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Optimization of Gantry Crane PID Controller Based on PSO, SFS, and FPA

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Abstract: The problem of gantry crane automation has become increasingly important due to its wide application in ports and construction. Operating errors can cause various problems such as damage to goods, delays in operations, excess costs, and threaten the lives of workers. Therefore, automatic control needs to be applied to control the position and its sway angle. To obtain an accurate movement and minimal sway, optimization of the controller in gantry crane automation should be considered. This paper will introduce an alternative method of optimization techniques namely Stochastic Fractal Search (SFS) and Flower Pollination algorithm (FPA) for the PID controller, which is applied to control the position and sway angle of the gantry crane. For the comparison purposes, the control results will be compared with the PID controller optimized using PSO technique. For position control, SFS and FPA lead to better speed response and accuracy than compared to PSO. In terms of sway-cancellation PSO has a better settling time, but with the trade-off of longer settling time for angles, SFS and FPA are still able to provide better results because the sway angle settling time is below the position settling time.

Keywords: PID Controller, PSO, SFS, FPA, Optimization, Gantry Crane

1. INTRODUCTION

There are two focuses in building a gantry crane control system, namely the position and the sway angle control system. The position control system to obtain a fast and precise system response so that the trolley can move to the desired position with the minimum time and stop at the desired position as accurately as possible. Also, a sway angle control system is needed that can provide the smallest possible swing deviation and quickly eliminate the deviation oscillations [1]-[2].

Researchers developed methods to control gantry cranes. The developed control algorithm is divided into two methods, namely open-loop control and closed-loop control. Open-loop control on cranes was studied by G.A Manson [3] who attempted to use time-optimal open-loop control on overhead cranes. However, this method has a disadvantage when the system parameters change. In [4] the open-loop input shaping method was applied to control gantry cranes. Gantry crane control with a feedback loop is more attractive to researchers because can be made robust to system parameters and disturbances. Proportional Derivative (PD) controllers have been applied to control the position and swing angle of gantry cranes [5]. Fuzzy Logic is applied by Solihin et.al [6] for intelligent system operation of gantry crane. A combination of PID and Fuzzy controllers was also applied to eliminate swing problems in gantry cranes. To obtain an accurate movement and minimal sway, optimization of the controller in gantry crane automation should be considered.

The well-known PID controller has been chosen because it has many implementations in various control systems, making the PID controller a robust controller [7]. The gantry crane system is modeled using two degrees of freedom so that the level of complexity is not high and the PID controller can be optimized. A PID controller is applied for position control and a PD controller for swing angle control. To obtain good control stability and performances, the parameters of the PID and PD controllers need to be appropriately selected by means of tuning. The tuning process is carried out through three optimization algorithms, namely Particle Swarm Optimization (PSO), Flower Pollination Algorithm (FPA), and Stochastic Fractal Search (SFS).

PSO algorithm is the result of a development inspired by natural phenomena, namely the behavior of birds and fish when they are engaged in a colony or swarm motion. PSO is a metaheuristic optimization algorithm with an efficient computation processor [8]. PSO was introduced quite earlier, i.e., in 1995, and up to now, it has been applied to various fields. PSO has also been used and is widely used as a reference in the optimization of gantry crane control. In [9][10], PSO was applied as an optimization of PID control parameters to control gantry crane movement.

SFS which was proposed in 2015, has been applied as an optimization method for system reliability, surface grinding process, and Solar PV parameters [11], whereas FPA, introduced in 2012, has been used to optimize ratios, feature selection, and PV parameters [12]. Both of these methods have provided excellent performance. So far, SFS is concerned with the optimization of control which mostly applies to control of power [13], turbine thermal system [14], DC Servo [15]. FPA is generally applied in the control of power systems [16], and DC motors [17]. However, until now, no articles have been published yet in the literature with regard to the application of SFS and FPA for the optimization of gantry crane control. It is also expected,

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that a comparison of these three optimization techniques, namely PSO, SPS, and FPA, for the case of controlling the gantry crane should also bring new ideas and concepts for this kind of application. In addition, the optimization studies mentioned above were applied to the PID [14], Fractional Order PID (FOPID) [17], PI-PID cascade [16], PI-PD cascade [13] and PID+ Differential Filter (PID+DF) [15]. Gantry crane control has a uniqueness, namely that two controllers must operate in tandem, namely position control, and swing angle control to obtain the desired performance specifications. In this research, SFS, FPA, and PSO optimization will be challenged to handle tuning problems of the PID and PD controllers to control the position and sway angle of the gantry crane. The results of tuning the controller parameters will be tested and implemented into the gantry crane model.

