there are not many detailed studies regarding its application to SEA control. In a related example Rupert et al. utilized MPC with impedance control on a low-impedance robot to reduce oscillations while maintaining a desired level of compliance [18]. Essentially, the MPC algorithm generates a control signal from an optimization problem based on model predictions. High computation needs arise from the optimization problem of MPC to be solved in real-time [6]. With the increasing computational capacities of current computer technology, model predictive controllers can be implemented in systems with fast dynamics [6], [8].The model predictive controller has a natural disturbance rejection property. Applying disturbance observer to the MPC can further improve the robustness of SEA control.

With the advent of recently developed observer-based methods, the robustness of force controllers for SEAs sufficiently improved. Despite the recent developments, these methods have not been compared with the state-of-the-art MPC-based controllers which are also capable of suppressing disturbances. Therefore, this study is conducted to examine three aspects: i) to what extent MPC-based methods are useful for force control of SEAs, ii) can we improve the force tracking performance of MPC by adding a disturbance observer, iii) which controller configuration provides the best force tracking performance. In particular, we will implement the best-performing controller

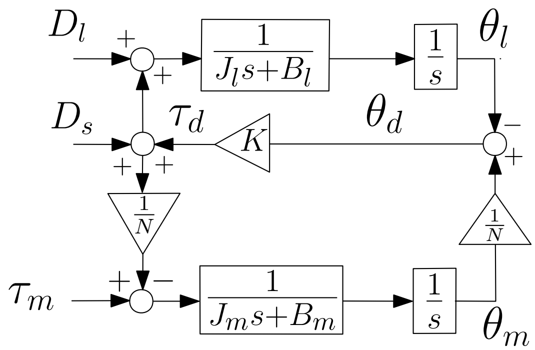


Fig. 1. Two mass system model of a SEA

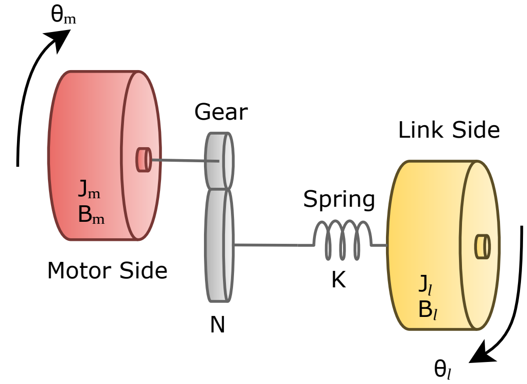


Fig. 2. Mechanical Representation of SEA

to our state-of-the-art SEA modules to power exoskeleton systems that are currently built at the Biomechatronics Lab of the Ozyegin University [19].

The reminder of this paper is organized as follows. In Section II, SEA dynamics and control methods presented. Section III presents simulation environment and comparison results. Section IV concludes the paper.

II. Robust SEA Control

A. SEA Dynamics

In this work, a SEA is modeled as a two-mass system which is shown in Fig. 2. Open loop dynamics of the system can be observed in Fig. 1. Mechanical representation of the system respectively includes motor and link sides with a spring and gear between them. Even though the link dynamics may be complicated and nonlinear, these effects can be considered external disturbances [1].

Since there is a linear relation between the angular deflection and output force of the SEA, force control problem can be converted into position control problem [2]. Therefore, deflection is chosen as a feedback term to achieve feedback control. The transfer function from motor torque command to deflection can be obtained as in (3) which is the same nominal model used for both control methods and disturbance observers [1].

J_m, J_l, B_m, B_l are motor and link inertias and viscous damping coefficients respectively. K is the spring constant and N is the gear ratio of the SEA. θ_m, θ_l, θ_d are the motor, link and deflection angles respectively. τ_m is the motor torque, τ_l is the torque delivered to the link side, D_l and D_s are disturbances acting on the link and spring, respectively.

