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Optimization Analysis of Nonlinear Process Using Genetic Algorithm

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Controlling the nonlinear process is a very challenging task in the process plant, whereby it depends on the practitioners' knowledge and skills. This paper aims at developing Gain Scheduling (GS) based controller tunings to obtain the trade-off controller tunings for both servo and regulatory control objectives at the Low, Medium and High operating levels supported by optimization analysis. At first, the research obtains First Order plus Dead Time (FOPDT) models of various operating levels from the Gravity Drained function of LOOP-PRO software. The dynamic characteristics of GA are compared with Particle Swarm Optimization (PSO), which showed GA produced more desirable responses and performance indexes. The analysis also compares process responses and performance indexes of GA with manually calculated controller tunings. The overall result shows that GA optimization analysis produces the most reasonable controller tunings for consistent control performance compared to other methods. Ultimately, GA algorithms were adopted into a Graphical User Interface (GUI) of MATLAB software, allowing the automated generation of the controller tunings for the identified models.

Keywords: gain scheduling, genetic algorithm, performance indexes, trade-off controller tunings, graphical user interface

1. INTRODUCTION

In plant operations, regulating water levels of a nonlinear process could be a complex task due to the nonlinear dynamic behaviors at various operating levels. A single set of controller actions is not adequate to deal with all operating levels; thereby, it should perform repetitive calculations on controller tunings to various operating levels [1]. Furthermore, a controlled process has two distinct control objectives known as servo and regulatory controls. The servo control reflects how well the process value (PV) is driven to a new setpoint (SP) whereas, the regulatory control reflects how well the controlled process can deal with load changes by maintaining PV close to SP. The classical controller tuning formulas only work well for one objective [2] but degrades the performance for the other control objective.

The Proportional-Integral-Derivative (PID) controller is a commonly applied control strategy in the industrial automation processes [3, 4] because of high flexibility in various process designs and ease of implementation. There are many tuning approaches whereby Ziegler-Nichols (ZN) [5] and Internal Model Control (IMC) [6] are most widely applied.

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Gain scheduling (GS) method is used to determine controller tunings for a nonlinear process [7] as the plant's dynamic behavior varies at different operating levels [8]. However, it's highly dependent on the user's knowledge, skills and leads to human errors while performing the manual calculation.

In reflecting on the complexity and limitations of the manual calculation mentioned above, this research aims to analyze the automated and trade-off optimized controller tunings that provide the best performance in both servo and regulatory controls of a nonlinear process. Section 2 elaborates on the literature review of GS, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) analysis. Section 3 explains methodology in process identification and settings of PSO and GA analysis. Section 4 verifies the responses of optimization analysis and various control strategies. Last but not least, Section 5 concludes all research findings and explaining the future prospect.

2. LITERATURE REVIEW

This section explains the literature researches for GS, PSO and GA. The research gap and motivation are highlighted to emphasize the purpose of this research.

2.1 Gain Scheduling

Initially, the GS method was adopted to adaptive Fuzzy Logic [9] to determine the optimum PI controller based on a timely error of a Wind Energy Conversion System, whereby the research can be extended to evaluating overshoots that reflect the aggressiveness and robustness of the system. A systematic GS controller [10] was designed for a feedback controller that seemed to gain credits for the Linear Fractional Transformation on the plants' improved regional stability and robust performance of the plants and ventilation control systems [11]. In [8], PSO-based Fuzzy method applied GS to update the Subspace Predictive Control for a nonlinear system. [12] applied convex optimization technique for GS, whereby the sufficient conditions of a dynamic controller were derived by identifying the D-stability region for a class of nonlinear systems. [13] applied GS-based controller by directly expressing polynomial and coefficient parameters of a nonlinear pneumatic clutch actuator installed in heavy-duty trucks. Besides, [14] proposed the GS-based controller for the Linear Parameter-Varying (LPV) model of commercial vehicle air brake systems based on the nonlinear mathematic model.

