Robust PID controller design using particle swarm optimization-enabled automated quantitative feedback theory approach for a first-order lag system with minimal dead time

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This paper presents the design of a robust proportional integral and derivative (PID) controller for a first-order lag with pure delay (FOLPD) model using particle swarm optimization (PSO)-enabled automated quantitative feedback theory (QFT). The plant model considered here can be approximated as a first-order system with a non-minimum phase (NMP) zero. Synthesis of controller for the FOLPD model via manual graphical technique involved in the QFT method is always a challenging and cumbersome task, because an NMP system stabilizes by a small gain. In this paper, a proposal is being presented to automate the loop-shaping phase in the QFT design method to synthesize a robust controller that can undertake the exact amount of plant uncertainty even in the presence of larger uncertainties than those assumed initially and can ensure a proper trade-off between robust stability and tracking performance specifications over the entire range of design frequencies. In this paper, the PSO technique has been employed to tune the controller automatically, which can significantly reduce the computational effort compared with manual graphical techniques. It has also been demonstrated that this methodology not only automates loop shaping but also improves design quality and, most usefully, improves performance with optimally tuned PID controller in quantitative manner.

Keywords: FOLPD model; NMP system; quantitative feedback theory; particle swarm optimization

1. Introduction

The proportional integral and derivative (PID) controller, perhaps, is the most widely accepted controller in industrial automation. The potential of PID controller can be efficiently utilized only if it is tuned properly. The use of the PID controller is omnipresent in the industry; it has been stated, for example, that in process control applications, more than 95% of the controllers are of PID type (Åström, Hägglund, Hang, & Ho, 1993).

However, there is general agreement that PID controllers are not well suited for the control of dominant delay processes. It has been suggested that the PID implementation is recommended for the control of processes of low to medium order, with small delays, when the controller parameter setting must be done using tuning rules and when the controller synthesis may be performed a number of times (Isermann, 1989).

The dynamics of a process can also be determined from the response of the process to step inputs. The dynamics of a linear system are in principle uniquely given from such a transient response, provided that the system is at rest initially and the measurement is noise free. In practice, these conditions are not fulfilled, which limits the order of the resulting models. For PID controllers tuning, however, simple models are often sufficient. An advantage of step response methods is that they are very simple to use and are intuitively easy to understand. The approximate step response process model often can be represented as follows:

\[ P(s) = \frac{Ke^{-\theta s}}{\tau s + 1} \]  

The model (1) has three parameters: the static gain \( K \), the time constant \( \tau \) and dead time \( \theta \). This is the most common model in the PID tuning literature, and is often called the first-order lag with pure delay (FOLPD) model. The parameters of the model can be determined from step response dynamic data. Although the model seems very simple, it is widely used in the process industry. Reasons for this are its simplicity and its applicability to many processes. Often a FOLPD process model can be approximated as a first-order system with non-minimum phase (NMP) zeroes, with the consideration of very small dead time. The approximated process model is as follows:

\[ P(s) = \frac{K(1-\theta s)}{\tau s + 1}. \]  

The choice of appropriate PID controller parameters (\( k_p \) (proportional gain), \( T_i \) (integral time constant) and \( T_d \) (derivative time constant)) for a FOLPD process model may be achieved experimentally, e.g. by manual tuning.