With the given parameters, motor plant and link dynamics can be examined in (1) and (2).

$$P_m = \frac{\theta_m}{\tau_m} = \frac{1}{J_m s^2 + B_m s} \tag{1}$$

$$P_l = \frac{\theta_l}{\tau_l} = \frac{1}{J_l s^2 + B_l s} \tag{2}$$

Furthermore, the nominal plant model (P_n) without disturbances is as follows,

$$P_n = \frac{\theta_d}{\tau_m} = \frac{N^{-1}P_m}{1 + KP_l + KN^{-2}P_m} \tag{3}$$

Deflection (θ_d) can be written as a difference between motor and link angles with gear reduction,

$$\theta_d = N^{-1}\theta_m - \theta_l \tag{4}$$

With the effects of external disturbances, the transfer function from input to the deflection can be expressed as below [1],

$$\theta_d = \frac{N^{-1}P_m\tau_m - P_l D_l - (N^{-2}P_m + P_l)D_s}{1 + KP_l + KN^{-2}P_m} \tag{5}$$

B. Model Predictive Control

Model Predictive Control (MPC) uses the nominal model (3) to predict future states of the plant within the desired prediction horizon. The procedure follows as solving an optimization problem to obtain future control moves within a specified control horizon in accordance with the restrictions on a plant such as actuator limits. Applying the first control move to the system, other future moves will be discarded and the procedure repeats for every sampling time [6]. A block diagram of MPC control for a single-input-single-output (SISO) system with a DOB is represented in Fig. 3.

The equations of the MPC algorithm can be written as follows [9]. The objective function to be minimized is,

$$\begin{aligned} \min_{\Delta u(t)..\Delta u(t+M-1)} = & \sum_{j=1}^{P}[e^T(t+j)W_e e(t+j)] + \\ & \sum_{j=0}^{M-1}[u^T(t+j)W_u u(t+j)] \end{aligned} \tag{6}$$

where W_e and W_u are weighting matrices on prediction error and input respectively. P and M are prediction and control horizons respectively. Optimization problem of the objective function is to be solved subject to the following constraints on input and outputs. (7), where u^L and u^H are input saturations,

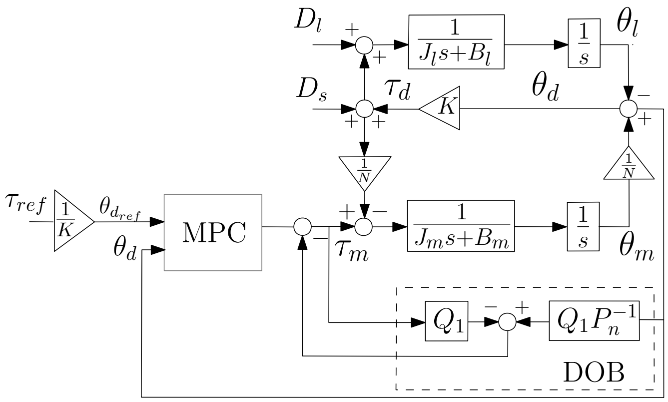


Fig. 3. Block diagram of the MPC method

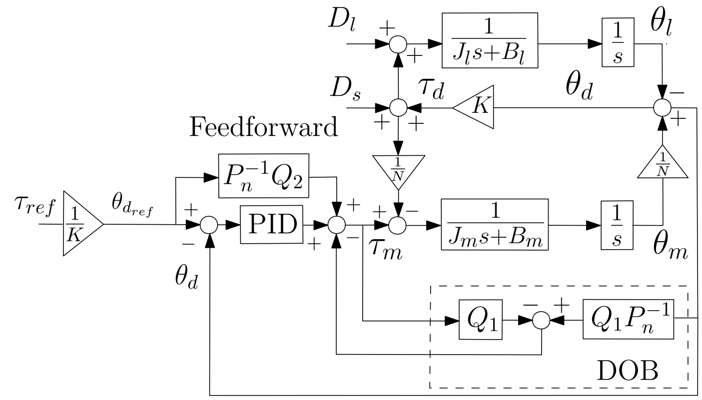


Fig. 4. Block diagram of the FF-PID method

y^L and y^H are output limits and e(t+j) represents prediction error (8),

$$\begin{aligned} u^L &\leq u(t+j) \leq u^H \\ y^L &\leq y(t+j) \leq y^H \\ \Delta u(t+j) &= 0, j > M \end{aligned} \tag{7}$$

$$e(t+j) = \hat{y}(t+j) - r(t+j) \tag{8}$$

For our case, dynamics of a SISO system can be represented as follows,

$$\begin{aligned} \hat{y}(t) &= \sum_{k=1}^{\infty} A(k)\Delta u(t-k) \quad , \\ \Delta u(t) &= u(t) - u(t-1) \end{aligned} \tag{9}$$