2.2 Particle Swarm Optimization Analysis

As one of many metaheuristic optimization methods, PSO was applied to improve the anti-jamming ability and reduced overshoots for the oil pump system operation [15]. In [16], PSO can search for the optimal weighting matrices that reduce the oscillation of pitch motion for a helicopter. Automatic Voltage Regulator Control [17] applied PSO to improve the transient response and robustness against external disturbance. PSO was adaptable to Fuzzy controller [18] for empirical parameter selection and invariances to the robot tracker with the reduced overshoot and settling time. Furthermore, [19] proposed an easy particle that improves premature convergence by diversifying the searching direction in solving the nonlinear constrained optimization (NCO) problem. Besides, [20] utilized the PSO to correlate the velocity and acceleration improve the robotic arms' position control and obstacle avoidance.

2.3 Genetic Algorithm Optimization Analysis

GA is another optimization approach used to solve many engineering problems. It was adapted to the modeling and PID self-tuning control of a single control loop [21] and setpoint analysis with minimum error [22]. GA analysis was excelled to feedforward plus feedback control loop for self-regulating process [23]. Furthermore, a GA-based Linear Quadratic Gaussian controller can be incorporated with Kalman Filter to the controller [24] for reducing the frequency deviations and settling time, providing a better power quality to the customer. [25] proposed a new hybrid GA analysis to solve the minimum vertex cover problem. Furthermore, [26] analysed the GA's improvement on temperature field and reconstruction speed for the boiler system. [27] applied an integer programming technique for improving the production machine's performance. [28] applied multi-objective GA optimization algorithm to improve the internal combustion engine's power generation efficiency and operating cost. [29] proposed GA to improve optimization problem-solving in reasonable time via automated generation of EQ-algebras. Besides, [30] has parallelized program and instruction problems using GA and found the new method has better recovered time to achieve the theoretical results.

Given the faced problems discussed in Section 1, a nonlinear process might need an automated approach to determine the controller tunings that reduce dependency on the knowledge and skills and prevent human errors. Moreover, it is good to propose a method to determine the trade-off optimized controller tunings for both servo and regulatory controls at various operating levels, rather than mathematic formulas of deterministic approach that only gives the reasonable control for either servo or regulatory controls scenario. For this reason, GA and PSO optimization techniques are studied and analyzed, whereby the better approach is then incorporated into the developed Graphical User Interface (GUI). Besides, the performance responses also will be compared with manually calculated controller tunings.

3. METHODOLOGY

This section explains the methodology for model identification, stability analysis, performance measurement and the applied optimization algorithms for the analysis.

3.1 Model Identification and PI Controller Model using LOOP-PRO Software

Analysis of the nonlinear process is conducted to the Gravity Drained Tank function of the LOOP-PRO simulation software available in the university's computer lab. The dynamic behavior of water level is approximated to the First Order plus dead time (FOPDT) model, which is a realm to common model identification of physical plants. In closed-loop control, the water level is regulated by the control valve located to the feedwater supply. Whereas the load changes or regulatory control is performed by adjusting the value of the Pumped Flow.

The empirical model identification is an identical approach to model a process without developing the dynamic model of the process. The parameters include process gain (K_p), time constant (τ_p) and dead time (θ_p) are obtained from the developed process response curve in the open loop test method as illustrated in Eq. (1):

Process model, $G_p = [K_p \exp(-\theta_p s)]/[\tau_p s + 1]$. (1)

Similarly, the structure of disturbance model is represented in Eq. (2):

Disturbance model, $G_d = [K_d \exp(-\theta_d s)]/[\tau_d s + 1]$. (2)

where, K_d is the disturbance gain, τ_d is the disturbance time constant and θ_d is the disturbance dead time.

The Proportional-Integral (PI) controller algorithm is presented in Eq. (3):

PI controller algorithm, $G_c = [K_c\tau_i s + K_c]/\tau_i s$ (3)

where, K_c is the proportional gain and τ_i is the integral time constant and $K_i = K_c/\tau_i$ is the integral gain. In manual calculation, the PI controller tunings are obtainable via the derived mathematical formulas for IMC [31] and Z-N [5].

