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FRIT-based integral action state feedback controller tuning using PSO for a liquid slosh suppression system

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ABSTRACT

This paper presents a model-free approach of controller tuning to a liquid slosh suppression system. The sloshing is the usual occurrence happening to the liquid in a moving container. An integral action state feedback controller was proposed as the selected control structure. A fictitious reference signal was formulated using the recorded input-output data generated from a one-shot experiment and later be used to design the appropriate performance index. The minimization of the performance index of the controlled system was achieved by employing the PSO algorithm. Numerical analyses using MATLAB software have been conducted to evaluate the effectiveness of the proposed model-free approach. The results manifested that the tuned controller had exhibited good transient response performance regarding the trajectory tracking of the cart motion and reduction of slosh level motion.

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1. INTRODUCTION

The nature of the slosh motion phenomenon commonly exists in some engineering applications [1]. The phenomenon is due to sway motion to the open free liquid surface area inside the container. Some of the examples where the existence of the sloshing phenomenon may create functionality problems to the overall operations can be found in the molten-metal industries [2], food packaging [3], and even in a space launch system [4]. Extracting undesired force from the slosh motion may be performed by adequately designing the overall container structure or imposing control actions to improve the comprehensive system's performance.

Over the past few years, many research works have introduced and developed control strategies to iron out the slosh problems of the liquid in a moving container. However, most of the proposed approaches focus on implementing feedback or closed-loop control than open-loop control, which is less sensitive to disturbance and variations parameters. For instance, in [5], the authors implemented sliding mode control (SMC) for slosh control in a container using a nonlinear sliding surface in the controller design. Due to the high frequency of the chattering effects from SMC, the boundary layer design technique is developed to reduce the impact. The findings showed that the proposed method portrayed a better outcome than the conventional SMC. Besides that, the studies in [6], [7] employed the H-infinity optimization technique by defining the optimal finding subject to certain constraints. In the end, the approach assures a good performance response and can be adapted to the uncertainties. Our previous work in [8] focused on implementing the LQR-LMI approach to seek the optimal state feedback gains. A model-based approach has been considered to obtain the optimal state feedback controller's parameters. In addition, the work in [9] employed active force control (AFC) combined with a conventional PID control scheme. PID-AFC can see a promising result in suppressing liquid sloshing compared to standalone PID. In terms of optimizing the controller, the PID scheme control can be tuned by various methods of data-driven techniques, such as simultaneous-perturbation-stochastic-approximation (SPSA) [10], safe-experimentation-dynamic (SED) [11], exponential-based-simulated-Kalman-filter (EbSKF) [12], and fuzzy control [13]. Even though it was highlighted that these techniques did not require the plant's dynamic function as part of the requirement in the tuning process, the actual controlled system was still being utilized to attain the optimal controller parameters.

Most of the proposed studies on the controller design of the slosh suppression system focus on the model-based control in the design process. This type of control strategy utilizes the preliminary knowledge of the controlled system in the design steps. The design steps include formulating the plant's model, which involves deriving the dynamic equation based on Lagrange's energy dissipation principle [14] or system identification techniques [15]. Generally, modeling a complex system might be challenging as it requires specific skills and mathematical procedures [16]. Furthermore, it is almost impossible to build a global model because of the internal complexities and external disturbances. Hence, from a control designer's point of view, a model-free control approach may offer the best alternative solutions to ensure such factors' inclusiveness for obtaining the optimal parameters of the controllers.

The fictitious-reference-iterative-tuning (FRIT) is one of the model-free techniques of controller designs. Term coined by Kaneko *et al.* [17], FRIT requires only one-shot experimental data of the closed-loop system for tuning [18]. The algorithm works by iteratively updating the designed controller's variable parameters to minimize the performance index or the cost functions formulated by the designer. Although FRIT seems to be similar to virtual-reference-feedback-tuning (VRFT) [19], [20], the distinction between these two algorithms is in the formulation of the fictitious signal. Unlike in VRFT, where the virtual signal is computed using the input, the FRIT, on the other hand, utilizes the output. Both techniques, in general, focus on the optimization of the controller by minimizing/maximizing the performance index. It is achieved by employing either deterministic [21] or metaheuristic [22] optimization algorithms in the computation.

In 1995, Kennedy and Eberhart introduced particle swarm optimization (PSO) [23] as one technique of classical metaheuristic [24] optimization algorithms. Inspired by nature, the PSO algorithm mimics the behavioral swarm or flocking of the birds seeking food to search for optimal solutions to a given optimization problem. The algorithm has been successfully implemented in combination with the FRIT to determine the optimal coefficients of the Laguerre network to obtain a matched impedance between the master-slave manipulators of a bilateral teleoperation system [25]. Therefore, this algorithm offers a practical advantage that warrants further studies on its applicability to other engineering problems.