2. DYNAMIC GANTRY CRANE MODEL

The gantry crane is modeled using the prototype shown in Fig. 1. There are two degrees of freedom namely position (x) and swing angle (θ). A gantry crane consists of a trolley (m_2) that moves along the gantry, the load (m_1) which is connected to the trolley using a rope of length (l). And there is a motor to drive the trolley [10] [18]

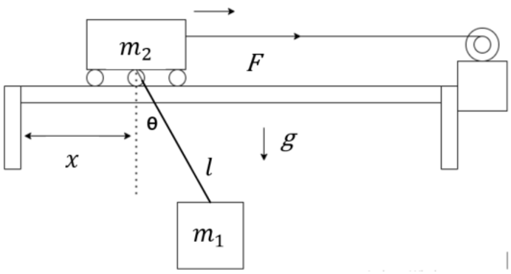

Fig 1. Gantry Crane Model

2.1 Gantry Crane Model

The Lagrange equation is applied to get the dynamic equation.

$$\frac{d}{dt}\left(\frac{\partial L}{\partial q_i}\right) - \frac{\partial L}{\partial q_i} = \boldsymbol{Q_i} \tag{1}$$

$$L = T - P \tag{2}$$

Q_i is a non-conservative force, T is the total of the kinetic energy of the system, and P is the total of the potential energy of the system. And the q_i independent generalized coordinate. A review of each component is applied to facilitate system modeling.

Based on the load component (m_1), the equation of the load kinetic energy (T_1) and the load potential energy (P_1) can be stated as follow.

$$T_1 = \frac{1}{2} m_1 v_1^2 \tag{3}$$

$$v_1^2 = \dot{x}^2 + l^2\dot{\theta}^2 + 2\dot{x}l\dot{\theta}\cos\theta \tag{4}$$

$$T_1 = \frac{1}{2} m_1(\dot{x}^2 + l^2\dot{\theta}^2 + 2\dot{x}l\dot{\theta}\cos\theta) \tag{5}$$

$$P_1 = -m_1 gl\cos\theta \tag{6}$$

Based on the assessment of the trolley components (m_2), the kinetic energy equation of the trolley (T_2) is attained, with the trolley position as a reference, the potential energy of the trolley is zero ($P_1 = 0$).

$$T_2 = \frac{1}{2} m_2\dot{x}^2 \tag{7}$$

By substituting Eq (5), Eq (6), and Eq (7) to Eq (2), The Lagrange equation L will be given by the following relation

$$L = \frac{1}{2} m_1(\dot{x}^2 + l^2\dot{\theta}^2 + 2\dot{x}l\dot{\theta}\cos\theta) + \frac{1}{2} m_2\dot{x}^2 + m_1 gl\cos\theta \tag{8}$$

Then the Lagrange operation is carried out on Eq (1) so that Eq (9) and Eq (10) show the dynamic equation of the model.

$$(m_1 + m_2)\ddot{x} + m_1 l\ddot{\theta}\cos\theta - m_1 l\dot{\theta}^2\sin\theta + D\dot{x} = F \tag{9}$$

$$m_1 l^2\ddot{\theta} + m_1 l\ddot{x}\cos\theta + m_1\dot{x}l\dot{\theta}\sin\theta + m_1 gl\sin\theta = 0 \tag{10}$$