3.2 Stability Analysis of First Order Plus Dead Time Model

Stability analysis intends to determine the region area of the controller tunings for stable control performance [32]. The exponential function is approximated by using Taylor series approximation, $[\exp(-\theta_p s) \approx 1 - \theta_p s]$ gives equation shown as Eq. (4):

$G_p = [K_p \exp(1 - \theta_p s)]/[\tau_p s + 1]$. (4)

The closed-loop transfer function is depicted as Eq. (5):

Closed-Loop transfer function, $C/R = (G_pG_c)/(1 + G_pG_c)$ (5)

Incorporating both Eqs. (3) and (4) into Eq. (5) to obtain Eq. (6):

$$C/R = [(K_pK_c - K_iK_p\theta_p)s - K_pK_c\,\theta_p s^2 + K_pK_i] / [(\tau_p s^2 + s) + (-K_pK_c\theta_p s^2 + (K_cK_p - K_pK_i\theta_p)s + K_iK_p)]. \quad (6)$$

Note that the denominator of Eq. (6) determines the closed-loop stability. Take the denominator to obtain Eq. (7):

$$(\tau_p - K_pK_c\theta_p)s^2 + (1 + K_pK_c - K_iK_p\theta_p)s + K_pK_i = 0. \quad (7)$$

For a stable control performance, all the parameters of the polynomial equation should have a similar sign to fulfill the necessity criterion of Rourth-Hurwitz stability. By assuming all parameters of the polynomial are > 0, the term s^2 of Eq. (4) obtains Eq. (8).

$K_c < \tau_p / K_p\theta_p$ (Upper Limit) (8)

As all parameters must have a similar sign for stabile control performance, $K_c > 0$ and the stability range of K_c can be determined in the range of 0 and upper limit.

$0 < K_c < \tau_p / K_p\theta_p$.

From the term s of Eq. (4), $1+K_pK_c - K_iK_p\theta_p > 0$,

$K_i < (1+K_pK_c) / K_p\theta_p$.

As $K_i = K_c / \tau_i$, it gives $\tau_i > K_pK_c\theta_p / (1 + K_pK_c)$ (Lower Limit) (9)

3.3 Performance Indexes Measurement

Minimum integral error measurement [33] evaluates the control performance of the process by using quantitative performance statistics measurement that produces indices or total area in-between process curve and the setpoint condition via multiplication of the scan interval, $t(s)$ and the absolute value of the error, $|e|$. The minimum integral error measurement [3] consists of Integral Absolute Error (IAE), Integral Square of Error (ISE), and Integral over Time for Absolute Error (ITAE), where the smaller error values, the better control performance. IAE value integrates the absolute error over a period. ITAE multiples the absolute error with the time factor and then integrates it over the duration of the time factor, reflecting the error's weight for the long run period. Besides, ISE integrates the square of the error value over the period. The mathematical expression of IAE, ITAE and ISE are illustrated from Eqs. (10)-(12).

$$\text{Integral Absolute Error, IAE} = \int_0^\tau |e(t)| dt \tag{10}$$

$$\text{Integral Time Absolute Error, ITAE} = \int_0^\tau t\,|e(t)| dt \tag{11}$$

$$\text{Integral Square Error, ISE} = \int_0^\tau e(t)^2 dt \tag{12}$$

3.4 Particle Swarm Optimization Analysis

PSO operates on random selection and survival of the fittest by regenerating new particles in continuous iterations. The generated particles are applied to the predefined fitness function for determining the personal best position, P_{id} and global best position, P_{gd} [38]. Two algorithms are defined in PSO analysis: random position, X_{id} and the random velocity, V_{id}, respectively shown in Eqs. (18) and (19).

$$\text{Velocity update, } V_{id(t+1)} = WV_{id(t)} + c_1r_1(P_{id} - X_{id(t)}) + c_2r_2(P_{gd} - X_{id(t)}) \tag{18}$$

$$\text{Position update, } X_{id(t+1)} = X_{id(t)} + V_{id(t+1)}t \tag{19}$$

where, W = inertia weight, t is 1 in each interactive step, r_1 and r_2 are random values in the range of 0 to 1, c_1 and c_2 are coefficient of the particle acceleration value in range of 0 to 2, $X_{id(t)}$ is initial position, and $V_{id(t)}$ is initial velocity. Besides, some critical settings cover the lower and upper limits are set to 5-18 (%/m) for the K_c and 0.5 – 5(s) for τ_i. Population size of 20 and generation of 100 are set, which is adequate for the optimization analysis of the single loop process.