The main study of this work is to implement and tune an integral state feedback controller of a liquid slosh suppression system. Using the same controller structure as in [6], the optimal parameter's controller is obtained based on a model-free approach by utilizing FRIT to define and generate the virtual signal. By the appropriate selection of the cost function, the swarm intelligence was then employed to compute and seek the final solution that reached the best performance in the closed-loop system. The proposed validation process was carried out through numerical analyses using MATLAB software.

This paper is organized as follows. In section 2, the mathematical modeling and linearization of the slosh suppression system are concisely explained. Next, in section 3, the general concepts of the model-free controller tuning utilizing the FRIT and PSO algorithm are provided. A numerical analysis to elucidate the feasibility of the proposed controller tuning is presented in section 4. Finally, the conclusion of the findings is provided in section 5.

2. PROBLEM FORMULATION

Mathematical Preliminaries: Let $\mathscr{R}$ and $\mathscr{R}^n$ are denoted as the sets of a real number and real vector with n - dimension, respectively. Meanwhile, the notation $\mathscr{R}^{m\times n}$ represents the real matrices with m - number of rows and n - number of columns. Suppose $v \in \mathscr{R}^n$, then, the vector norm is expressed by $\|v\|^2 := \left(\sqrt{v^T v}\right)^2 = v^T v \in \mathcal{R},$ where T is the transposition. The notation $\| v(k) \|_K^2$ implies that $\|v(k)\|_K^2 := \sum_{k=1}^{K} \|v(k)\|^2 = \|v(1)\|^2 + \|v(2)\|^2 + \cdots + \|v(K)\|^2$.

2.1. Modeling of the slosh suppression systems

The slosh system modeled as a partially filled container is depicted in Figure 1. The mechanism of the slosh system can be represented by a simple pendulum system, as illustrated in Figure 2. Here, the mass pendulum is denoted as the slosh mass $m \in \mathcal{R}$, while the other elements directly uninvolved in the slosh motion (i.e., the container and cart) are lumped into a single rigid mass $M \in \mathcal{R}$. The movement of the mass pendulum depicted in Figure 2 can best represent the angular motion of the slosh motion $\theta(t) \in \mathcal{R}$, where it exhibits angular motion when the force $u(t) \in \mathscr{R}$ is applied to the cart's body.

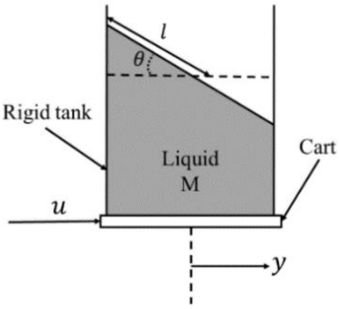

Figure 1. Slosh system of the partially filled container model

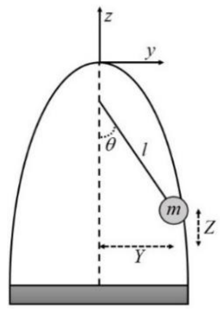

Figure 2. Slosh system by simple pendulum mechanism model

By utilizing the Euler-Lagrange equation, a nonlinear model of the dynamical slosh system can be denoted as [10]

$$M\ddot{y} + ml\cos\theta\,\ddot{\theta} - ml\dot{\theta}^2\sin\theta = u \quad (1)$$

$$ml\cos\theta\,\ddot{y} + ml^2\ddot{\theta} + d\dot{\theta} + mgl\sin\theta = 0 \quad (2)$$

where $y(t) \in \mathscr{R}$ is the total displacement of the cart, $d \in \mathscr{R}$ is the damping coefficient, and $g \in \mathcal{R}$ is the gravitational force. Meanwhile, $l \in \mathcal{R}$ is the assumed hypotenuse length of the slosh motion. The equations (1) and (2) can be categorized as a second-order underactuated system. This complexity may lead to difficulty in the tuning process. Therefore, one of the approaches to minimize the degree of complexity is to linearize the system around its operating point. Let $x(t) = [y(t) \quad \dot{y}(t) \quad \theta(t) \quad \dot{\theta}(t)]^T \in \mathscr{R}^4$ be the state vector. Hence, by partial linearization, the dynamic equations of (1) and (2) may be denoted by

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (3)$$

$$y(t) = Cx(t) \quad (4)$$

where $A \in \mathscr{R}^{4\times4}$, $B \in \mathscr{R}^4$, $C \in \mathcal{R}^{1\times4}$ are the system, input, and output matrices, as defined in (5), (6), and (7), respectively. Note that $\xi = \frac{\sin\theta}{\theta} \in \mathscr{R}$.