Prediction of the output for i^{th} step can be written as below,

$$\begin{aligned} \hat{y}(t+i) = \sum_{k=1}^{i} A(k)\Delta u(t+i-k) + \\ \sum_{k=1}^{\infty} A(k+i)\Delta u(t-k) + d(t) \quad , \end{aligned} \tag{10}$$

$$d(t) = y(t) - \hat{y}(t) \quad , \tag{11}$$

where $y(t)$ is the real time output and $\hat{y}(t)$ is output of SISO model under the action of previous inputs $(u(t-k)(k = 1 \ldots \infty)$. As a correction term, d(t) contains disturbances and modeling uncertainties. Manipulated variable is u(t) and A(k) is the dynamic matrix of system [9].

In this study, a model predictive controller is designed by using MATLAB MPC Toolbox. MPC Toolbox offers a user friendly tuning graphical interface which enables the user to design the controller and obtain rapid prototyping. [7] MATLAB MPC Toolbox has a built-in Kalman filter which estimates the states of the system from the output value. To this end, there is no additional state estimator designed in our controller scheme. [4].

C. Feedforward control with DOB Method

PID Control methods are widely used in motion control problems, therefore, a model based feedforward controller and disturbance observer with classical PID feedback controller scheme (FF+PID+DOB) that was proposed earlier by Oh and Kong in [1] is chosen in our benchmarking.

The feedforward term implements the inverse of the plant multiplied by a low-pass filter and a PID controller is tuned according to the nominal plant. Feedforward controller is represented as $P_n^{-1}Q_2$ where Q_2 is a low pass filter. Diagram can be seen in Fig. 4.

D. Disturbance Observer

To overcome disturbances, a disturbance observer was designed using the inverse of the plant nominal model (P_n^{-1}). To realize P_n^{-1}, a second order Butterworth filter with a cut-off frequency ω_c was implemented as below [21], [22].

$$Q_1 = \frac{\omega_c^2}{s^2 + \sqrt{2}\omega_c s + \omega_c^2} \tag{12}$$

III. Simulation Results

A. Simulation Environment

In this paper, a simulation study is conducted to compare the performances of controllers, in accordance with multiple scenarios, as listed below,

- Scenario 1: Square wave reference with a step disturbance
- Scenario 2: Square wave reference with a sinusoidal disturbance
- Scenario 3: Sinusoidal wave reference with a step external disturbance
- Scenario 4: Sinusoidal wave reference with a sinusoidal external disturbance
- Scenario 5.1: Square wave reference signal without disturbance but with a modeling uncertainty ($J_l = 1.5J_l$)
- Scenario 5.2 Square wave reference signal without disturbance but with a modeling uncertainty ($J_l = 0.75J_l$)
- Scenario 6.1: Square wave reference signal without disturbance but with a modeling uncertainty ($B_l = 0.75B_l$)

- Scenario 6.2 Square wave reference signal without disturbance but with a modeling uncertainty ($B_l = 1.5 B_l$)

For every scenario, the compared controllers are as follows

- Controller 1: Model Predictive Control (MPC)
- Controller 2: Model Predictive Control with Disturbance Observer (MPC+DOB)
- Controller 3: Model-based feedforward with PID feedback and Disturbance observer (FF+PID+DOB)

TABLE I
SIMULATION MODEL PARAMETERS

Parameters	***Explanation***	***Value***	***Unit***
J_m	Motor Inertia	1.2927e-04	kg m^2
B_m	Motor Viscous Friction	6.233e-05	Nm s / rad
K	Spring constant	5000	Nm / rad
N	Gear ratio	100	-
J_l	Link Inertia	0.03	kg m^2
B_l	Link Viscous Friction	5	Nm s / rad

While Scenarios 1-4 examine the combination of different reference and disturbance situations, Scenarios 5-6 examine the parameter variation. Gravitational force acting on the link side is considered as a disturbance on the link and added as follows

$$D_{lg} = sin(\theta_l).\frac{l_l}{2}.m_l.g \tag{13}$$

In (13), lg under-script indicates gravitational disturbance, l_l and m_l are the length and the mass of the arm attached to the SEA as link respectively.