The PSO analysis has randomly select initial group of particles, $V_{id(t)} = K_c \tau_i$, where $K_c = c1, c2....c(t)$, $\tau_i = i1, i2....i(t)$. The objective function consists of the process and disturbance models, control algorithms and integral error measurements. During the iteration, each particle is evaluated by the objective function that produces the respective integral error values. The particle with the least integral error value is chosen as P_{id}, and then is compared with $P_{gd(t)}$. When the $P_{id(t+1)} < P_{gd(t)}$, $P_{id(t+1)}$ substitutes the value of P_{gd} to obtain $P_{gd(t+1)}$. It would repeats in the next iteration, where the $X_{id(t+2)}$ are randomly selected particles. Overall, the iteration analysis results on the convergence of the P_{gd} until the most updated P_{gd} value possess the K_c and τ_i values and the least integral error value.

3.5 Genetic Algorithm Optimization Analysis

GA searches for the optimal solution through convergence to the targeted population in the better regions until it gets the best controller tunings. The flowchart for GA optimization is shown in Fig. 1.

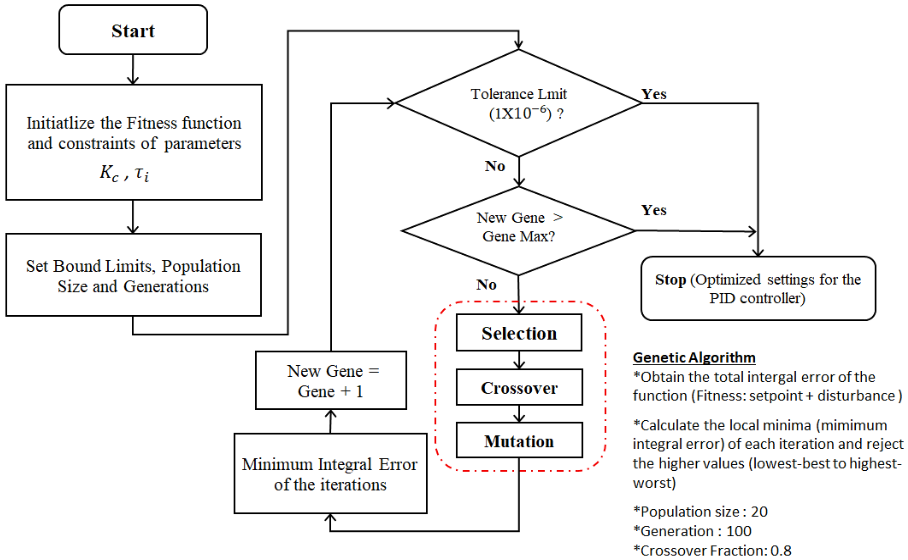


Fig. 1. GA optimization analysis flowchart.

Fitness value, F is the ultimate measurement obtained from the outcome of objective function [34]. The transfer function for servo control refers to Eq. (1), while the disturbance rejection's transfer function refers to Eq. (2). The designed chromosomes include; $K_c = x(1)$; $\tau_i = x(2)$ are shown in Eq. (13). The errors of both servo and regulatory controls are depicted in Eqs. (14) and (15). The total integral error is illustrated as Eq. (16) and F in Eq. (17) inverts the value J as the best solution.

$$\text{PI controller, } G_c = x(1) + [x(1) / x(2)s] \tag{13}$$

$$\text{Servo error, } e_{servo} = 1 - \text{step [closed loop (Output/Setpoint)]} \tag{14}$$

Regulatory error, $e_{regulatory}$ = 1 + step [closed loop (Output/Disturbance)] (15)

Total integral error, $J = \int abs(e_{servo})dt + \int abs(e_{regulatory})dt$ (16)

Fitness value, $F = (1/J)$ (17)

Critical settings for GA analysis include bound settings, population size and generations. The bound setting consists of upper and lower bound settings that provide the search areas of GA as analyzed in Section 3.2. From the mathematic calculations, the lower and upper limits are set to 5 – 18 (m/%) for the K_c and 0.5 – 5 (s) for τ_i. Population size justifies the number of randomly selected chromosomes or individuals in each generation and is set at 20. Meanwhile, generation identifies the number of iterations in the analysis and optimization analysis would stop after reaching the amount [37]. In this research, generation is set at 100. Besides, GA analyses the generation and Tolerance Function (TolFun) to end the optimization analysis, which is set at $1e^{-6}$ as one of the stopping criteria. In every iteration, the best-fixed chromosome is compared to the global best point and will halt when the difference error is less than the TolFun value.