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high-frequency gain are optimized by a population-based method based on the fact that performance, stability, and Li (1999) developed a GA-enabled automatic designed the convex optimization problem. Chen, Ballance, Feng, Voting, & Desbiens (1999) have manually synthesized a PID controller using the quantitative feedback theory (QFT) method. But the potential of the PID controller can be efficiently utilized only if it is tuned properly. The graphical loop shaping performed by using the QFT tool box involves a trial and error procedure and also the success of the design depends, to a large extent, on the experience of the designer. That is why in recent years researchers are concentrating more on the development of automatic loop-shaping algorithm. One of the first papers to address the automatic loop-shaping problem is by Gera and Horowitz (1980). This work uses Bode’s gain–phase integral to derive a nominal loop shape in an iterative fashion. There was no guarantee of convergence and rational function approximation was ultimately needed to obtain an analytical expression for the loop. This approach was automated in a QFT tool box (Ballance & Gawthrop, 1991), which specified the iteration process and allowed for higher order approximation of the integral. Thompson and Nwokah (1994) proposed that automatic loop shaping was achieved using nonlinear programming techniques where the QFT bounds were over bounded by disks. With the continuation of this work, Borghesani, Chait, & Yaniv (1994) proposed an automatic loop-shaping technique via linear programming. Actually this method is a continuation of the convex optimization problem. Chen, Ballance, Feng, and Li (1999) developed a GA-enabled automatic designed method based on the fact that performance, stability, and high-frequency gain are optimized by a population-based search technique, which ensures good robust stability and appreciable tracking performance with the use of minimum control effort. Cervera and Banos (2006) proposed an automatic loop-shaping method using a crone-based approach for fractional order systems. Patil, Nataraj, and Vyawahare (2012) developed an interval constraint satisfaction method for automated synthesis of a fixed structure QFT Fractional Order controller.

In this paper, PID controller design for the FOLPD process model using particle swarm optimization (PSO)-enabled automatic QFT has been demonstrated with the help of a suitable benchmark problem and the objective function has been defined to get optimized, considering the design constraints for the FOLPD process model. The design ensures a proper trade-off between robust stability specification and robust tracking performance over the entire range of frequencies. It has also been demonstrated that with the designed controller, the system remains within the specified performance, even in the presence of larger uncertainties than those assumed initially.

2. QFT overview

QFT is a unified frequency domain technique utilizing the Nichols chart (NC) for achieving the desired robust design over a specified region of plant uncertainty. This method was created and developed by Horowitz (1963). It is now recognized as a well-established method for the design of robust controllers for the plant with large classes of uncertainties, output/input disturbances, and noises. This method was successfully implemented in process control (Nataraj, 1992), flight control (Breslin & Grimble, 1997; Pachter, Houpis, & Trosen, 1997), marine control (Satpati & Sadhu, 2008; Satpati, Bandyopadhyay, Koley, & Ojha, 2008), missile control (Benshabat & Chait, 1993), power systems (Satpati, Bandyopadhyay, Das, & Koley, 2008; Shrikant Rao & Sen, 1999) and power electronics applications (Altowati, Zenger, & Suntio, 2007), robot manipulator control (Farsi, 1993), to name a few. The true importance of feedback is in “achieving desired performance despite uncertainty.” If so, then the actual design and the cost of feedback should be closely related to the extent of the uncertainty and narrowness of the performance tolerances. In short, it should be quantitative. Basically, the QFT design is based upon:

- Specifying the tolerances in frequency domain (time domain tolerances should be converted into corresponding frequency domain tolerances) by means of set of plant transfer functions and closed-loop control ratios;
- Determining the loop transmission functions and pre-filter functions to satisfy the various resulting bounds corresponding to the tolerances.
A single-loop two degrees of freedom (DOF) feedback control structure (providing freedom to shape the feedback and tracking responses independently) is shown in Figure 1. Here, \( P \) is the set of transfer functions \( \{P(s)\} \), which describe the region of plant parameter uncertainty, \( C(s) \) is the cascade compensator, and \( F(s) \) is an input pre-filter.

The output \( Y(s) \) is required to track the command input \( R(s) \) and reject the external disturbance \( D(s) \). The compensator \( C(s) \) is to be designed so that the variation of \( R(s) \) to the uncertainty in the plant \( P \) is within allowable tolerances, the robustness criterion is ensured and the disturbance rejection requirement is met. In addition, the pre-filter properties of \( F(s) \) must be designed to tailor the responses to meet the tracking specification requirements (Borghesani et al., 1994; Houpis, Rasmussen, & Garcia-Sanz, 2006).

