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LQG - Based Robust Tracking for the Magnetic Levitation Laboratory Plant

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Abstract: The paper deals with the design of robust LQG-based control for a maglev laboratory plant to ensure tracking of selected types of the levitating ball position reference and rejection of measurable input disturbance. The reference position tracking and the disturbance rejection are provided by the command generator tracker (CGT) – the LQ control designed for the modified state-space model augmented by the reference and disturbance state variable models. Robustness to model uncertainty guarantees that the linear CGT is applicable over the full range of the levitating ball distances from the upper coil and is achieved through adjusting the process- and measurement noise covariances in the Kalman filter design. The proposed CGT – LQG design for the real maglev system proceeds in several steps using simulations and experiments providing the insight into specific control problems.

Keywords: magnetic levitation system, tracking, Kalman filter, robust control, LQG.

1. INTRODUCTION

Magnetic levitation (maglev) has become a widely used advanced technology applied in various applications featuring a contactless and frictionless motion of an object suspended in the air solely by magnetic fields. The maglev technology has been applied in countless different engineering applications, e.g. magnetically levitated trains, flying cars, wind turbines, space crafts, weapons, building facilities, air conditioning systems, automotive as well as advertisement applications (Yaghoubi, 2013).

Laboratory maglev systems (MLS) are favored laboratory devices in control education as they incorporate various engineering issues encountered in control of nonlinear unstable real systems starting from first principles modelling, identification of model parameters and linearization. A variety of standard and advanced control approaches can be verified on MLS (Li et al, 2023) including PID, state-feedback (Hypiusova et al., 2020), model predictive control (Chalupa et al., 2017), robust control (Hypiusova and Kozakova, 2017), QFT (Jeyasenthil and Choi, 2019), LMI design (Hypiusová and Rosinová, 2021), gain-scheduling (Rosinová et al., 2021), fuzzy control (Ahmad, 2010) as well as neural networks-based control (Rubio et al., 2017).

Mechatronics is a multidisciplinary field synergistically integrating mechanics, electronics, informatics and automatic control. Motivating mechatronics students to study automatic control is particularly important because they find it quite difficult. Demonstrations of laboratory model control, especially the MLS, usually attract students and arouse their interest in the field. Therefore, the MLS is regularly showcased during open days to promote the study of mechatronics (Kučera et al., 2020). In the control laboratory at the authors´ workplace equipped with laboratory plants from Inteco (2008) mainly graduating students prepare their final theses or dissertations. The MLS has been used to verify selected robust approaches and methods. Robustness of a system signifies its ability to remain functional despite large changes caused by model uncertainty and effect of external disturbances. Basically, robustness can be achieved by applying controller design for the controlled plant modelled as an uncertain system given by the nominal model and a suitable form of uncertainty (Hypiusova and Kozakova, 2017; Jeyasenthil and Choi, 2019; Hypiusová and Rosinová, 2021), or through quadratic optimization leading to a LQG controller (Bhattacharyya, 2017). The latter approach combines the optimal state-feedback LQ controller with the Kalman filter designed for a stochastic model including the process- and measurement noises described by white Gaussian noises with zero means and known covariances.

The paper deals with the design of robust control for a laboratory MLS to ensure tracking of selected types of the levitating ball position reference and rejection of respective measurable disturbances. This kind of problem also called LQ servo design is handled e.g. in Kim et al. (2017), Rubio et al. (2021) and Teppa-Garan and Fabbioni (2023). The solution proposed in this paper is LQG-based. The reference position tracking and the disturbance rejection are provided by the command generator tracker (CGT) – the LQ control designed for the modified linear state-space model augmented by the reference and disturbance state variable models. Robustness to model uncertainty guarantees that the linear CGT is applicable over the full range of the levitating ball distances from the upper coil and is achieved through adjusting the process- and measurement noise covariances in the Kalman filter design. Considered types of reference and disturbance variables were step, ramp and sinusoid functions.