In Scenarios 1 and 3, as disturbance, D_l and D_s were assigned as a step function at time $t = 3.5s$ and $t = 6.5s$

References were given as desired forces multiplied by the inverse of the spring constant, $\theta_{d_{Ref}} = K^{-1}\tau_{d_{Ref}}$ and in all scenarios, all reference amplitudes were $10Nm$, all disturbance amplitudes were $\%10$ of the reference amplitude which was $1Nm$. Sinusoidal reference and disturbances had a frequency of $6.28rad$. Moreover, the cut-off frequency of the DOB filter was 150Hz.

TABLE II
CONTROLLER PARAMETERS

Parameters	***Explanation***	***Value***
K_p	Proportional Gain	3
K_i	Integral Gain	0.1
K_d	Derivative Gain	0.5
Q_2	LPF Cut-of frequency	60 π rad/s
P	Prediction Horizon	30
M	Control Horizon	10
$U_L, \quad U_H$	Input Saturation Limits	-/+ 10
W_u	Input weight	0.03
W_e	Output weight	225

While model parameters are represented in Table I, controller parameters are stated in the Table II. MATLAB & Simulink was used as a simulation environment. Block diagram of the controllers with the SEA dynamics was implemented in Simulink as shown in the Fig. 4 and 3.

B. Benchmarking

Comparison results of the reference tracking for six different scenarios are shown in Fig. 5 and 6. Hence, all the plots represent the results in a situation where disturbance observer is used. Some portions of the graphs are zoomed in order to be viewed easily by readers. In Table III, root mean square values of tracking errors for MPC without DOB, MPC with DOB and FF+PID with DOB are presented.

As can be seen in Table III, for all scenarios, the model predictive controller with disturbance observer (MPC+DOB) exhibits more desirable root mean square of tracking error records for all scenarios. Furthermore, it can be concluded that, even without disturbance observer, MPC is suppressing disturbances noticeably. In addition, the robustness of MPC can be improved significantly by using a disturbance observer.

In Scenario 5, where modeling uncertainty of link inertia is investigated, MPC+DOB introduced more overshoot and relatively poor tracking performance compared to FF+PID+DOB. However, the root mean square of the error is less than FF+PID+DOB. Considering this, it can be concluded that FF+PID+DOB configuration is relatively more robust to the modeling uncertainties than MPC+DOB.

In Scenario 6, where modeling uncertainty of link viscous friction is investigated, in contrast to scenario 5, MPC+DOB revealed more favorable results compared to FF+PID+DOB. Without the DOB, the performances of both controllers were not satisfactory as concluded from the RMS tracking errors. Therefore it can be observed that the disturbance observers significantly improved robustness.

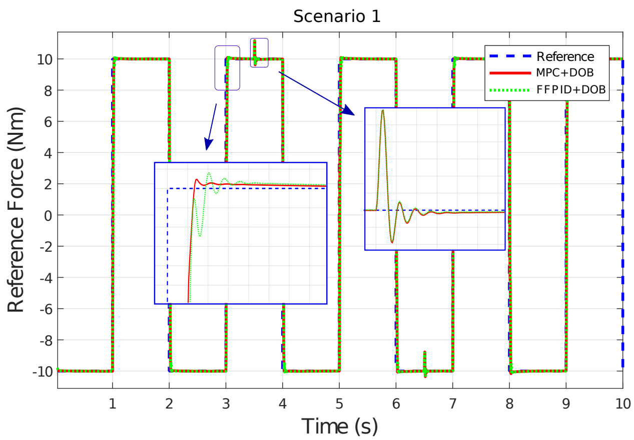
For scenarios 3 and 4, which reference is sinusoidal force, superiority of MPC+DOB performance over FF+PID+DOB can be seen both in RMS values and graphics in Fig. 5(c) and 6(a) clearly.