4. SIMULATION ANALYSIS AND DISCUSSION

This section verifies the accuracy and reliability of the proposed scheme through simulation and comparison of the process responses after using various tuning methods.

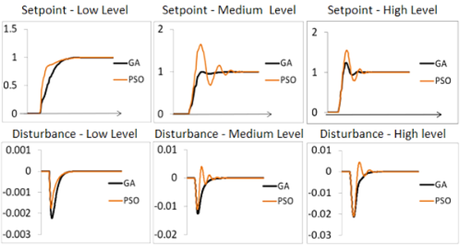
4.1 Model Identification and Controller Tunings of Low, Medium and High Operating Levels

The obtained models and PI controller settings are shown in Table 1. The model identification of Gravity Drained Tank function was started in the open loop mode. A surge of MV for 10% and disturbance of 1 l/m are respectively applied to cause the process reaction and enabling the model generations of Low, Medium and High operating levels. Manually calculated PI controller tunings for IMC-Moderate, IMC-Aggressive and ZN are obtained by referring to the respective formulas. Whereas, the controller tunings for GA and PSO are simulated by using respective algorithms in the MATLAB software.

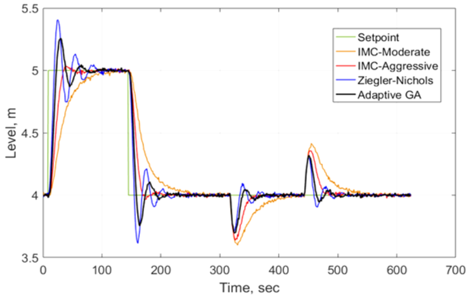
Table 1. Model identification and PID controller tunings.

Gravity Drained Tank	Model Identification		PID Controller Tunings									
	Process (MV=20%-30%)	Disturbance (2*l/m–3 l/m–2 l/m)	IMC-Moderate		IMC-Aggressive		ZN		PSO		GA	
			K_c (m/%)	τ_i (sec)	K_c (m/%)	τ_i (sec)	K_c (m/%)	τ_i (sec)	K_c (m/%)	τ_i (sec)	K_c (m/%)	τ_i (sec)
Low Operating Level	$\frac{0.0385\,e^{-0.2721s}}{0.7584s+1}$	$\frac{-0.1049\,e^{-0.154s}}{0.015s+1}$	4.359	0.846	8	0.846	35.3	1.3	33.74	4.04	14.23	0.83
Medium Operating Level	$\frac{0.0915\,e^{-0.5416s}}{1.149s+1}$	$\frac{-0.3318\,e^{-0s}}{0.5128s+1}$	3.02	1.11	6.42	1.6	25.2	1.62	17	0.63	13.68	1.47
High Operating Level	$\frac{0.1289\,e^{-0.6812s}}{1.538s+1}$	$\frac{-0.4946\,e^{-0s}}{0.8427s+1}$	2.97	1.62	4.17	1.62	19.6	1.9	12.34	0.93	13.43	1.65

* l/m is the liter/meter



Operating Level	Error	PSO	GA
High Operating Level	IAE	3.576	2.003
	ISE	2.21	1.143
	ITAE	116.8	43.28
Medium Operating Level	IAE	1.847	1.564
	ISE	0.912	0.931
	ITAE	33.89	32.91
Low Operating Level	IAE	1.526	1.058
	ISE	0.879	0.527
	ITAE	21.12	15.97



Tuning Method	IAE	ISE	ITAE
IMC-Moderate	6.325	2.9486	201.5
IMC-Aggressive	4.505	2.2101	116.8
Z-N	3.0701	1.4764	68.36
GA	2.0029	1.1432	43.28

(a) (b)

Fig. 2. Analysis and comparison of responses; (a) GA and PSO; (b) High operating level.