Designed CGT–LQG controllers were verified via simulation 1. on the MLS model linearized in the selected working point, 2. on the linearized model corrupted by plant and sensor noises modelled as white Gaussian noises with zero means and known covariances; 3. on the nonlinear plant model, and experimentally 4. on the real system over the whole feasible working distance of the levitating ball from the upper coil.

The paper is organized as follows: in Section 2, the laboratory MLS and its nonlinear and linearized models are presented along with Problem formulation. Section 3 summarizes background theory on state-space tracking and disturbance rejection and presents selected results for the MLS. In Section 4 the steady-state Kalman filter design is recalled and applied for the MLS. Section 5 presents results obtained from experimental verification of the LQG-based robust tracking and disturbance rejection on the real MLS.

2. THE MAGNETIC LEVITATION SYSTEM

2.1 Laboratory plant description

The laboratory MLS by Inteco (2008) in Fig. 1 is a nonlinear, open-loop unstable time varying frictionless dynamic system. The voltage applied to the upper electromagnet keeps a ferromagnetic ball levitated. The ball can follow a desired position value varying in time. To levitate the ball, a real-time controller has to keep it in a desired distance from the magnet maintaining the equilibrium of the gravitational and the electromagnetic forces.

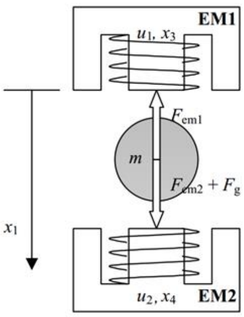

Figure 1. Magnetic levitation laboratory system (MLS)

The system is fully integrated with MATLAB/Simulink and operates in the real-time in MS Windows.

2.2 Mathematical model

The nonlinear MLS model is derived by combining first principles to obtain the model structure, and experimental identification to find values of its parameters. The nonlinear and linearized models are supplied by the manufacturer; here we consider their corrected versions (Balko and Rosinová, 2017; Hypiusová and Rosinová, 2021).

A. Nonlinear MLS model

$$\begin{aligned} \frac{dx_1}{dt} &= x_2 \\ \frac{dx_2}{dt} &= \frac{1}{2m}\frac{dL(x_1)}{dx_1}x_3^2 + g \\ \frac{dx_3}{dt} &= \frac{1}{f(x_1)}(k_i u + c_i - x_3) \end{aligned} \tag{1}$$

Where $x_1(t) = x(t)$ is position of the ball with respect to the upper coil; $x_2(t) = \dot{x}_1(t)$ is the ball velocity; $x_3(t) = I(t)$ is the current in the upper coil; m is the ball mass; $L(x_1)$ is a function describing the coil inductance as a function of x_1; g is gravitational acceleration; k_i, c_i are respectively the slope and the intercept of the line approximating the dependence between the current flowing through the coil and the voltage.

B. Linearized MLS model

The nonlinear MLS model (1) was linearized in the working point $x_{10} = 0.01$ m considering the medium-sized ball mass m = 0.023 kg. The linear state-space model is as follows:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) \end{aligned} \tag{2}$$

where

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 1684.669 & 0 & -21.467 \\ 0 & 0 & -288.77 \end{bmatrix};\ B = \begin{bmatrix} 0 \\ 0 \\ 1270.6 \end{bmatrix};\ C = [1 \quad 0 \quad 0] \tag{3}$$

2.3 Problem Formulation

For the laboratory MLS, a controller is to be designed to guarantee proper tracking of selected types of references (step, ramp and sinusoid) and rejection of disturbances of similar types within the whole operating range of the plant given by the feasible distance of the levitating ball from the upper coil. The design proceeds in following steps:

1. Design of command generator trackers (CGT) for the linearized model and selected types of reference and disturbance variables, their verification via simulation around the chosen working point of the nonlinear model, and implementation on the real device.
2. Kalman filter (KF) design for the linearized model using properly estimated and tuned process and noise covariances.
3. Verification of the CGT-LQG controller (KF connected with individual CGTs) via simulation on the nonlinear model (1) over the full feasible range of distances of the ball from the upper coil; if successful, implementation on the real MLS with iteratively fine-tuned process- and measurement noise covariances.