### 3. Introduction to PSO

The PSO is a population-based optimization tool, which is developed by Kennedy (2010) motivated by the social behavior of bird flocking and fish schooling. Population is formed by a pre-determined number of particles; each particle is a candidate solution to the problem. In a PSO system, particles fly around in a multi-dimensional search space until relatively unchanging positions have been encountered or computational limits are exceeded.

During the flight, each particle adjusts its position according to its own experience and that of its neighboring particles (Kennedy, 2010). In PSO algorithm, every particle remembers its best solution (local best, "\( J_p \text{best} \)") as well as the group’s best solution (global best, "\( J_g \text{best} \)”). In PSO, each particle adjusts its flight according to its own and its companion’s flying experiences.

Let \( X \) and \( V \) represent the particle position and flight velocities in the given search space, respectively. Therefore, the \( i \)th particle is represented as \( X_i = (x_{i1}, x_{i2}, \ldots, x_{im}) \) in the \( m \)-dimensional search space. The base previous position of the \( i \)th particle is recorded and represented as \( J_{p \text{best}} = (J_{p \text{best}1}, J_{p \text{best}2}, \ldots, J_{p \text{best}m}) \). The index of the best particle among all the particles in the group is represented by \( J_{g \text{best}} \). The rate of the velocity for particle \( i \) is represented as \( V_i = (v_{i1}, v_{i2}, \ldots, v_{im}) \). The modified velocity and position of each particle can be calculated using the current velocity and distance from \( J_{p \text{best}} \) and \( J_{g \text{best}} \) using the following equations:

\[
V_{i}^{t+1} = QV_{i}^{t} + K_1\text{rand}_1(X_{p \text{best}} - X_{i}^{t}) + K_2\text{rand}_2(X_{g \text{best}} - X_{i}^{t}),
\]

\[
X_{i}^{t+1} = X_{i}^{t} + \gamma \cdot V_{i}^{t+1},
\]

where \( K_1 \) and \( K_2 \) are two positive constants, \( \text{rand}_1 \) and \( \text{rand}_2 \) are random numbers in the range \([0–1] \), and \( Q \) is the inertia weight. \( X_{i}^{t} \) represents the current position of the \( i \)th particle and \( V_{i}^{t} \) is its current velocity. The positions of the particles are updated using Equation (4), where \( X_{i}^{t+1} \) is the new position of the \( i \)th particle at \( m \)-dimensional search space.

The weight \( Q \) is updated using the following equation:

\[
Q = Q_{\text{max}} - \frac{Q_{\text{max}} - Q_{\text{min}}}{\text{iter}_{\text{max}} - \text{iter}} \text{iter},
\]

where \( \text{iter} \) is the iteration count.

### 4. Definition of objective function for automated loop shaping in QFT

In the proposed approach, the controller structure is predetermined and given by (Chen et al., 1999)

\[
C(s) = \frac{b_1s^4 + \cdots + b_1s + b_0}{a_ms^m + \cdots + a_1s + a_0}.
\]

The coefficients \( b_1, \ldots, b_1, b_0 \) and \( a_m, \ldots, a_1, a_0 \) are searched by the PSO algorithm to satisfy the constant equations. \( a_m \) can be set to 1.

The objective function \( J \); comprises robust performance, stability criterion, restriction in gain crossover frequency and high-frequency gain which is required to minimize the use of control effort, \( s \) to be optimized. The objective function is given by Equation (7).