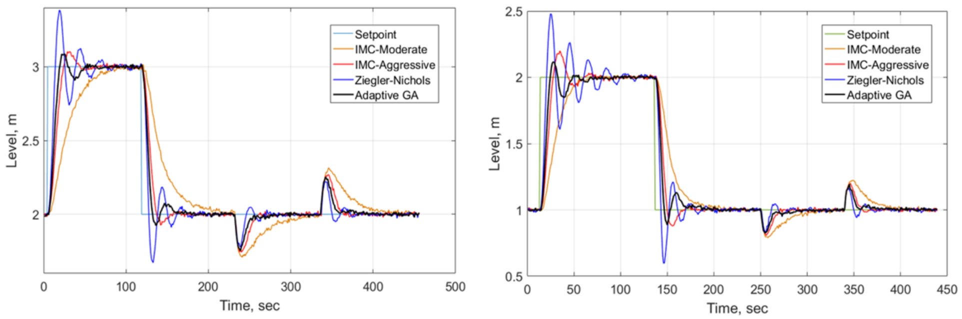
4.2 Analysis of the Process Responses and Performance Indexes

Fig. 2 (a) reflects the control performance for both GA and PSO analysis. The process responses have been compared by applying various K_c and τ_i values in Table 1. It verifies which of the optimization analysis are better fixed to the identified models. Both GA and PSO provided reasonable responses for the Low operating level. PSO produces smaller overshoots than GA in the regulatory control. However, PSO analysis seems to control the processes more aggressively, resulting in significant oscillations than GA for Medium and High operating levels. From the perspective of performance indexes, most of the error values produced by GA have smaller integral values. Overall, GA analysis is considered a more desirable approach for the optimum control of the modeled process.

Fig. 2 (b) shows the process responses and performance indexes of various controller tunings at the High operating level. IMC-Moderate and IMC-Aggressive produce a slower response for the setpoint (servo) control, consequence a higher overshoots for disturbance (regulatory) control. On the other hand, Z-N produces the most aggressive responses for both controls. Interestingly, GA analysis produces a more reasonable response in terms of speed and overshoots. From the performance indexes, GA produces the least integral error values reflecting better controllability than other tuning methods.

Fig. 3 (a) shows the process responses of various controller tunings at the Medium operating level. In setpoint control, both IMC-Moderate and IMC-Aggressive tunings drive PV slowly to the new setpoint. Z-N tuning gave the most aggressive response causes significant oscillations in setpoint control. For overall responses of both setpoint and disturbance controls, GA is the most favorably accepted. Besides, GA holds the least integral error values as compared with all other controller tunings.

Fig. 3 (b) illustrates the process responses of various controller tunings at the Low operating level. IMC-Moderate provides slower response for the setpoint control and causing larger overshoots at the disturbance control. IMC-Aggressive and Z-N tunings seem to provide a more aggressive response than GA analysis, resulting in more oscillations in disturbance controls. Based on the performance indexes, GA has once again possessed the least integral error values for all IAE, ITAE and ISE.



Tuning Method	IAE	ISE	ITAE
IMC-Moderate	5.35	2.5415	125.86
IMC-Aggressive	3.668	1.1398	82.49
Z-N	2.7298	1.2841	55.18
GA	1.5635	0.9307	32.91

(a)

Tuning Method	IAE	ISE	ITAE
IMC-Moderate	5.5709	2.662	103.88
IMC-Aggressive	3.0353	1.50833	49.63
Z-N	3.4374	0.98281	68.42
GA	1.0578	0.527	15.969

(b)

Fig. 3. Comparison of responses; (a) Medium operation level; (b) Low operating level.

4.3 Graphical User Interface for Genetic Algorithm Optimization Analysis

Fig. 4 depicts the developed GUI for GA optimization analysis. The GUI incorporates GA analysis of three operating levels into a single platform. The optimum PID tunings can be obtained by inserting process parameters, bound limits, population size and generation and then clicking the "Optimization" button. GA analysis would operate and ultimately provide the optimum PI tunings applied to the Gravity Drained Tank function based on the identified models. Upon completing optimization analysis, all the PI controller settings are displayed at the output columns, and the respective process responses are shown at the right part of the GUI platform.