3. REFERENCE TRACKING AND DISTURBANCE REJECTION: CGT DESIGN

The design of optimal reference tracking and disturbance rejection is based on the standard LQ optimal control theory; (Lewis, 1992). Considering the infinite time horizon $T \to \infty$, the LQ feedback control law

$$u(t) = -Kx(t) \tag{4}$$

guarantees that the state $x(t)$ of the dynamic system (2) asymptotically converge to zero (to the working point) from arbitrary initial conditions minimizing the quadratic performance index

$$J(t_0) = \frac{1}{2}\int_{t_0}^{\infty}[x^T(t)Qx(t) + u^T(t)Ru(t)]dt \tag{5}$$

if the weighting matrices $Q \geq 0, R > 0$ and the feedback gain in (4) is calculated as follows:

$$K = -R^{-1}B^TP \tag{6}$$

where $P = P^T, P > 0$ is the solution of the matrix algebraic Riccati equation

$$PA + A^TP - PBR^{-1}B^TP + Q = 0 \tag{7}$$

The LQ design is feasible only if all system´s states are measurable; otherwise an observer has to be designed to provide state estimates for implementation of the LQ controller. The Kalman filter (KF) is a stochastic observer estimating the state vector from measured outputs of the system corrupted by measurement and process noises specified by their covariances.

3.1 Reference tracking

The LQ regulator can be converted into a command generator tracker (CGT) by adding additional feedforward terms. CGT design (Lewis, 1992) is an efficient technique yielding simultaneously the feedback and the pre-compensator gains guaranteeing proper tracking of polynomial and harmonic reference variables. It is based on the state-space model (2) augmented by the dynamics of the reference variable (Lewis, 1992; Franklin et al., 2006; Kozakova, 2014).

Consider the linear state-space model (2). A state-feedback controller is to be designed to guarantee that the selected output variable called performance output

$$z(t) = Hx(t) \tag{8}$$

tracks a reference function described by an *n*-th order linear differential equation with constant coefficients $a_i \in R$ (this is the case of polynomial and harmonic functions):

$$r^{(d)} + a_1r^{(d-1)} + \cdots + a_dr = 0 \tag{9}$$

The feedback control law $u(t)$ has to minimize the performance index

$$J = \int_0^\infty [e^T(t)Qe(t) + u^T(t)Ru(t)]dt \tag{10}$$

where $e(t) = r(t) - z(t)$ is the tracking error.

Denote $\Delta(s)$ the characteristic polynomial of (9):

$$\Delta_r(s) = s^d + a_1s^{d-1} + \cdots + a_d \tag{11}$$

Eq. (11) expressed in the controllable canonical form is the command generator model, e.g. for $d = 3$, the command generator is as follows

$$\dot{\rho}(t) = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -a_3 & -a_2 & -a_1 \end{bmatrix}\rho(t) = F\rho(t)$$

$$r(t) = [1 \quad 0 \quad 0]\rho(t) \tag{12}$$

Using the operator $\Delta_r(s)$, we obtain the following relations:

$$\Delta_r(s)r = 0 \tag{13}$$

$$\Delta_r(s)e = \Delta_r(s)r - \Delta_r(s)Hx = -H\xi \tag{14}$$

$$\xi = \Delta_r(s)x = x^{(d)} + a_1x^{(d-1)} + \cdots + a_dx \tag{15}$$

Rewriting (14) in the matrix form we obtain

$$\dot{\varepsilon} = F\varepsilon + \begin{bmatrix} 0 \\ -H \end{bmatrix}\xi \tag{16}$$

where

$$\varepsilon(t) = [e \quad \dot{e} \quad \ldots \quad e^{d-1}] \tag{17}$$

Dynamics of $\xi(t)$ (15) can be expressed as follows:

$$\dot{\xi} = A\xi + B\mu \tag{18}$$

where $\mu = \Delta_r(s)u = u^{(d)} + a_1u^{(d-1)} + \cdots + a_du$ (19)