2.2 DC Motor

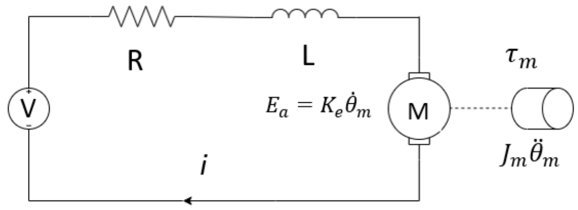

Fig 2. DC Motor Model

Eq (11) gives the differential equation of the DC motor model in Fig. 2.

$$V = Ri + L\frac{di}{dt} + K_e\dot{\theta}_m \tag{11}$$

V, R, L, i, K_e, and $\dot{\theta}_m$ are the values of voltage, resistance, inductance, armature current, and the change in motor rotation angle. The inductance value which is very small compared to the resistance value makes the reactance of the inductor negligible $(R \gg L)$. Then the following relation gives the DC motor torque (τ_m).

$$\tau_m = K_t i \tag{12}$$

K_t is the torque constant.

$$J_m\ddot{\theta}_m = \tau_m - \frac{\tau}{r} \approx 0 \tag{13}$$

the wheel dimensions are very small so that the inertia value (J_m) is close to zero. Eq (14) provides the relationship of torque (τ) and force (F).

$$\tau = F.r_p \tag{14}$$

Rotation of the pulley will pull the trolley and move the wheels on the trolley, thus creating a relationship between pulley rotation (r_p, pulley radius) and trolley displacement (r, the ratio of wheel radius and pulley) as shown in Eq (15).

$$\theta_m r_p = rx \tag{15}$$

Furthermore, the integration of the DC motor with the gantry crane model from Eq (12-15) is carried out to obtain the dynamic equation of the gantry crane model system with the DC motor actuator. The equation is then linearized by assuming the swing angle is very small ($\theta \approx 0$), so the relationship is $\sin\theta \approx \theta$, $\cos\theta \approx 1$, and $\dot{\theta} \approx 0$. The linear model equation is Eq (16) and Eq (17).

$$V = a\ddot{x} + b\dot{x} + c\ddot{\theta} \tag{16}$$

$$a = \left(\frac{R.r_p}{K_t.r}\right)(m_1 + m_2)\text{ , b} = \left(\frac{D.R.r_p}{K_t r} + \frac{K_e.r}{r_p}\right),$$

$$c = \left(\frac{m_1 l. R. r_p}{K_t. r}\right)$$

$$l\ddot{\theta} + \ddot{x} + g\theta = 0 \tag{17}$$

The studied gantry crane system parameters are as follows. m_1 = 1 kg, m_2 = 1.5 kg, l =0.5m, g =9.81m/s^2, D =12.32 Ns/m, R =0.5 Ω, K_t=0.0071619 Nm/A, K_e = 0.0071619 VS/rad, r_p = 0.012 m, $r = 1$. The dynamic equations of the Eq (16) and Eq (17) models are integrated with the positional PID controller and the PD controller as the model block input which is illustrated in Fig. 3.

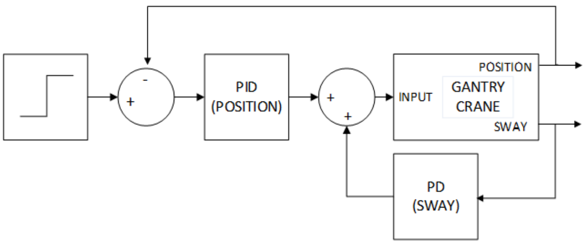

Fig 3 System Block Diagram

3. OPTIMIZATION ALGORITHM FOR PID PARAMETER TUNING

3.1 Particle Swarm Optimization

The application of the PSO algorithm is started by defining the maximum number of iterations ($Iter$), the number of particle populations (m), and the dimensions of the particle position (k), therefore resulted in a matrix with the size of $m \times k$. A velocity vector matrix (v) is created with the same dimensions. At each iteration, the cost value for each particle is computed, the cost function is adjusted according to the needs. The process of updating the velocity vectors of each particle ($v_i, dim(1x5)$) and the position of each particle (p_i, dim $(1x5)$) occurs with Eq (18) and Eq (19).