TABLE III
REFERENCE TRACKING RMS COMPARISON

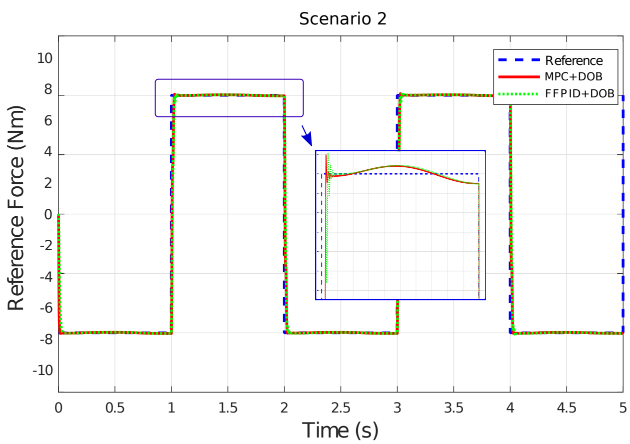
Scenario	***MPC***	***MPC+DOB***	***PID+FF+DOB***
Scenario 1	1.5567	1.4626	1.6509
Scenario 2	1.5630	1.4111	1.5954
Scenario 3	0.2894	0.1037	0.4728
Scenario 4	0.7209	0.0607	0.4361
Scenario 5.1 (Jl = Jl)	1.5514	1.4618	1.6507
Scenario 5.2 (Jl = 0.75 Jl)	1.6432	1.5519	1.7304
Scenario 5.3 (Jl = 1.5 Jl)	1.4379	1.4568	1.5709
Scenario 6.1 (Bl = 0.75 Bl)	2.4333	1.5871	1.7694
Scenario 6.2 (Bl = 1.5 Bl)	2.6049	1.3810	1.5690

IV. CONCLUSION

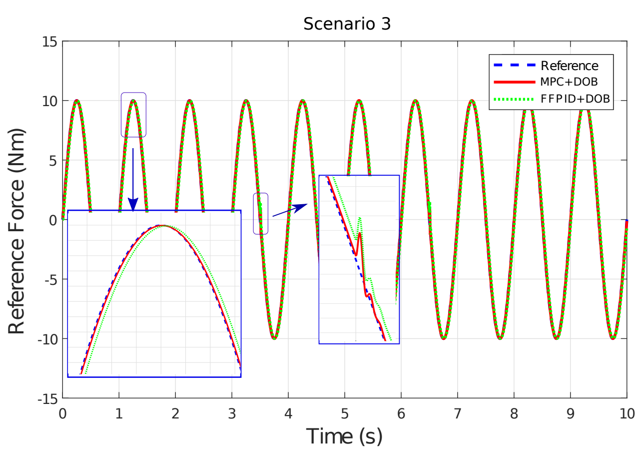
In this paper, a simulation study that includes three controller configurations was conducted for six different scenarios. SEA dynamics was modeled as two mass system and simulated in MATLAB Simulink. As a disturbance on link,