Combining (16) and (18), the state-space model of the augmented system including the command generator is

$$\frac{d}{dt}\begin{bmatrix} \varepsilon \\ \xi \end{bmatrix} = \begin{bmatrix} F & 0 \\ & -H \\ 0 & A \end{bmatrix}\begin{bmatrix} \varepsilon \\ \xi \end{bmatrix} + \begin{bmatrix} 0 \\ B \end{bmatrix}\mu$$

$$\upsilon = \begin{bmatrix} I & 0 \\ 0 & C \end{bmatrix}\begin{bmatrix} \varepsilon \\ \xi \end{bmatrix} \tag{20}$$

Applying the LQ output control design for the augmented system (20) and the augmented performance index

$$J = \int_0^\infty [\upsilon^T(t)Q\upsilon(t) + \mu^T(t)R\mu(t)]dt \tag{21}$$

the resulting control law is obtained:

$$\mu = \Delta_r(s)u = -[K_\varepsilon \quad K_y]\begin{bmatrix} \varepsilon \\ C\xi \end{bmatrix} = -K_\varepsilon\varepsilon - K_yC\Delta_r(s)x \tag{22}$$

To be applicable for the original system, the CGT control law (22) is modified to obtain the transfer function:

$$\frac{u + K_yy}{e} = \frac{K_1s^{d-1} + \cdots + K_{d-1} + K_d}{s^d + a_1s^{d-1} + \cdots + a_d} \tag{23}$$

CGT implementation according to (23) for d=3 is shown in Fig. 2. The control law is implemented as a feedback loop guaranteeing stability and a feedforward path ensuring reference tracking.

3.2 Reference tracking with disturbance rejection

A similar philosophy is applied when designing a CGT with disturbance rejection. Consider the disturbance described by the differential equation

$$d^{(q)} + p_1d^{(q-1)} + \cdots + p_d = 0 \tag{24}$$

acting on the system (2), hence

$$\dot{x}(t) = Ax(t) + Bu(t) + d(t) \tag{25}$$

If the dynamics of the measurable input disturbance

$$\Delta_d(s) = s^q + p_1s^{q-1} + \cdots + p_d \tag{26}$$

is included in $\Delta_r(s)$ (13) the CGT guarantees both reference tracking and disturbance rejection; otherwise, it has to be designed for $\Delta(s) = \Delta_r(s)\Delta_d(s)$ thus making the CGT include the dynamics of both the disturbance and the reference. Thus, the performance output (8) tracks the reference even if input disturbance *d*(*t*) acts on the system.

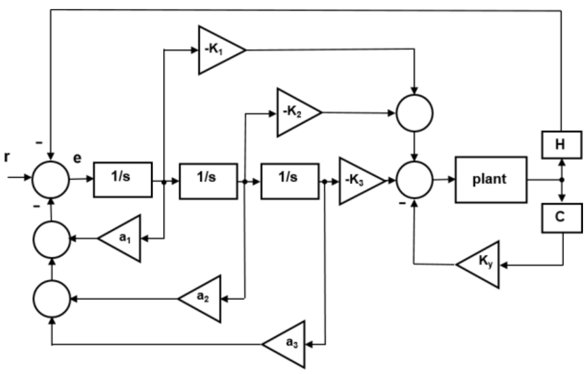

Figure 2. CGT block scheme according to (23) for $d = 3$.

3.3 Design of CGT with disturbance rejection for the MLS

The CGT design with disturbance rejection for the MLS was performed for the linearized model (3). The following reference variables were applied: a step $r(t) = 0.01\, m$, a sinusoid $r(t) = 0.001\sin\left(\frac{\pi}{2}t\right)$, and a superposition of ramps with different slopes $r(t) = \alpha t$ yielding a trapezoidal reference profile. The acting disturbances to be rejected were a step $d(t) = \pm 0.005\, m$, a sinusoid $d(t) = 0.005\sin\left(\frac{\pi}{2}t\right)$, and a ramp $d(t) = 0.1t$

For the nonlinear MLS model and the real plant the tracking error is

$$e = z - r = Hx - r, \qquad (27)$$

hence, when building the augmented model the respective signs had to be modified accordingly.