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & \frac{-g\zeta}{l} & \frac{-d}{ml^2} \end{bmatrix} \quad (5)$$

$$B = \begin{bmatrix} 0 & 1 & 0 & \frac{-\cos\theta}{l} \end{bmatrix}^T \quad (6)$$

$$C = [1 \quad 0 \quad 0 \quad 0] \quad (7)$$

The dynamical system of (3) and (4) can be formulated into their discrete-time representation. With the selected sample time $T_s \in \mathscr{R}$, the discrete-time linear time-invariant (LTI) system is denoted as:

$$x(k+1) = \boldsymbol{A}x(k) + \boldsymbol{B}u(k) \quad (8)$$

$$y(k) = \boldsymbol{C}x(k) \tag{9}$$

where $\boldsymbol{A} = exp(AT_s) \in \mathscr{R}^{4\times4}$, $\boldsymbol{B} = \int_0^{T_s} e^{A\lambda} d\lambda \bullet B \in R^4$ and $\boldsymbol{C} = C \in \mathscr{R}^{1\times4}$, respectively.

2.2. Selection of the control law

The dynamical system is assumed to fulfill the controllability condition in this configuration. Let C be the controllability matrix defined by

$$\mathcal{C} = [\boldsymbol{A} \quad \boldsymbol{AB} \quad \boldsymbol{A^2B} \quad \boldsymbol{A^3B}]. \tag{10}$$

The system (8) is said to be controllable if and only if $\text{rank}(\mathcal{C}) = 4$.

The state feedback controller with integral action is considered in this study. Generally, a state feedback controller could sufficiently be designed by obtaining the set of optimal parameters' gains to relocate the poles' location of the controlled closed-loop system to achieve the desired design specification. However, implementing only the state feedback would yield the system exhibiting constant non-zero steady-state error as $k \to \infty$. Hence, adding the integral term as part of the controller structure is ideal for attenuating this error signal. The complete schematic of the controlled system with control action is shown in Figure 3. The reference signal depicted in the figure is denoted by $r(k) \in \mathcal{R}$. Meanwhile, $e(k) = r(k) - y(k)$ is the system error.

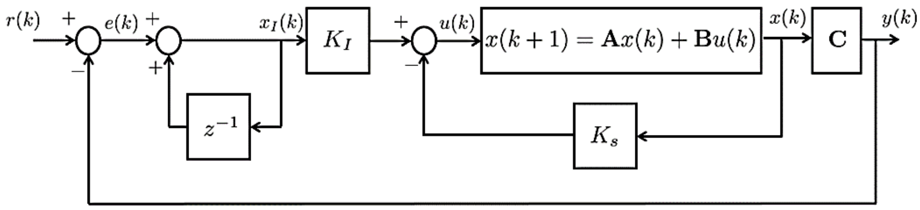

Figure 3. Block diagram with selected control law

By introducing an additional integral state of $x_I(k) \in \mathscr{R}$, the control law is defined in the form of

$$u(k) = [-K_s \quad K_I] \begin{bmatrix} x(k) \\ x_I(k-1) \end{bmatrix}, \tag{11}$$

where $K_s \in \mathscr{R}^{1\times4}$ are the state feedback controller gains. Meanwhile, $K_I \in \mathscr{R}$ is the integral gain. Hence, with the selection of the control law (11), the augmented closed-loop dynamical system may be written as:

$$\begin{bmatrix} x(k+1) \\ x_I(k) \end{bmatrix} = \begin{bmatrix} \boldsymbol{A} & 0 \\ -\boldsymbol{C} & 1 \end{bmatrix} \begin{bmatrix} x(k) \\ x_I(k-1) \end{bmatrix} + \begin{bmatrix} \boldsymbol{B} \\ 0 \end{bmatrix} u(k) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} r(k) \tag{12}$$

$$y(k) = [\boldsymbol{C} \quad 0] \begin{bmatrix} x(k) \\ x_I(k-1) \end{bmatrix} \tag{13}$$

Problem 1. For the discrete-time dynamical system of (8), there exist state feedback gains K_s and integral gain K_I in (11) such that $\lim_{k\to\infty} e(k) = 0$.