(a) Scenario 1

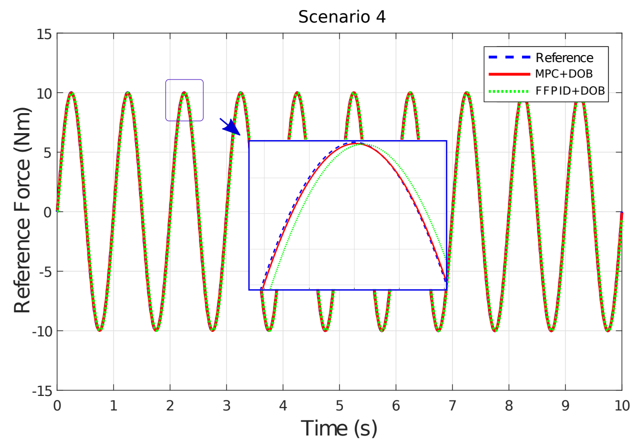


(b) Scenario 2

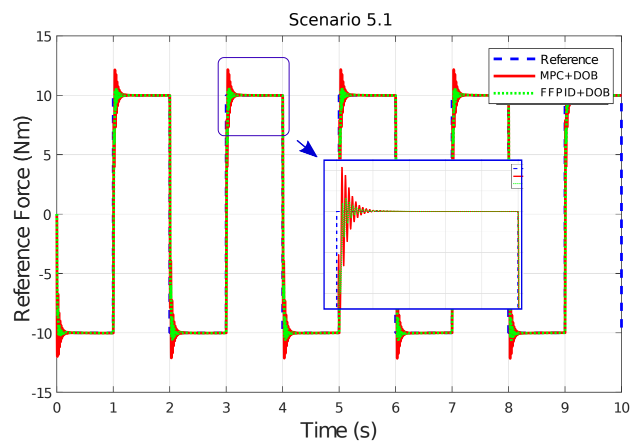


(c) Scenario 3

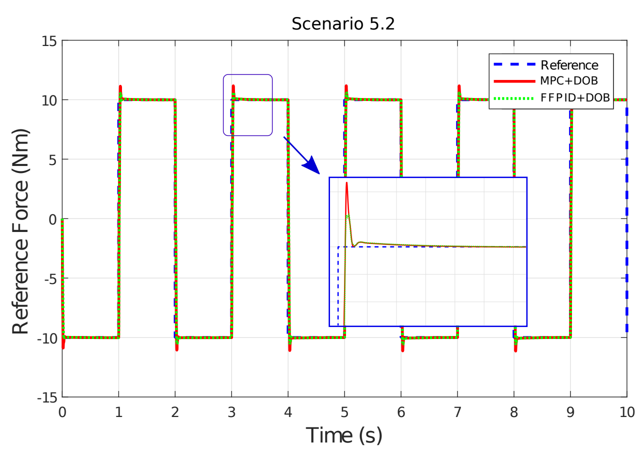
Fig. 5. Simulation results for different scenarios, disturbance observer is implemented for both controllers.



(a) Scenario 4



(b) Scenario 5.1 ($J_l = 1.5J_l$)



(c) Scenario 5.2 ($J_l = 0.75J_l$)

Fig. 6. Simulation results for different scenarios, disturbance observer is implemented for both controllers.

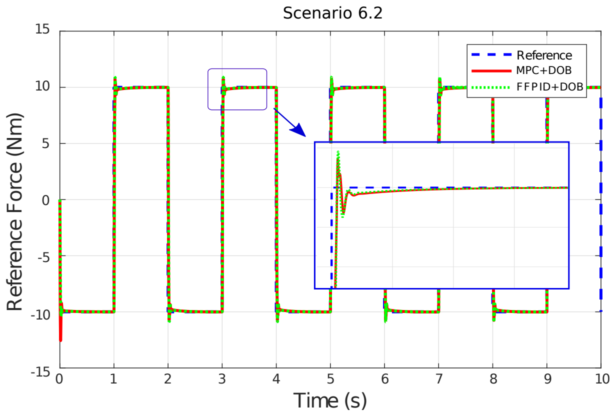


Fig. 7. Simulations results for Scenario 6.2

gravitational force acting on the link was implemented for all scenarios.

As a comparison result, MPC with DOB outperformed other controllers in the terms of RMS values for all scenarios. It can be seen that, even without DOB, MPC can reject disturbances naturally by itself, furthermore, DOB noticeably improves the robustness of MPC.

Considering the current computer technology, advanced control methods as MPC can be advantageous in the sense of robust control. However, in model parameters variation case, MPC+DOB overshoots more than FF+PID+DOB that in further studies, the effect of the filters on the force control of SEAs can be examined.

Both controllers were intuitively tuned, it can be argued that parameters are optimal. We are not drawing a bold conclusion, that being said, in future work, experiments will be conducted to support the results of the simulations studied on this paper, with same controller configurations and existing series elastic actuator, to choose suitable robust control method for an ongoing exoskeleton study.

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References

[1] S. Oh and K. Kong, 2017, "High Precision Robust Force Control of a Series Elastic Actuator", IEEE/ASME Transactions on Mechatronics, 22(1), 71-80.

[2] G. A. Pratt and M. M. Williamson, "Series elastic actuators," Proceedings 1995 IEEE/RSJ International Conference on Intelligent Robots and Systems. Human Robot Interaction and Cooperative Robots, Pittsburgh, PA, 1995, pp. 399-406 vol.1

[3] E. Sariyildiz, G. Chen and H. Yu, "An Active Disturbance Rejection controller design for the robust position control of Series Elastic Actuators," 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Daejeon, 2016, pp. 266-272.

[4] A. Bemporad M. Morari and N. L. Ricker Model Predictive Control Toolbox for Matlab - User's Guide. The Mathworks Inc. 2004 http://www.mathworks.com/access/helpdesk/help/toolbox/mpc/.