Design of CGTs with disturbance rejection was successfully completed for all combinations of the above references and disturbances, yet for space reasons we will demonstrate only CGT design to track the sinusoid reference and reject the step disturbance. The differential equation (9) of a sinusoid reference is

$$\ddot{r} + \omega_0^2 r = 0, \qquad (28)$$

the corresponding characteristic equation is

$$\Delta_r(s) = s^2 + \omega^2. \qquad (29)$$

Practical implementation of the designed control law requires getting the ball to the working point first and only then start tracking the sinusoid reference. Hence, the augmented model needs to include dynamics of both the sinusoid and the step. As a result, rejection of the input step disturbance is guaranteed as well. So, the CGT has been designed for

$$\Delta(s) = \Delta_r(s)\Delta_d(s) = (s^2 + \omega^2)s. \qquad (30)$$

The respective augmented state-space model is

$$\frac{d}{dt}\begin{bmatrix} e \\ \dot{e} \\ \ddot{e} \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & -2467.4 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1684.7 & 0 & -21.5 \\ 0 & 0 & 0 & 0 & 0 & -288.8 \end{bmatrix}\begin{bmatrix} e \\ \dot{e} \\ \ddot{e} \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1270.6 \end{bmatrix}\mu \qquad (31)$$

For the selected weighting matrices

$$Q = \mathrm{diag}\{1000\ \ 1\ \ 0\ \ 0\ \ 0\ \ 0\}; \quad R = 0.005, \qquad (32)$$

the resulting gain matrix was obtained:

$$K = [-447.21 \quad -260.52 \quad -107.60 \quad -46.19 \quad -1.066 \quad 0.07]$$

where $K_\varepsilon = [K(1) \quad K(2) \quad K(3)]$ are the feedforward gains and $K_y = [K(4) \quad K(5) \quad K(6)]$ are the feedback ones. The simulation scheme is in Fig. 3, simulated responses are depicted in Fig. 4.

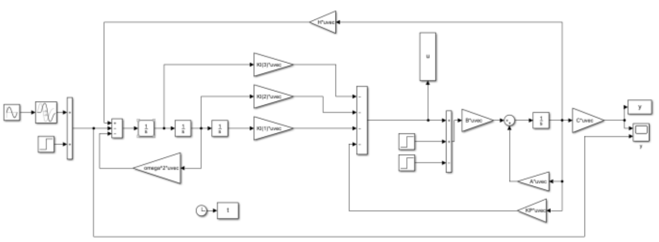

Figure 3. Simulation scheme with the linear MLS model and the CGT with disturbance rejection (sinusoid reference, step disturbance)

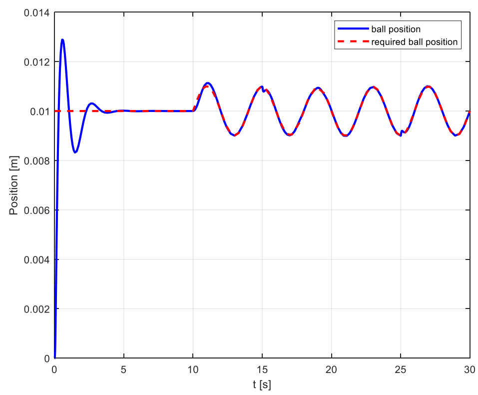

Figure 4. Simulation results (linear MLS model): step disturbances in $t_1 = 15\ s$ and $t_2 = 25\ s$ were successfully rejected

The same scenario was verified on the nonlinear model (Fig. 5), corresponding time responses are in Fig. 6.