\[
J = \beta_1 J_{\text{hfg}} + \sum_{i=1}^{N} (\beta_2 J_{\text{sta}} + \beta_3 J_{\text{b1}}) + \beta_4 J_{\text{gcf}},
\]

where \( J_{s1} \) are the robust stability indices, \( J_{\text{sta}} \) is the stability index, \( J_{\text{hfg}} \) is the high-frequency gain, and \( J_{\text{gcf}} \) is the index for upper limit in gain crossover frequency for compensated loop transmission, \( \beta_1, \beta_2, \beta_3, \beta_4 \) are weighting factors. In general, \( \beta_1 \) should be reasonably large. In this paper, \( \beta_1 \) is simply chosen as large as 1.83e3. Penalties associated with the respective indices for stability, robust stability index and gain crossover frequency bound are \( \beta_2, \beta_3, \beta_4 \), respectively, and \( N \) indicates the number of discrete points taken as designed frequencies. For an automated design, the stability is analyzed by checking the roots of the characteristics equation of compensated nominal loop \( (L(s)) \). A simple cost function to penalize unstable design is

\[
J_{\text{sta}} = \begin{cases} 0 & \text{if stable} \\ 1 & \text{if unstable.} \end{cases}
\]

To obtain the cost function \( J_{s1} \) for robust stability indices at all designed frequencies, it is required to generate robust
stability bound for the given robust stability specifications and amount of plant uncertainties by using the QFT technique. Then, with the capability and flexibility of an evolutionary algorithm, these numerical bounds can be used directly in an automated design. At each frequency point, the gain and phase of the open-loop transmission $L(j\omega)$ is calculated and then checked to see whether or not the QFT bound at all designed frequencies is satisfied. A simple robust stability bound index is given by

$$J_{hi} = \begin{cases} 0 & \text{if QFT bound at } \omega_i \text{ satisfied} \\ d_{bi} & \text{otherwise} \end{cases}$$

where $d_{bi}$ is the distance to the QFT bound at $i$th frequency point. Since the nominal plant is fixed, the cost function for gain crossover frequency restriction is defined as follows:

$$J_{gcf} = \begin{cases} 0 & \text{if } |L(j\omega_{gcf})| = 1 \\ 1 & \text{otherwise} \end{cases}$$

In case of a FOLPD process model occurrence of the gain crossover frequency is restricted by the location of NMP zero and $|L(j\omega_{gcf})|$ is then checked to see whether it is unity or not. A simple performance index function for the gain and phase of the open-loop transmission directly in an automated design. At each frequency point, these numerical bounds can be used in the evolutionary algorithm, these numerical bounds can be used directly in an automated design. At each frequency point, the gain and phase of the open-loop transmission $L(j\omega)$ is calculated and then checked to see whether or not the QFT bound at all designed frequencies is satisfied. A simple robust stability bound index is given by

$$J_{hi} = \begin{cases} 0 & \text{if QFT bound at } \omega_i \text{ satisfied} \\ d_{bi} & \text{otherwise} \end{cases}$$

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$$J_{gcf} = \begin{cases} 0 & \text{if } |L(j\omega_{gcf})| = 1 \\ 1 & \text{otherwise} \end{cases}$$

5. PSO-enabled QFT algorithm
The PSO-enabled QFT algorithm comprises several steps which are shown in the flow chart of Figure 2.

6. Uncertain process model and design specification
Consider a FOLPD process model, which can be approximated as a first-order lag with a NMP zero by using an approximation, the process model can be represented as follows:

$$\Delta(s) = \{P(s)\} = \frac{s + a}{s + \theta s} = \frac{K(1 - \theta s)}{s + a}. \quad (8)$$

where

$$\theta = 0.5, \quad k \in [1, 3] \quad \text{and} \quad a \in [1, 2], a \in [1, 2] \quad (9)$$

and nominal plant is taken as

$$P_0(s) = \frac{1}{s + 1} \cdot e^{-0.5s}. \quad (10)$$

The parametric uncertainty given in Equation (9) generates a set of plant transfer function $\Delta$. It is desired that $\forall R \in \Delta$, the closed-loop system possesses the following specifications:

- Tracking specifications:
  - Overshoot < 2%
  - Rise time $1s < t_r < 3s$
  - Steady state error Nil