[5] E. Sariyildiz, G. Chen and H. Yu, "Robust position control of a novel series elastic actuator via disturbance observer," 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hamburg, 2015, pp. 5423-5428.

[6] M. Morari, J. H. Lee, Model predictive control: past, present and future, In Computers & Chemical Engineering, Volume 23, Issues 4-5, 1999, Pages 667-682

[7] A. Bemporad, "Model Predictive Control Design: New Trends and Tools," Proceedings of the 45th IEEE Conference on Decision and Control, San Diego, CA, 2006, pp. 6678-6683.

[8] P. Cortes, M. P. Kazmierkowski, R. M. Kennel, D. E. Quevedo and J. Rodriguez, "Predictive Control in Power Electronics and Drives," in IEEE Transactions on Industrial Electronics, vol. 55, no. 12, pp. 4312-4324, Dec. 2008.

[9] J. Yang, S. Li, X. Chen, Qi Li, "Disturbance rejection of dead-time processes using disturbance observer and model predictive control", in Chemical Engineering Research and Design, vol. 89, no. 2, 2011, pp. 125-135

[10] G. A. Pratt, P. Willisson, C. Bolton and A. Hofman, "Late motor processing in low-impedance robots: impedance control of series-elastic actuators," Proceedings of the 2004 American Control Conference, Boston, MA, USA, 2004, pp. 3245-3251 vol.4.

[11] P. Tomei, "A simple PD controller for robots with elastic joints," in IEEE Transactions on Automatic Control, vol. 36, no. 10, pp. 1208-1213, Oct 1991.

[12] K. Kong, J. Bae and M. Tomizuka, "Control of Rotary Series Elastic Actuator for Ideal Force-Mode Actuation in HumanRobot Interaction Applications," in IEEE/ASME Transactions on Mechatronics, vol. 14, no. 1, pp. 105-118, Feb. 2009.

[13] K. Kong, J. Bae, M. Tomizuka, "A compact rotary series elastic actuator for human assistive systems," IEEE/ASME Trans. Mechatronics, vol. 17, no. 2, pp. 288-297, Apr. 2012.

[14] N. Paine, S. Oh and L. Sentis, "Design and Control Considerations for High-Performance Series Elastic Actuators," in IEEE/ASME Transactions on Mechatronics, vol. 19, no. 3, pp. 1080-1091, June 2014.

[15] E. Sariyildiz and K. Ohnishi, "An Adaptive Reaction Force Observer Design," in IEEE/ASME Transactions on Mechatronics, vol. 20, no. 2, pp. 750-760, April 2015.

[16] W. Roozing, J. Malzahn, D. G. Caldwell and N. G. Tsagarakis, "Comparison of open-loop and closed-loop disturbance observers for series elastic actuators," 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Daejeon, 2016, pp. 3842-3847

[17] C. R. Cutler, and D. L. Ramaker, "Dynamic matrix control - a computer control algorithm," In Proceedings of the Joint Automatic Control Conference (JACC), San Francisco, CA, 1980.

[18] L. Rupert, P. Hyatt and M. D. Killpack, "Comparing Model Predictive Control and input shaping for improved response of low-impedance robots," 2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids), Seoul, 2015, pp. 256-263.

[19] M. C. Yildirim, P. Sendur, O. Bilgin, B. Gulek, G. G. Yapici, and B. Ugurlu, "An Integrated Design Approach for a Series Elastic Actuator: Stiffness Tuning, Fatigue Tests, Thermal Management," in proc. of the IEEE Int. Conf. Humanoid Robots, 2017, UK, In print.

[20] K. Ohnishi, M. Shibata and T. Murakami, "Motion control for advanced mechatronics," in IEEE/ASME Transactions on Mechatronics, vol. 1, no. 1, pp. 56-67, March 1996.

[21] M. A. Hopkins, S. A. Ressler, D. F. Lahr, A. Leonessa and D. W. Hong, "Embedded joint-space control of a series elastic humanoid," 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hamburg, 2015, pp. 3358-3365

[22] T. K. Tasooji, O. Bebek, B. Ugurlu, "A Robust Torque Controller for Series Elastic Actuators: Model Predictive Control with a Disturbance Observer" Turkish National Conference on Automatic Control (TOK), Istanbul, Turkey pp. 398-402, 2017 [in Turkish].