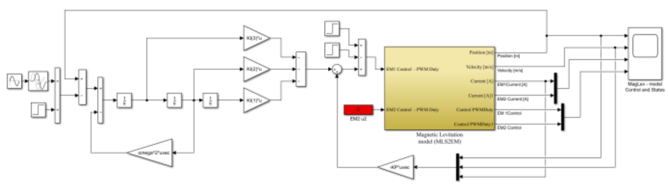

Figure 5. Simulation scheme with the nonlinear MLS model and CGT with disturbance rejection (sinusoid reference, step disturbance)

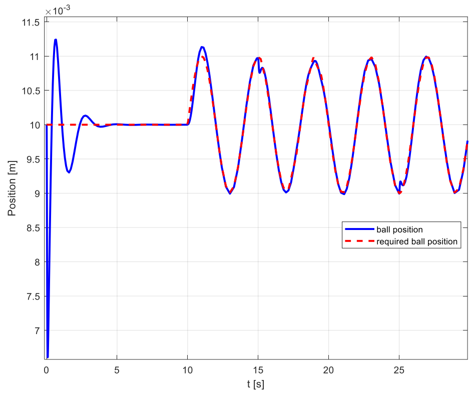

Figure 6. Simulation results (nonlinear MLS model): step disturbances in t_1 = 15 s and t_2 = 25 s were successfully rejected.

4. ROBUSTNESS: KALMAN FILTER DESIGN

Due to the nonlinear MLS dynamics, the CGT designed for the linearized model guarantees reference tracking and disturbance rejection only within ± 0.001 cm around the working point $x_{10} = 0.01\ m$ (Fig. 4, Fig. 6). To guarantee proper CGT operation over the full working range, the stochastic observer - Kalman filter was designed for the stochastic MLS model corrupted by process noise $w(t)$ (representing model uncertainty) and measurement noise $v(t)$, both modelled as white Gaussian noises with zero mean and known covariances yielding the state vector estimate $\hat{x}(t)$.

State-space model of the stochastic system is

$$\dot{x}(t) = Ax(t) + Bu(t) + Gw(t)$$
$$y(t) = Cx(t) + v(t) \tag{33}$$

where

$$w \approx (0, Q_f), Q_f = Q_f^T \geq 0 \tag{34}$$
$$v \approx (0, R_f), R_f = R_f^T > 0 \tag{35}$$

The steady-state KF has the observer structure:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K_f[y(t) - C\hat{x}(t)] \tag{36}$$

where $\hat{x}(t)$ is the state vector estimate. When designing KF, the aim is to minimize the estimation error covariance P by K_f:

$$J = \min_{K_f} P = \min_{K_f} E\left[\left(x(t) - \hat{x}(t)\right)\left(x(t) - \hat{x}(t)\right)^T\right] \tag{37}$$

KF design in dual to LQ design; the resulting optimal gain K_f is obtained as follows:

$$K_f = P_f C^T R_f^{-1} \tag{38}$$

where P_f is solution of the algebraic Riccati equation

$$0 = AP_f + P_f A^T - P_f C^T R_f^{-1} C P_f + G Q_f G^T, \tag{39}$$

$$P_f = P_f^T,\ P_f > 0 \tag{40}$$

A proper operation of the KF is achieved by tuning the covariances Q_f and R_f of the process- and the measurement noises, respectively. The resulting LQG controller encompasses the CGT implemented to state variables estimated by the KF.

4.1 Kalman filter design for the MLS

Considering the process noise at the input, $G = B$ in (33) and the stochastic model of MLS is as follows:

$$\dot{x}(t) = \begin{bmatrix} 0 & 1 & 0 \\ 1684.7 & 0 & -21.5 \\ 0 & 0 & -288.7 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 0 \\ 1270.6 \end{bmatrix} u(t) + $$
$$+ \begin{bmatrix} 0 \\ 0 \\ 1270.6 \end{bmatrix} w(t)$$
$$y(t) = Cx(t) + v(t), \tag{41}$$

the KF gain K_f was calculated using (39) and (40) and properly tuned covariances $Q_f = 50$, $R_f = 3 * 10^{-10}$. Using the Matlab command *lqe*, the resulting Kalman gain is

$$K_f = \begin{bmatrix} 4.19 \\ 8779.42 \\ -400648.02 \end{bmatrix} * 10^3$$

5. EXPERIMENTAL VERIFICATION OF THE CGT- LQG ON THE REAL MLS

Implementation of the KF with the CGT (CGT - LQG) is shown in Fig. 8. Measured responses are shown in Fig. 7. For properly tuned $Q_f > R_f$ in the KF design, robustness against model uncertainty is ensured. As a result, the levitating ball can track the reference over the full working range of ball distances from the upper coil (8-12 mm).