$$v_{ij}^{n+1} = w.v_{ij}^{n} + c_1.\gamma_1.\left(p_{ijbest}^{n} - p_{ij}^{n}\right) + c_2.\gamma_2.\ \left(p_{jgbest}^{n} - p_{ij}^{n}\right) \tag{18}$$

$$p_{ij}^{n+1} = p_{ij}^{n} + v_{ij}^{n+1} \tag{19}$$

$$n = 0,1,2, \ldots, Iter.\ \ i = 0,1,2, \ldots, m,.\ \ \ j = 0,1,2, \ldots, k$$

where p_{best} is the particle with the best position on the i^{th}particle, p_{gbest} is the best particle for the entire particle population, and p_i is the i^{th}particle. γ_1 and γ_2 are random numbers (uniform distribution) from 0 to1 Furthermore, it takes three values of w, c_1, and c_2, namely inertia weight, cognitive weight, and social weight to determine the portion of global and local search in the computation process [10] [18] [19]

3.2. Stochastic Fractal Search

SFS algorithm is applied by predefining the number of points (M), the maximum number of iterations ($Iter$), the dimension of the position of the points (n), the maximum number of points diffusion (D), and the lower-upper limit of the point position (LB,UB). In the initialization stage of the point position (P), the LB and UB boundaries are implemented with Eq (20)

$$P_j = LB + \varepsilon\,(UB - LB) \tag{20}$$

j is the index representing the j^{th} dimension point and ε is a random number (uniform distribution) from 0 to1. Then enter the diffusion stage, the diffusion stage contains two types of processes which are then given the terms gaussian walk 1 and 2 (GW1, GW2). The name gaussian walk is given because of the use of a gaussian distribution for the running process. The use of GW1 and GW2 is determined by first defining a constant that ranges from (0-1) as a reference for using GW1 or GW2.

$$GW1 = N(\mu_{BP}, \sigma) + (\varepsilon \times BP - \varepsilon' \times P_i) \tag{21}$$

$$GW2 = N(\mu_p, \sigma) \tag{22}$$

With N is Gaussian distribution, μ average value where $\mu_{BP} = BP$ and $\mu_p = P_i$. BP is the point with the most optimal cost value of the entire population of points. σ is the standard deviation from Eq (23).

$$\sigma = \left|\frac{\log(it)}{it} \times (P_i - BP)\right| \tag{23}$$

where it is the index expressing the iteration condition to it^{th}. Then enter the update stage which consists of two stages. The first update stage begins with ranking (ρ) each point based on the value of the resulting cost. This ranking has the role to assign a probability value (Pa_i) to each point, which satisfies Eq (24).

$$Pa_i = \frac{\rho(P_i)}{M} \tag{24}$$

This probability value allows a change in the position of points with a cost value that is not optimal. Then the updating process is carried out if it meets the conditions $\varepsilon > Pa_i$, with Eq (25).

$$P_i'(j) = P_r(j) - \varepsilon \times \left(P_t(j) - P_i(j)\right) \tag{25}$$

where P_i' is the most recent point position, P_i is the previous point position, P_r and P_t are the positions randomly selected from the population with $P_t \neq P_r$.
After the first update has been made to all points, the ranking is carried out as in Eq (24). In the second update stage, the update process is carried out with Eq (26) and Eq (27).

$$P_i'' = P_i' - \hat{\varepsilon} \times (P_t' - BP) \mid \varepsilon' \leq 0.5 \tag{26}$$

$$P_i'' = P_i' + \hat{\epsilon} \times (P_t' - P_r') \mid \varepsilon' > 0.5 \quad (27)$$

where P_i'' is the newest point position, P_i' is the point position of the first stage update, P_t' and P_r' is the point position randomly selected based on the first stage update [20][21].