3. ALGORITHM FOR MODEL-FREE CONTROLLER TUNING

3.1. General concepts of the model-free approach

The standard approach to a trajectory control problem is to obtain the output parameter $y(k)$ to follow the set-point or the reference signal $r(k)$, as depicted in Figure 3. However, this condition could be relaxed whereby instead of designing the control system to obtain $\lim_{k\to\infty} e(k) = 0$, one could design the control system to reach the state $\lim_{k\to\infty} e_d(k)$=0. For $Y_d(z) \coloneqq \mathcal{Z}\{y_d(k)\}$ and $R(z) \coloneqq \mathcal{Z}\{r(k)\}$, where $Z\{\cdot\}$ is the Z-transform operator, a desired plant's transfer function is defined by $T_d(z) \coloneqq \frac{Y_d(z)}{R(z)}$. It implies that the new error signal is now redefined $e_d(k) = y_d(k) - y(k)$. Figure 4 illustrates the modified block diagram with the addition of the desired plant's model $T_d(z)$. With the new definition of the error signal, **Problem 1** can be restated into **Problem 2** as follows:

Problem 2. For the discrete-time dynamical system of (8), there exist state feedback gains K_s and integral gain K_I in (11) such that $\lim_{k\to\infty} e_d(k)$=0.

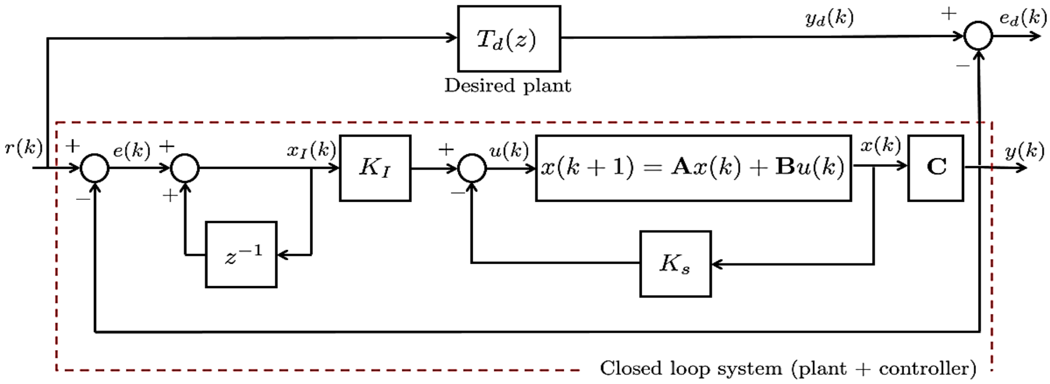

Figure 4. Modified block diagram with the desired plant model being introduced

As a general remark, to solve **Problem 2**, one needs to have the preliminary information of the plant-to-be-controlled, i.e., the parameters of $\boldsymbol{A}$, $\mathbf{B}$ and $\mathbf{C}$. This design procedure is known as the *model-based* approach to controller design. On the other hand, the *model-free* method only employs the information based on the set of recorded input-and-output data to obtain the optimal controller parameters. This technique offers significant advantages whereby for any variations occurring in the controlled system (i.e., due to system degradation, parasitic errors, etc.), one may reobtain a new set of data for controller re-tuning. Hence, the necessity of having accurate plant parameters commonly needed in the steps of model-based controller design can be avoided. In Figure 5, the modified block diagram illustrates the formulation of the fictitious reference signal $\tilde{r}(k) \in \mathcal{R}$, where the set of recorded input data $u^0(k) \in \mathcal{R}$, states data $\boldsymbol{x}^0(k) = [x^{0,T}(k^5) \quad x_I^0(k)]^T \in \mathcal{R}^5$, and output data $y^0(k) \in \mathcal{R}$ had been used to define the fictitious signal. Notice the absence of the controlled plant's model (indicated with the dashed box in Figure 5), which is now omitted and replaced by the recorded input-output data.

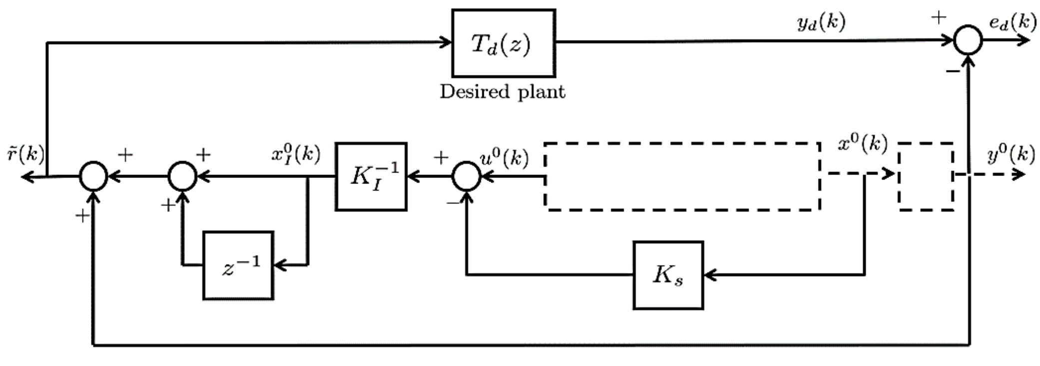

Figure 5. The modified block diagram illustrates the fictitious reference signal formulation, where the actual plant model (originally in the dashed box) is now omitted