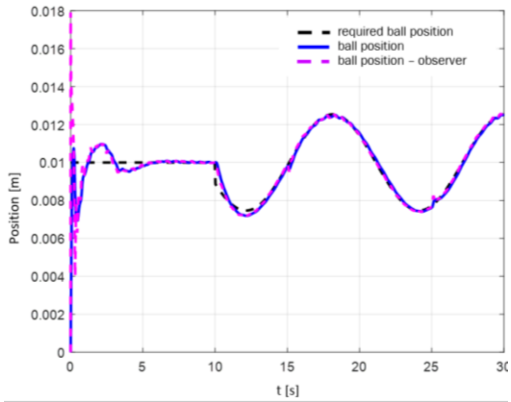

Figure 7. Experimental verification of the CGT-LQG (real MLS): step disturbances in t_1 = 15 s and t_2 = 25 s were successfully rejected within the operating range 7 – 12 mm

CONCLUSION

The CGT-LQG control design methodology for the laboratory maglev system is currently included in the master's degree course on advanced control methods for mechatronic systems.

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REFERENCES

Ahmad, A. K., Saad, Z., Osman, M. K., Isa, I. S., Sadimin S. and Abdullah, S. S. (2010). Control of Magnetic Levitation System Using Fuzzy Logic Control. In 2010

2nd Int. Conference on Computational Intelligence, Modelling and Simulation, Bali, Indonesia, pp. 51-56.

Balko, P. and Rosinová, D. (2017). Modeling of magnetic levitation system. In *Proceedings of the 2017 21st International Conference on Process Control (PC), Štrbské Pleso, Slovakia, June 6 – 9*, *2017*, pp. 60–65.

Bhattacharyya S. P. (2017). Robust control under parametric uncertainty: an overview and recent results. *Annual Reviews in Control*, 44, 45-47.

Chalupa, P., Novák, J., Malý, M. (2017). Modelling and Model Predictive Control of Magnetic Levitation laboratory plant. In *31st European Conference on Modelling and Simulation (ECMS 2017)*, Budapest, Hungary.

Franklin, G.F., Powel, J.D. and Ememi-Naini, A. (2006). *Feedback control of dynamic systems*. Pearson Prentice Hall. 5th edn.

Li, F., Sun, Y., Xu, J., He, Z., Lin, G. (2023). Control Methods for Levitation System of EMS-Type Maglev Vehicles: An Overview. *Energie*s, 16, 2995.

Kim, C.-H., Ahn, H., Lee, J. and Lee, H. (2017). Linear quadratic servo design for magnetic levitation systems considering disturbance forces from linear synchronous motor. *J. Electr. Eng. Technol*., 12 (2), 944-949.

Hypiusova, M. and Kozakova, A. (2017). Robust PID controller design for the magnetic levitation system: Frequency domain approach. In *21st International Conference on Process Control, (PC ´17),* pp. 274-279.

Hypiusová, M., Rosinová, D. and Kozáková, A. (2020). Comparison of State Feedback Controllers for the Magnetic Levitation System. In Proceedings of *2020 Cybernetics & Informatics (K&I), Velke Karlovice, Czech Republic,* pp. 1-6.

Hypiusová, M., and Rosinová, D. (2021). Discrete-Time Pole-Region Robust Controller for Magnetic Levitation Plant. *Symmetry,* 13, No. 1.