3.2 Flower Pollination Algorithm

The pollination process on flowers consists of two types, namely local pollination and global pollination. [22] [23] In the global pollination process, the x_i^t flower parameter update process applies as follows:

$$x_i^{t+1} = x_i^t + L(g_* - x_i^t) \quad (28)$$

where L is a parameter of pollination strength using the Levy flight approach which fulfills the Levy distribution as follows:

$$L \sim \frac{\lambda\Gamma(\lambda)\ \sin(\pi\lambda/2)}{\pi} \frac{1}{s^{1+\lambda}} \quad (29)$$

where Γ is a gamma function with $\lambda = 1{,}5$. In the local pollination process, the following flower parameter update process applies:

$$x_i^{t+1} = x_i^t + \epsilon\left(x_j^t - x_k^t\right) \quad (30)$$

where ϵ is a random number from a uniform distribution in the interval [0,1], and x_j^t and x_k^t are randomly selected by $i \neq j \neq 1$. The choice between local and global pollination is set using the probability switch p.

In the implementation of the FPA algorithm, initially, it is necessary to define a set of initial populations, *m*, with each population having a parameter of *n* (in this case *n*=5 as the number of parameters to be optimized). From the initial population, the cost function is calculated for the next global or local pollination iteration. If a solution is found with a smaller cost function than before, the cost and g_* values will be updated for the next population.

3.3 Global Parameter

The global parameter is a parameter with the same value for each different optimization algorithm process. The global parameters are Max Iteration=30, Max Simulation =5, Population =20, and Space Dimension = 5. Position limits are used to make it easier for optimization to perform global minimum searches in a clearly defined area. [3] Those Position limits are $K_p(min, max)$ = (-50, 200), $K_i(min, max)$ = (-50, 50), $K_d(min, max)$ = (-50, 100), $K_{ps}(min, max)$ = (-50,200), $K_{ds}(min,\ max)$= (-50, 100). The cost function is an ITSE performance index which is useful for calculating the error value between the simulated system response path and the reference path. In this case, the cost function will be as follows:

$$J = \int_{t_0}^{t_1} t\left(x - x_{ref}\right)^2 dt + \int_{t_1}^{t_{end}} t(\theta)^2 dt + \int_{t_2}^{t_{end}} t\left(x - x_{ref}\right)^2 dt \quad (31)$$

where t_0 is the initial time to simulate the system, t_1 and t_2 are the rise time and settling time values based on the trajectory reference ($t_1 = 2.6\ s, t_2 = 4.24\ s$). Then x and θ are the output positions and angles from the model, while x_{ref} is the reference trajectory in Fig. 4.

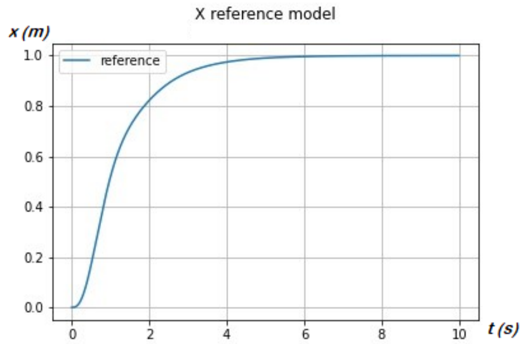

Fig 4. Position-Shift Trajectory Reference

3. IMPLEMENTATION AND RESULTS

The two proposed methods (SFS and FPA) have been implemented and delivered the following results. Five parameters have been optimized, namely $K_p, K_i, K_d, K_{ps}, K_{ds}$. Table 1 shows the several parameters which were applied during the optimization process.

Table 1. PSO, SFS, PFA Parameter

Algorithm	Parameter	Value
PSO	$w(max, min)$	0.9,0.4
	c_1(cognition)	2
	c_2(social)	2
SFS	Max Diffusion	3
	Gaussian Walk probability	0.5
PFA	λ	1.5
	p	0.5

In the PSO algorithm, each particle has a velocity vector. To keep the global minimum position search process, the velocity vector limitation for each dimension is carried out (Eq 32). Inertia weight (w) has a value that changes gradually based on Eq (33).

$$v_j = \left(k_j(max) - k_j(\min)\right) \times 0.01 \quad (32)$$

$$j = (0,1,\ldots,k$$

$$w = w_{max} - \frac{w_{max} - w_{min}}{Iter} \times \text{it} \quad (33)$$

Table 2. PID and PD Optimized Parameter

Parameter	PSO	SFS	FPA
K_p	8.69106	8.70872	8.69758
K_i	0.00404	0.00594	0.00290
K_d	2.27953	1.12517	1.54447
K_{ps}	24.45196	13.25603	16.94624
K_{ds}	5.50633	2.76868	3.94190