3.2. Fictitious-reference-iterative-tuning

The FRIT is one of the model-free approaches for controller tuning. Introduced by Kaneko *et al.* [17], the FRIT requires only a single shot of experimental data of the closed-loop system to formulate the fictitious reference signal. Based on the modified block diagram of Figure 5, the fictitious reference signal $\tilde{r}(k)$ is defined by:

$$\tilde{r}(k) = y^0(k) + (1 - z^{-1})\left(\frac{K_S}{K_I}x^0(k) + \frac{1}{K_I}u^0(k)\right). \quad (14)$$

As for simplifying $\tilde{r}(k)$, new variables are introduced as:

$$K_1 = \frac{K_S}{K_I} \in \mathbb{R}^{1\times 4}, \quad (15)$$

$$K_2 = \frac{1}{K_I} \in \mathbb{R}. \quad (16)$$

Suppose the state feedback controller gains are parametrized in the form of $\rho \coloneqq [K_1 \quad K_2]^T \in \mathscr{R}^5$. It can be shown that the fictitious reference signal of (14) can be re-written as:

$$\begin{aligned}\tilde{r}(k) &= y^0(k) + (1-z^{-1})\left(K_1 x^0(k) + K_2 u^0(k)\right)\\ &= y^0(k) + \left(1-z^{-1}\right)\left(x^0(k)^T K_1^T + K_2 u^0(k)\right)\\ &= y^0(k) + \left(1-z^{-1}\right)\left[x^0(k)^T \quad u^0(k)\right]\rho.\end{aligned} \quad (17)$$

By utilizing the fictitious reference signal of (17) and for each iteration of k, a cost function $J \in \mathcal{R}$ can be introduced in the form of

$$J(\rho, k) \coloneqq \|y^0(k) - T_d\tilde{r}(k)\|_K^2. \quad (18)$$

Problem 3. Given the desired plant's transfer function $T_d(z)$ and the fictitious reference of (17), there exists an optimal solution $\rho^* \in \mathscr{R}^5$such that

$$\rho^* \coloneqq \arg\min_{\rho} J(\rho). \quad (19)$$

The subsequent section will briefly describe our proposed algorithm to solve (19).

3.3. Particle swarm optimization

Kennedy and Eberhart developed the PSO algorithm in 1995 [23]. The algorithm was inspired by a swarm of birds or fish schooling social and cooperative behaviors to fill their needs in the search area. The optimization mechanism started by placing the M −number of agents in a random position $p_i \in \mathcal{R}^{1\times N}$and velocity $q_i \in \mathcal{R}^{1\times N}$in N is the dimension of the search area. Each particle/agent i will move and update its position based on the global best position at each iteration k. For each selected agent's position, there will be certain rewards measured in terms of the value of the selected fitness function, f_{fit}. Based on those reward's values, the current agent's velocity will be updated by the following function of

$$q_i(k+1) = \omega q_i(k) + \eta_1 r_1\left(p_{best_i} - p_i(k)\right) + \eta_2 r_2\left(g_{best} - p_i(k)\right) \quad (20)$$

where $\omega \in \mathcal{R}$ is the inertia function to balance between the local and global search capability, $\eta_1, \eta_2 \in \mathcal{R}$ are the cognitive and social learning parameters, and $r_1, r_2 \in \mathcal{R}$ are the real numbers randomly generated between 0 to 1. Meanwhile, $p_{best_i}$is the best position for current agents and g_{best} is the best solution among the current agents p_{best_i}. Then, based on the velocity (20), the agent's position will be subsequently updated by:

$$p_i(k+1) = p_i(k) + q_i(k+1). \quad (21)$$

The value of ω is similarly updated in every iteration by ensuring it is linearly decreasing from the maximum weight $\omega_{max} \in \mathrm{R}$ to the minimum weight $\omega_{min} \in \mathrm{R}$ expressed by:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \times iter. \quad (22)$$

The $iter_{max} \in \mathcal{R}$ and $iter \in \mathcal{R}$ in (22) are the maximum iteration number and current iteration, respectively. At the final iteration, suppose the optimal agent location $p^* \in \mathscr{R}^{1\times N}$ is found such that it yields to the minimum value of the fitness function, then all agents are expected to converge to this location which implies that

$$p^* \coloneqq arg \min_{p_i} f_{fit}, \forall i. \tag{23}$$

To delineate the approach in employing the PSO algorithm to solve **Problem 3**, the following algorithm implementing the formulated fictitious signal as depicted in Figure 5 are devised:

Step 1: By arbitrarily choosing the initial gains of K_{s_0} and K_{I_0}, a one-shot experiment is run to generate and record the input data $u^0(k)$, states data $x^0(k)$, and output data $y^0(k)$, respectively.
Step 2: From recorded data, a fictitious reference signal is formulated based on (17) with a tunable gain of ρ.
Step 3: Define the agent's search area, the number of particles and parameters. Then, randomize the initial position of all agents to be within the specified search area. Next, the value of the fitness function of each position is evaluated. Since the optimization problem is to solve **Problem 3**, equation (18) may be the feasible candidate for the fitness function, such as $f_{fit} = J$.
Step 4: Update the agents' velocities (20) and positions (21) at each iteration. As the iteration reaches $iter_{max}$, all agents shall converge to the optimal position, p^* corresponding to the optimal solution (18).
Step 5: Assign the optimum parameters' gain, $\rho^* \coloneqq p^*$. Validate the performance in the actual system. Repeat beginning from **Step 2** if the result is unsatisfying.

4. RESULTS AND DISCUSSION

This section presents a numerical analysis to illustrate the proposed model-free controller tuning performance on a slosh suppression system. The simulation work was conducted using the MATLAB Simulink software package to validate the devised tuning algorithm. Based on a similar design as in [6], the parameters of nonlinear dynamics of (1) and (2) are tabulated in Table 1.

Table 1. Parameters of the slosh suppression system

Parameters	Value
M	6.0 kg
m	1.32 kg
l	0.052126 m
g	9.18 m/s^2
d	3.0490×10^{-4} kgm^2/s

The reference signal was selected in terms of the step input $r(k) = 0.8u(k)$. The initial states were set as $\mathbf{x}(0) = [0 \quad 0 \quad 0 \quad 0 \quad 0]$, and the initial controller gains were arbitrarily chosen as $K^0 \coloneqq [K_S^0 \quad K_I^0] = [100 \quad 92 \quad -9 \quad -1 \quad 0.2]$. A set of recorded input data $u^0(k)$, states data $x^0(k)$, and output data $y^0(k)$ were then generated and used to formulate the fictitious reference signal (17). The pole's locations of the desired continuous-time closed-loop system were arbitrarily chosen as $s = -2, -3, -4, -5, -100$. The desired plant model in the discrete-time domain was obtained as $T_d(z) = \frac{(0.0016z^5+0.0920z^4+0.4795z^3+0.0876z^2+0.0015)\times 10^{-11}}{z^5-4.8909z^4+9.5649z^3-9.3494z^2+4.5676z-0.8923}$ with the sample time $T_s = 1$ ms. Subsequently, by utilizing the formulated fictitious signal (17), the PSO algorithm was then employed to seek the optimal controller gains by solving **Problem 3**.

The selection of parameters for the PSO algorithm is as follows. The agent's number and the maximum number of iterations were selected as $M = 50$ and $iter_{max} = 80$, respectively. Since the dimension of the tunable parameters is 5, such that $\rho \in \mathcal{R}^5$, then the dimension of the PSO search area was also set to 5. Meanwhile, the weight ω was computed to be within the range of $\omega_{min} = 0.4$ and $\omega_{max} = 0.9$, with both learning parameters were chosen as $\eta_1 = \eta_2 = 1.4$, and r_1, r_2 randomly selected. The cost function (18) was computed at each iteration, and the algorithm terminates when either (23) is satisfied or the maximum iteration has been reached. Based on this selection, the minimizer (19), which yields the minimum value of the cost function (18), corresponding to $J = 0.076$ was obtained as

$$p^* \coloneqq \rho^* = [K_1^* \quad K_2^*]^T = [1.291 \quad 0.6003 \quad -1.2726 \quad -0.1142 \quad 0.04]^T \times 10^3 \tag{24}$$

Comparing (24) with (15) and (16), the results implied that the state feedback controller and the integral gains were obtained as $K_s = [32.554 \quad 15.1369 \quad -32.0869 \quad -2.8794]$ and $K_I = 0.0252$, respectively. Figure 6 depicts the convergence of the cost function J starting from the value of $J = 530.202$ at $k = 0$ to $J = 0.076$ at $k = 80$.