Jeyasenthil, R. and Choi, S.B. (2019). A robust controller for multivariable model matching system utilizing a quantitative feedback theory: Application to magnetic levitation. Applied Sciences (Switzerland) Open Access, Vol. 9, Issue 91.

Kučera, E., Haffner, O., Leskovský, R., Matišák, J., Drahoš, P. and Stark, E. (2020). Popularization of Mechatronics by Fan Film Inspired by Avengers: Infinity War. In *2020 Cybernetics & Informatics (K&I), Velke Karlovice, Czech Republic*, 1-6.

Lewis, F. L. (1992). *Applied Optimal Control & Estimation*. Prentice Hall and Texas Instruments Inc.

Kozakova, A. (2014). Discrete-time asymptotic reference tracking for an industrial robot. In Proceedings *23rd International Conference on Robotics in Alpe-Adria-Danube Region (RAAD), Smolenice, Slovakia*, pp. 1-6.

Magnetic Levitation System 2EM (MLS2EM) – User´s manual. [CD-Rom]. Inteco Ltd, Krakow, Poland, 2008.

Rosinová, D. et al. (2021). Novel robust gain scheduled PID controller design using DR regions. *Asian Journal of Control*, 24, pp. 2062 - 2073.

Rubio, J.J., Zhang, L., Lughofer, E. and Francisco, P. (2017). Modeling and control with neural networks for a magnetic levitation system. *Neurocomputing*, 227, pp. 113-121.

Rubio, J.J. et al. (2021). Adapting H-infinity controller for the desired reference tracking of the sphere position in the maglev process. *Information Sciences*, 569, 669-686.

Teppa-Garan, P. and Fabbioni, M. (2023). Robust tracking in 2DoF control systems: magnetic levitation system. *Latin American Applied Research,* 53(4), 303-308.

Yaghoubi H. (2013). The most important maglev applications. *Journal of Engineering*, (Article ID537986).

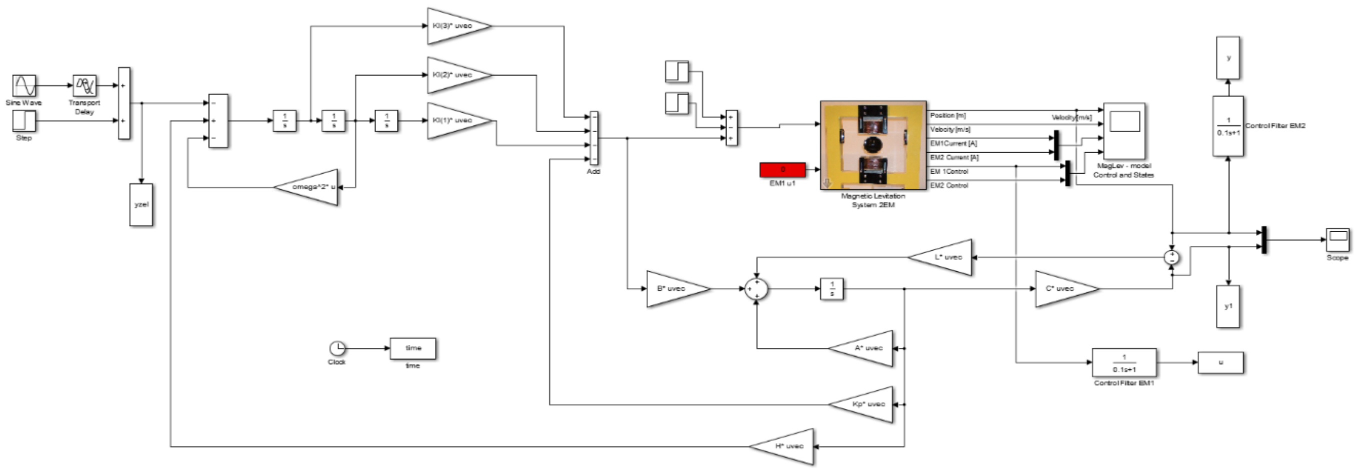

Figure 8. Simulation scheme with the LQG-CGT for sinusoid reference and step disturbance (real MLS)