Table 3. Trolley Displacement Dynamic Characteristics

Algorithm	T_s(s)	T_r(s)	Steady State Error
PSO	4.41 s	2.66 s	0,00045
SFS	4.29 s	2.64 s	0,00076
FPA	4.35 s	2.66 s	0.00031

Table 4. Swing Angle Deviation

Algorithm	T_s(s)	Max Amplitude	Min Amplitude
PSO	4.35 s	0.0725	-0.1942
SFS	4.35 s	0.0944	-0.1888
FPA	4.35 s	0.0849	-0.1864

Table 5. Optimization Error and Runtime Process

Algorithm	Error	Runtime
PSO	0.001250	2 min 53 s
SFS	0.00126	9 min 21 s
FPA	0.00122	3 min 5 s

After implementing the three optimization algorithms for tuning the PID and PD controller parameters, the system response can be seen in Fig. 5 and Fig 6. To facilitate the review, quantitative data were collected which were tabulated in Tables (3 - 5). As mentioned above, fast and accurate response in terms of position displacement is required for better performance of the gantry crane. In this case, optimization parameters using the SFS method with a settling time value of (T_S) 4.29s will be the best controller parameters in response speed but with a little difference of 0.06s to FPA with a settling time of 4.35s (see Table 3). In terms of the accuracy of the final position, it is found that the optimization parameters of FPA provide better performance with a steady-state error value of 0.00031 for a displacement of 1 m. SFS though has the best speed but its steady-state error is the largest Based on the performance of the parameter position control, the optimization results of FPA provide more performance in terms of response speed and value accuracy.

In terms of swing angle control, the gantry crane is needed to have a very small swing angle and the ability to quickly eliminate oscillations. The simulation results in Table 4 explain in terms of the ability to quickly eliminate oscillations PSO, SFS and FPA give the same performance with a settling time (t_s) of 4.35 s. However, when viewed from the maximum and minimum amplitude generated by the angle, the value of the smallest peak-to-peak value is given by the optimization result parameter of PSO with a value of 0.2667 and followed by FPA 0.2713, SFS 0.2832. However, PSO has a longer settling time at the control position (table 3), meaning that the system as a whole has not been at a steady- state until 4.41s. FPA has reached a steady-state at 4.35s. In addition, the very small difference in peak-to-peak amplitude between FPA and PSO is 0.005 so that FPA's performance is considered to be better.

In general, the performance of the system response after the optimization provides optimal performance without significant difference. This explains that in the gantry crane model system those three optimization algorithms have provided good system response performance. In terms of the error value based on the cost function (Eq (31)) shown in Table 5, FPA optimization gives the smallest error value, with the order of FPA, PSO, and. SFS. Fig. 7. Shows the error convergence during the optimization process. FPA gives fast convergency at 0-150th iteration. SFS gradually reach the same convergence at 150th and PSO at 250th. In this period PSO has the slower convergency. After the 250th iteration, these methods perform error convergency equally well. In the final, at the 500th iteration, PFA gives the lowest error (Table 5). The comparison analysis of the optimization process speed of each algorithm is also tested.

The computation process is carried out using a mobile CPU Intel Core i7 10th Gen, the results are presented in Table 5. Based on the PSO runtime data, it has a slight advantage over FPA, while SFS differs considerably. So that in terms of performance, the optimization process of FPA has an advantage over PSO and SFS. FPA succeeded in providing better optimization results with a time difference of 12s compared to PSO. The length of the iteration process is caused by the level of complexity of the computation process so that the order of the higher complexity levels is SFS, FPA, and PSO. This also confirms that PSO has a faster computation process.