- Stability specifications:
  - Gain margin > 5.26 dB
  - Phase margin > 49.25 deg

The robust stability specifications are determined as

$$\left| \frac{P(s)G(s)H(s)}{1 + P(s)G(s)H(s)} \right| \leq \mu = 1.2 \quad (11)$$

this corresponds to the lower gain margin

$$K_M = 1 + \frac{1}{\mu} = 1.833 = 5.26 \text{ dB} \quad (12)$$

and a lower phase margin

$$\phi_M = 180^\circ - \cos^{-1}(0.5/\mu^2 - 1) = 49.25^\circ. \quad (13)$$

From the given tracking performance specifications, the resulting upper and lower tracking bounds have been obtained after adding pole and zero to the ideal lower and upper tracking models respectively, to increase the span at high frequencies (Borghesani et al., 1994; Nataraj, 1992; Shrikant Rao & Sen, 1999). The upper and lower tracking models are identified as follows:

$$TL(s) = \frac{4}{s^2 + 3.3s + 4}, \quad (14)$$

$$TR(s) = \frac{9}{s^2 + 7s^2 + 15s + 9}. \quad (15)$$

where

$$T_L(j\omega) \leq \left| F(j\omega) \cdot \frac{P(j\omega)C(j\omega)}{1 + P(j\omega)C(j\omega)} \right| \leq T_U(j\omega). \quad (16)$$

Design frequencies are selected as $\omega = [0.1, 0.2, 0.5, 1, 2, 5, 8, 10, 50]$ rad/s.

7. Synthesis of PID controller and pre-filter using PSO-enabled QFT
For PSO-enabled automatic loop shaping, a PID controller is tentatively chosen as

$$C(s) = \frac{a_2 s^2 + a_1 s + a_0}{s}. \quad (17)$$

Compensated nominal loop $L(s)$ is given by

$$L_0(s) = P_0(s)C(s) = \frac{1}{s + 1} \cdot e^{-0.5s} \cdot \frac{a_2 s^2 + a_1 s + a_0}{s}. \quad (18)$$

To permit optimization, all the coefficients of the chosen controller are allowed to vary in the four dimensional search
Table 1. Search range of controller parameters.

| Parameter of the controller | Lower bound | Upper bound |
|-----------------------------|-------------|-------------|
| $a_0$                       | $1\times10^{-2}$ | $1\times10^1$ |
| $a_1$                       | $1\times10^{-3}$ | $1\times10^1$ |
| $a_2$                       | $1\times10^{-2}$ | $1\times10^1$ |

spaces. During the optimization process the upper and lower bounds of the coefficients within which each parameter can vary are given in Table 1.

From the above design specifications, Equations (12) and (17), and nominal plant composite bounds are generated at all designed frequencies, as shown in Figure 3 (Borghesani et al., 1994; Shrikant Rao & Sen, 1999). The objective of this is to ensure that the synthesized nominal open loop ($L(s)$) is lying on or just above the composite bound. The gain and phase contributions of the open-loop transmission $L(j\omega)$ at all designed frequencies are obtained graphically to satisfy the robust stability and tracking performance at each frequencies are given in Table 2.

The objective function for Robust stability indices is defined in such a way that if the numerical value obtained
Table 2. Graphically obtained values of robust stability.

| Design frequencies | Phase (degree) | Magnitude (dB) | \( L(j\omega) \) |
|--------------------|---------------|----------------|-------------------|
| 0.1                | -93.45        | 29.99          | -1.9-j31.52       |
| 0.2                | -96.35        | 24.09          | -1.8-j15.91       |
| 0.5                | -103.61       | 15.50          | -1.4-j5.786       |
| 1                  | -111.23       | 8.52           | -0.96-j2.48       |
| 2                  | -116.31       | 0.00           | -0.44-j0.89       |
| 5                  | -121.75       | -8.66          | -0.19-j0.31       |
| 10                 | -141.35       | -14.92         | -0.14-j0.112      |
| 50                 | -332.24       | -26.19         | 0.043+j0.023      |

Figure 4. Loop shaping on NC.