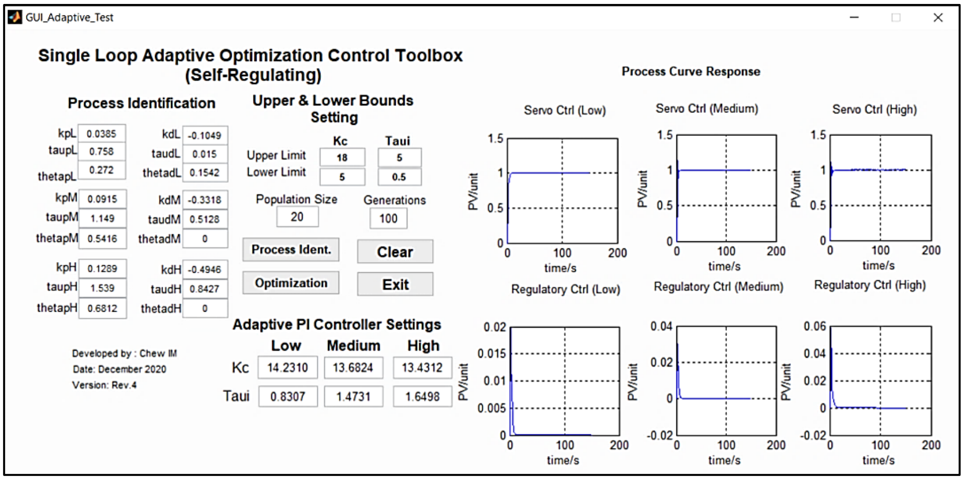
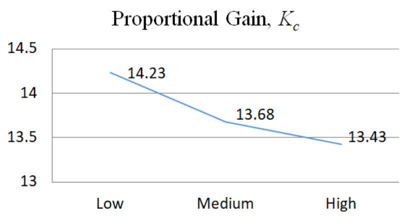


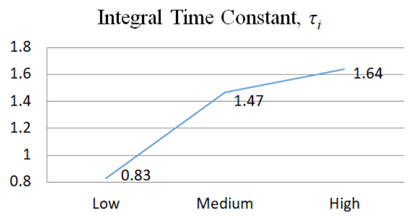
Fig. 4. Graphical User Interface for GA-based optimization analysis of High, Medium and Low operating levels.

4.4 Gain Scheduling of Nonlinear Process by Genetic Algorithm

Figs. 5 (a) and (b) show the obtained controller scheduling for the optimum control of the nonlinear Gravity Drained Tank function. The produced controller scheduling is a finite reference of controller settings for the nonlinear Gravity Drained Tank at different operating levels. The increased operating level applies the lower controller gain settings with the higher integral time constant values, which means less controller action is required. In contrast, the decreased operational level requests more controller actions. Therefore, the larger controller gain and smaller integral time constant are needed.



(a)



(b)

Fig. 5. Scheduling of controller tunings for the optimum process responses; (a) Proportional gain; (b) Integral time constant.

5. CONCLUSION

This research aimed at developing the best controller tunings for servo and regulatory controls of a nonlinear process. Model identification is obtained via Drained Tank function of the LOOP-PRO software. Controller tunings are determined through deterministic approaches, GA and PSO. Besides, the performance indexes are compared for various operating levels. Both process curve response and performance indexes show that GA optimization analysis produces the best control performance in all three operating levels. GUI has been developed to incorporates the optimization analysis for various operating levels. It has been identified that $K_{c(L)}$=14.23 %/m and $\tau_{i(L)}$=0.83 sec is the best tunings for the Low operating level. $K_{c(M)}$=13.68 %/m and $\tau_{i(M)}$=1.47 sec are the optimum controller tunings at the Medium operating level. Besides, the $K_{c(H)}$=13.43 %/m and $\tau_{i(H)}$=1.64 sec are the optimum controller tuning at the High operating level. The optimization analysis adopted to the GS method simplifies the industrial practices in determining the trade-off optimized tuning for the controlled process. Last but not least, this research is expendable towards in-depth analysis to more complex control loops such as cascade and three-element control, which possesses nonlinear characteristics in the process operations.

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