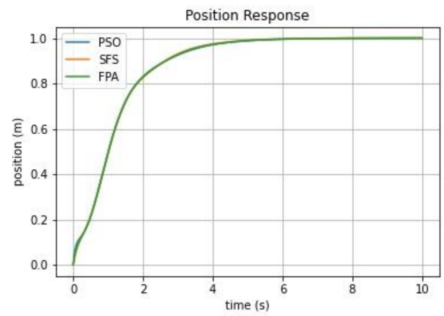

Fig 5. Tuned Trolley Position Comparison

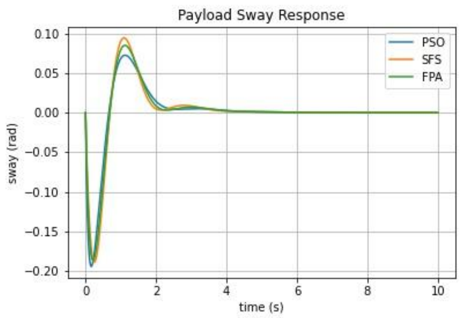

Fig 6. Tuned Payload Sway Comparison

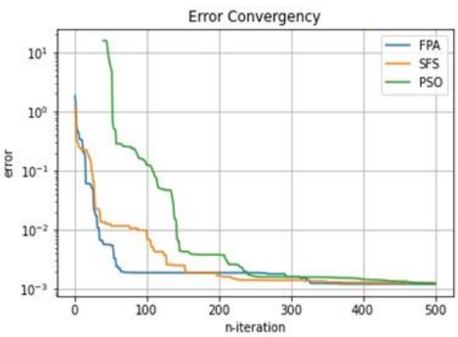

Fig 7. Error Convergence Comparison

5. CONCLUSIONS

Three optimization methods are applied on gantry crane PID and PD control system namely the SFS, FPA, and PSO methods. The results show that FPA has smaller optimization errors and followed by PSO and SFS. FPA in the optimization process also is faster to converge and PSO is the slowest. PSO has the fastest runtime process with a slight difference from FPA. In terms of control performance, SFS is able to provide smaller settling times but FPA has smaller steady-state error for position control. In terms of sway-cancellation, PSO, SFS, and FPA have the same settling time and PSO has a better peak-to-peak amplitude with a slight difference from FPA. But FPA is able to give better results because the PSO settling time of sway angle is still below its position's settling time. The results showed that the use of FPA, in improving performance was better than SFS and PSO. Future research will be dedicated to a real-time laboratory-scale gantry crane automation system using the proposed optimal PID controller introduced in this paper.

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REFERENCES

[1] M.Z. Mohd Tumari, L. Shabudin, M. A. Zawawi and L. H. Ahmad Shah. "Active sway control of a gantry crane using hybrid input shaping and PID control*", IOP Conf. Ser.: Materials Science and Engineering 50 012029*, DOI: 10.1088/1757-899x/50/1/012029 .2013.

[2] M.S. Korytov, V.S. Shcherbakov, and V.V. Titenko, "Effect of the payload mass on forces acting from the overhead crane drives during movement in the mode of suppressing uncontrolled oscillations", *In Journal of Physics: Conference Series*, Vol. 1546, No. 1, p. 012134, IOP Publishing, 2020.

[3] G.A. Manson, "Time-optimal control of and overhead crane model", *Optimal Control Applications & Methods*, Vol. 3, No. 2 , pp. 115-120, 1992.

[4] W.E. Singhose, L.J. Porter, and W. Seering, "Input shaped of a planar gantry crane with hoisting", *Proc. of the American Control Conference* , pp. 97-100, 1997

[5] H.M. Omar, "Control of gantry and tower cranes", *Ph.D. Thesis*, M.S. Virginia Tech, 2003.

[6] Wahyudi and J. Jalani., "Design and implementation of fuzzy logic controller for an intelligent gantry crane system", *Proceedings of the 2nd International Conference on Mechatronics*, pp. 345- 351, 2005.

[7] Borase, D.K. Maghade, S.Y. Sondkar, and S.N. Pawar, *A review of PID control, tuning methods and applications. International Journal of Dynamics and Control*, pp.1-10, 2020

[8] C. Zhou, H.B. Gao, L. Gao, and W.G. Zhang, "Particle Swarm Optimization (PSO) Algorithm", *Application Research of Computers*, Vol. 12, pp.7-11, 2003.