Table 3. PSO parameters.

| Parameters     | Values          |
|----------------|-----------------|
| Maximum iteration | 10000           |
| Population size    | 20              |
| Dimension         | 3               |
| Value of K2        | 2.0             |
| Maximum weight     | 0.90            |
| Minimum weight     | 0.40            |

The convergence of coefficients representing the minimum value of objective function for a population size of 20 candidates is given in Table 4 and Global minimum value of objective function \( J = 9.87 \).

The controller design has reduced the variations in the closed-loop frequency response to the desired range. A pre-filter is now required to achieve the required shape of the closed-loop frequency response. The suitable pre-filter that satisfies the required tracking performance specification perfectly is given by

\[
F(s) = \frac{1}{((1/1.58)s + 1)((1/3.69)s + 1)}. \tag{20}
\]

Figure 5 shows the Bode magnitude plot of the closed-loop frequency response with a pre-filter, together with the tracking frequency response specifications plotted with dashed lines.
8. Design validation

Figure 6 shows the validation of robust stability specification. The worst closed-loop response magnitude (covering all uncertainty cases) is plotted in the solid line, together with the design specification plotted in the dotted line, it can be observed that robust stability specification matches perfectly for desired stability value ($\mu = 1.2 = 2.0 \text{ dB}$).

It has also been demonstrated that with the designed controller $C(s)$ can work satisfactorily even in the presence of larger uncertainties than those assumed initially.

This can be established as follows: considering the uncertain plant,

$$P(s) = (D_p(s)) = \frac{N_p(s)}{s + a} e^{-0.5s},$$

(21)

where the value of the coefficients $K$ and $a$ are $k \in [1, 3]$, and $a \in [1, 2]$, respectively. $C(s)$ is the designed fixed controller, designated by

$$C(s) = \frac{N_C(s)}{D_C(s)} = \frac{0.035s^2 + 1.811s + 3.23}{s},$$

(22)

Nominal plant

$$P_0(s) = \frac{N_0}{D_0} = \frac{1}{s + a} e^{-0.5s}.$$  

(23)

Here the primary objective is to investigate the stability of the feedback system when the loop gain is perturbed from its nominal value $L_0(s)$, where

$$L(s) = \frac{N(s)}{D(s)} = \frac{N_C(s)N_P(s)}{D_C(s)D_P(s)}$$

(24)

and

$$L_0(s) = \frac{N_0(s)}{D_0(s)} = \frac{N_C(s)N_0(s)}{D_C(s)D_0(s)}.$$  

(25)

Now sensitivity function $S_0(s)$ and complementary sensitivity function $T_0(s)$, respectively, can be defined as follows

$$S_0(s) = \frac{D_0(s)}{D_0(s) + N_0(s)}$$

and

$$T_0(s) = \frac{N_0(s)}{D_0(s) + N_0(s)}.$$  

(26)

Two stable proper weighting function $W_1(s)$ and $W_2(s)$ are taken as follows:

$$W_1(s) = \frac{1}{s + 1}$$

and

$$W_2(s) = \frac{0.2}{0.5s - 1}.$$  

(27)

These two weighting functions can be selected satisfying the inequality given by

$$K_{D_p}(j\omega, 1) \frac{D_P(j\omega)}{D_0(j\omega)} - K_{N_p}(j\omega, 1) \frac{N_P(j\omega)}{N_0(j\omega)} < |W_1(j\omega)|,$$

(28)

$$K_{N_p}(j\omega, 1) + K_{D_p}(j\omega, 1) \frac{N_p(j\omega)}{D_p(j\omega)} < |W_2(j\omega)|,$$

(29)

where $K_{D_p}(j\omega, 1)$ and $K_{N_p}(j\omega, 1)$ denote any of the Kharitonov polynomials of $D_p(s)$ and $N_p(s)$, respectively (Bhattacharyya et al., 1995).