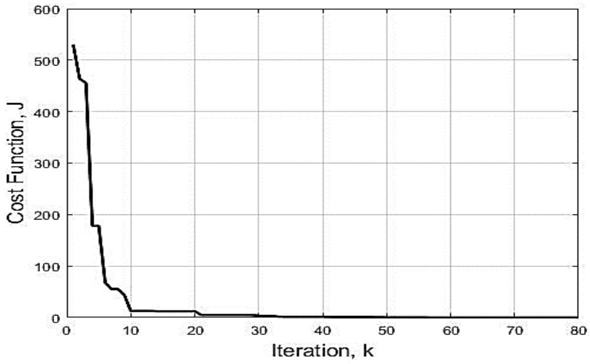

Figure 6. Convergence of the cost function J

As an empirical comparison between the proposed tuning method and a model-based controller design, the pole-placement approach in obtaining the state feedback controllers' parameters with integral gain [26] was considered. The resulting controller parameters that were obtained based on the model-based design are:

$$[K_s \quad K_I] = [95.3704 \quad 44.0768 \quad \text{-}118.9235 \quad \text{-}6.6937 \quad 0.0737]. \tag{25}$$

The output responses in terms of the cart's displacement in the y −direction are depicted in Figure 7. Note that the dashed yellow line represents the output response of the controlled system before tuning (at $k = 0$). Meanwhile, the green, dashed-blue, and dotted-red lines represent the output responses of the desired plant, the controlled system after tuning by the model-free approach (at $k = 80$), and the controlled system with a controller designed using model-based pole placement. Based on the trajectory result, improvement can noticeably be seen in the cart movement after being tuned by the model-free technique. The oscillating response from the initial condition is minimized. Furthermore, it is also delighted to point out that the proposed model-free technique could yield results comparable to the model-based approach. The depicted results show that the controlled system's output responses are almost identical to the output response of the desired system. In addition, by comparing the time response performance as tabulated in Table 2, the controlled system reached identical settling time, rise time, and percentage overshot as per the desired system.

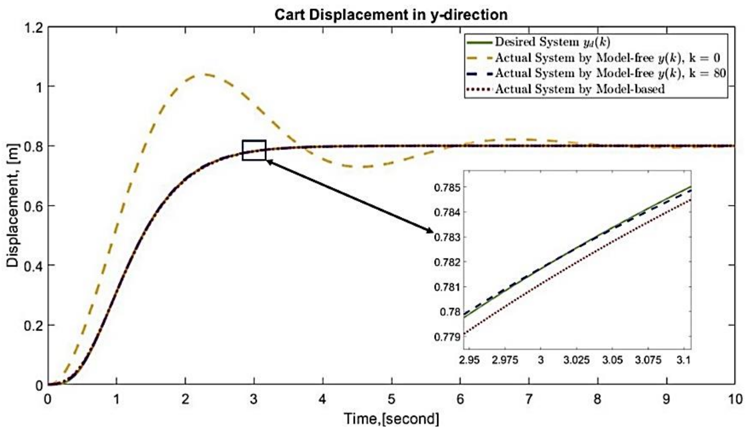

Figure 7. The cart's trajectory in the y-direction

Conversely, the model-based controller tuning indicates a slight difference in the desired system response: settling time is 0.02 seconds, and time rise is 0.03 seconds. Thus, a performance system based on model-free tuning is more accurate than a model-based technique. In Figure 8, the output responses in terms of the velocity of the cart are depicted to illustrate the performance comparison of the controlled system before and after tuning by both model-free and model-based tuning methods.

Table 2. Times response performance of cart movement response

System performance	Desired system	Actual system by model-free, $k = 0$	Actual system by model-free, $k = 80$	Actual system by model-based
Settling time, s	3.07	7.46	3.07	3.09
Rise time, s	1.65	0.94	1.65	1.68
Overshoot, %	0	0	0	0
Steady-state error, e_{ss}	0	0	0	0

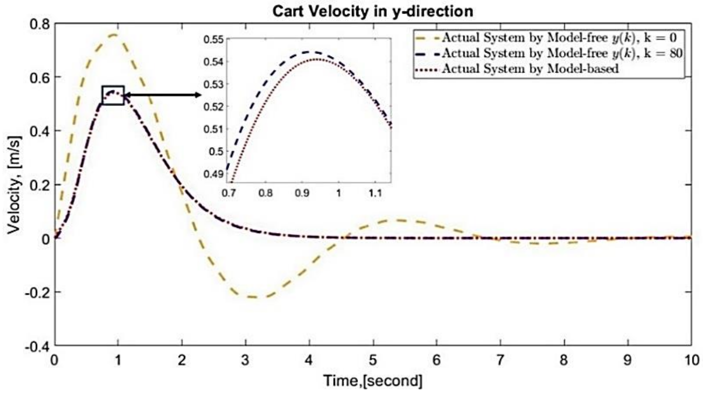

Figure 8. The velocity of cart movement response in the y-direction

The trajectory of the angular slosh motion of the controlled system tuned by model-free and model-based approaches is presented in Figure 9. Meanwhile, Figure 10 depicts the velocity of the slosh motion response. In these figures, the slosh motion angle is suppressed under 0.07 radians for the model-based technique and settled within 3.61 seconds with a maximum of 0.29 radians per second. For the case of the slosh motion, before tuning by the proposed model-free algorithm, the system started in an unsteady response with a maximum angle of 0.177 radians and a settling time of 7.02 seconds. However, after tuning by the proposed model-free algorithm, it could be seen from the plots that the slosh motion became more stable with the suppressed angle under 0.07 radian and settled within 3.47 seconds.