[9] H.I. Jaafar, Z. Mohamed, A.F.Z. Abidin, and Z. Ab Ghani, "PSO-tuned PID controller for a nonlinear gantry crane system", *IEEE International Conference on Control System, Computing and Engineering*, pp. 515-519, IEEE, 2012.

[10] M. I. Solihin, Wahyudi, M. A. S. Kamal, and A. Legowo, "Optimal PID controller tuning of automatic gantry crane using PSO algorithm," *Proceeding 5th Int. Symp. Mechatronics its Appl. ISMA 2008*, doi: 10.1109/ISMA.2008.4648804, 2008.

[11] X. Chen , H. Yue, and K. Yu, "Perturbed stochastic fractal search for solar PV parameter estimation". *Energy*, 189, 116247, 2019.

[12] D. F. Alam, D. A. Yousri, and M. B. Eteiba, "Flower pollination algorithm based solar PV parameter estimation". *Energy Conversion and Management*, 101, 410-422, 2015.

[13] S. Padhy, and S. Panda, "A hybrid stochastic fractal search and pattern search technique based cascade PI-PD controller for automatic generation control of multi-source power systems in presence of plug in electric vehicles", *CAAI Transactions on Intelligence Technology*, 2(1), 12-25, 2017.

[14] D. Saha , and L.C. Saikia, "Automatic generation control of an interconnected CCGT - thermal system using stochastic fractal search optimized classical controllers". *International Transactions on Electrical Energy Systems*, 28(5), e2533, 2018.

[15] E. Çelik , & H. Gör, "Enhanced speed control of a DC servo system using PI+ DF controller tuned by stochastic fractal search technique". *Journal of the Franklin Institute*, 356(3), 1333-1359, 2019.

[16] P. Dash, L. C. Saikia, & N. Sinha, "Flower pollination algorithm optimized PI-PD cascade controller in automatic generation control of a multi-area power system". *International Journal of Electrical Power & Energy Systems*, 82, 19-28, 2016.

[17] D. Puangdownreong, "Fractional order PID controller design for DC motor speed control system via flower pollination algorithm". *ECTI Transactions on Electrical Engineering, Electronics, and Communications*, 17(1), 14-23, 2019.

[18] N. I. M. Azmi, N. M. Yahya, H. J. Fu, and W. A. W. Yusoff, "Optimization of the PID-PD parameters of the overhead crane control system by using PSO algorithm", *MATEC Web Conf.*, vol. 255, no. January 2019, p. 04001, doi: 10.1051/matecconf/201925504001, 2019.

[19] J. Kennedy and R. Eberhart, "Particle swarm optimization," *Proceedings of ICNN'95 - International Conference on Neural Networks*, Perth, WA, Australia, pp. 1942-1948 vol.4, doi: 10.1109/ICNN.1995.488968, 1995.

[20] I. G. N. A. Indra Mandala, Franky, and Y. Y. Nazaruddin, "Optimization of Two Degree of Freedom PID Controller for Quadrotor with Stochastic Fractal Search Algorithm", *CCTA 2019 - 3rd IEEE Conf. Control Technol. Appl.*, pp. 1062–1067, doi: 10.1109/CCTA.2019.8920540, 2019.

[21] H. Salimi, "Stochastic Fractal Search: A powerful metaheuristic algorithm", *Knowledge-Based Syst.*, vol. 75, pp. 1–18, doi: 10.1016/j.knosys.2014.07.025, 2015.

[22] F. A. Ma'ani and Y. Y. Nazaruddin, "Optimization of Longitudinal Control of an Autonomous Vehicle using Flower Pollination Algorithm based on Data-driven Approach", *Int. J. Sustain. Transp. Technol.*, vol. 3, no. 2, pp. 58–65 , doi: 10.31427/ijstt.2020.3.2.4, 2020.

[23] X. S. Yang, "Flower pollination algorithm for global optimization", *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 7445 LNCS, pp. 240–249, doi: 10.1007/978-3-642-32894-7_27, 2012.