Now let $C(s)$ be a stabilizing compensator for the nominal plant $P_0(s)$. If $\|W_1(s)S_0(s)\|^2 + \|W_2(s)T_0(s)\|^2 \leq \epsilon$, then $C(s)$ robustly stabilizes the (Houpis et al., 2006) interval plant $P(s)$ for all $\mu < \mu_{\text{max}}$, where

$$\mu_{\text{max}} = \frac{1}{\sqrt{2\epsilon}}.$$  

(30)

Figure 7 shows the plot of function

$$\|W_1(s)S_0(s)\|^2 + \|W_2(s)T_0(s)\|^2,$$

(31)

where $\delta$ is the $\infty$ norm of the function (31). From function (31), the value of the $\mu_{\text{max}}$ is calculated as 1.908. It can be shown that designed fixed controller $C(s)$ can robustly stabilize the interval plant $P(s)$, for the parametric variation given in Table 5.

Time domain simulation of the closed-loop system, with the controller $C(s)$ and pre-filter $F(s)$ (considering six
Table 5. Variation of parameters in different intervals.

| Parameter | Interval | Variation (%) |
|-----------|----------|---------------|
| $K$       | $1.0–4.816$ | $±190.7$ |
| $\alpha$  | $1.0–2.906$ | $±95.3$ |

plants within the uncertainty range) is shown in Figure 8 together with the tracking requirement. Step response and tracking error comparison for the worst and best case uncertain process model with the proposed method are shown in Figures 9 and 10, respectively. This validation study reviles that satisfactory tracking performance has been obtained. A comparative study between proposed method and other advanced/intelligent PID tuning methods, namely IMC (Rivera, Morari, & Skogestad, 1986), bacterial foraging optimization (BFO) (Kou, Zhou, He, Xiang, & Li 2009), GA (Mitsukura, Yamamoto, & Kaneda, 1999) were performed to judge the performance of an uncertain plant under the worst case. Closed-loop time responses of such a worst case uncertain compensated system with all these four tuning methods are shown in Figure 11. This study demonstrates that PID controller tuned or synthesized by the proposed method can achieve desired tracking performance specification acceptably, compared with the existing advanced PID tuning methods (IMC, BFO and GA). It is also evident from this figure that the response of the proposed method and the BFO-based PID tuning method are almost indistinguishable, but a slightly faster time response is observed with the proposed method because of the employment of automated loop shaping in QFT environment. A comparative study between proposed method and the above-mentioned advanced PID tuning methods were performed to judge the plant output disturbance rejection sensitivity of an uncertain plant under the worst case. Closed-loop time responses with plant output disturbance rejection of such a worst case compensated system with all this four tuning methods are shown in Figure 12. This comparative study reveals that closed-loop output disturbance rejection is much better in the proposed method compared with IMC-, BFO- and GA-based PID tuning methods. Figure 13 represents a comparative study between the proposed method and other intelligent PID tuning methods for the worst case uncertain plant model in account of measurement noise sensitivity in the closed-loop output response. This study demonstrates that noise sensitivity is significantly less in the proposed method compared with IMC-, BFO- and GA-based PID tuning methods.
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9. Conclusion

A PSO procedure has been employed to automate the loop-shaping process in QFT. The automatic loop shaping using PSO minimizes the trial and error involved in the manual synthesis of nominal loop. This paper has described the application of PSO-enabled QFT technique to the development of a PID process controller for a first-order lag with pure delay (FOLPD) process considering the complexities of controller design for a NMP system. The proposed method has been compared with other sophisticated/intelligent PID tuning methods such as IMC, BFO and GA. The comparative study reveals that the compensated system under the proposed method is significantly less sensitive in account of plant output disturbances and measurement noises. The proposed method ensures proper trade-off between required robust stability specification and satisfactory tracking performance with the use of minimum control effort.

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