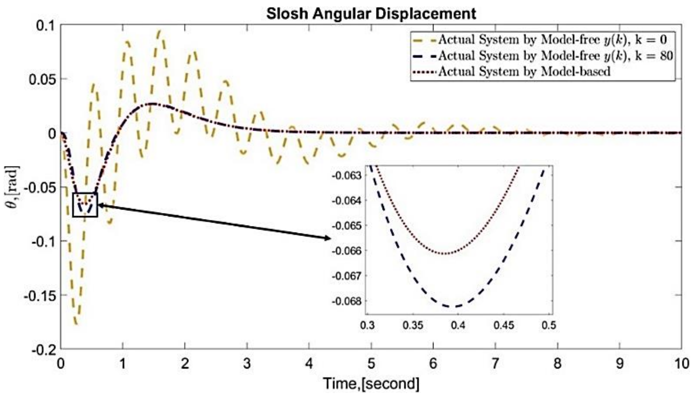

Figure 9. The slosh motion response in angular level

Furthermore, the decrement in the slosh rate from 1.23 radians per second to 0.3 radians per second portrayed the movement of the slosh becomes slower and more controlled to reach a steady-state condition, where angular motion at the origin level of 0 radians. Therefore, significant improvement occurs to indicate the reduction of slosh motion by implementing FRIT-based tuning using the PSO algorithm approach to find the optimum solution. The comparison of the system performance of the slosh motion before and after tuning is tabulated in Table 3. It can be observed the tuned controlled system yield a better transient response with minimum slosh angle. Although model-free and model-based design techniques produce comparable results, model-free techniques offer excellent potential to attain the optimal controller gain in suppressing the slosh motion while the cart is in motion. Suppose any variation in plant and degradation external disturbance happens. The designed controller will easily compensate for those particular changes because the proposed method only relies on input and output data in the tuning process. Hence, the proposed model-free tuning technique is superior to the model-based approach as better for tuning purposes.

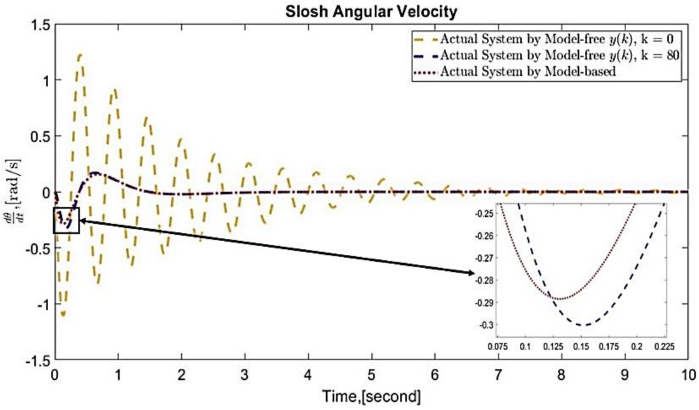

Figure 10. The velocity of slosh motion response in angular level

Table 3. The system performance in terms of the slosh motion

System performance	Initial response, $k = 0$	Final response, $k = 80$	Conventional pole placement
Maximum angle, θ(rad)	0.177	0.068	0.066
Settling time, s	7.02	3.47	3.61
Maximum rate, (rad/sec)	1.23	0.3	0.29

5. CONCLUSION

A model-free tuning of an integral action state feedback controller for a liquid slosh suppression system utilizing FRIT and PSO is presented in this paper. The proposed controller tuning algorithm could circumvent the necessity of obtaining the plant's model, whereby only the recorded input-output data obtained from a one-shot experiment to be used in the tuning process. It can be validated through numerical analysis that the proposed model-free tuning technique offers more perspective than the model-based technique to achieve stability in the closed-loop system. The trajectory results portrayed good transient responses performance where the cart successfully tracked the desired trajectory while maintaining minimum slosh motion. From the presented findings, it can be concluded that the proposed model-free tuning has a good potential and is much superior to model-based tuning in obtaining the optimal controller parameters.

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