Robust Controllers with Fuzzy Tuning

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Abstract - This paper presents a methodology using fuzzy logic and some engineering heuristics to continuously change the controller parameters in linearised control systems for improving robustness. Tuning schemes are applied for on-line adjusting the coefficients of a PI controller, a digital predictive observer, a dynamic feedforward controller and a robust modal controller, dependent on information of the control error. All the fuzzy schemes result in explicit expressions, thus the tuning process is easy and the computational cost is low. Simulation results are provided to verify the validity of the proposed approach.

Keywords - Fuzzy tuning, robustness, PI controller, observer, robust modal controller

1 Introduction

Robustness and intelligence are becoming increasingly important in modern control systems. Recent developments in power electronics and computer technology have made it possible to implement artificial intelligence in motion control [1]. The common goal for intelligent tools is to emulate the human thinking. Among current research studies, soft computational methods such as neural networks and fuzzy systems, coupled with powerful personal computers, micro-controllers, and digital signal processors, can provide high performance of motion control systems [2]. Human skills are normally utilised to tune the controller parameters to achieve robust performances. The application of auto-tuning formulae to process control has brought new insights into conventional controllers [3]. In the field of electrical drives, proportional-integral (PI) controllers with the auto-calibration method [4] inspired by the symmetric optimum principles can be used to tune the controller parameters. Auto-tuning or auto-calibration of controller parameters for plants with uncertainties is effective provided that knowledge of the control process is frequently updated. Fuzzy logic controllers [5], which are capable of providing an effective solution to some complex systems, can be designed with a minimum understanding of the plant. However, fuzzy logic controllers may suffer from a heavy computation burden required to translate the fuzzy inference into a control action. Furthermore, the derivation of fuzzy rules relies principally on human experience which sometimes limits fuzzy controller application to low order systems. An alternative approach is using fuzzy logic to tune the conventional controller parameters [6,7]. This paper gives a systematic overview of fuzzy tuning design in cascade control and state feedback (modal) control, and illustrates its applications in servo systems. Simulation results are given in each section to confirm the superiority of the proposed approach. Electrical drives are involved here, however fuzzy tuning can be applied to a variety of linearised systems.

2 PI-Controller with Fuzzy Tuning

Proportional-integral (PI) controllers are widely used in electrical drives because of their design simplicity. A typical speed control system with the conventional cascade control method is shown in Figure 1, where $n_{ref}$ is the reference speed, $T_{m}$ is disturbance torque, $e$ is error, $u$ is control signal and $n_{o}$ is output speed; and $K_{p}$, $T_{i}$, $T_{m}$, $K_{o}$ and $T_{o}$ are the PI controller gain, time-constant, current loop equivalent time-constant which is the smallest uncompensatable time-constant [4], prefilter time-constant, plant overall gain and mechanical time-constant, respectively. It is assumed that $T_{r} < T_{m}/4$ so that $1 + T_{o}s = T_{m}s$ for high frequencies, $\omega \geq 1/4T_{r}$. The design equations for $K_{p}$ and $T_{i}$ are given in Table 1. A comprehensive comparison between the symmetric, magnitude optimum (Butterworth in this case) and minimisation of the integral time absolute error (ITAE) for this specific configuration is given in [8]. With PI conventional controllers it is difficult to achieve a high tracking performance with respect both to parameter insensitivity and disturbance rejection. In order to improve the system robustness, a usual engineering practice is to tune the controller parameters. Fuzzy logic is introduced here to continuously change the coefficients $K_{p}$ and $T_{i}$, depending on the error control and its rate of change.

Tuning a coefficient, $K_{p}$, is a continuously smooth process of adjusting its value. A technical parameter, $X$, can be described in a simple way, as either large ($XL$) or small ($XS$)
### Table I. PI controller parameters with different criteria.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Controller parameters</th>
<th>Reference response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symmetric</td>
<td>( T_m/(2T_iK_p) )</td>
<td>( 4T_p )</td>
</tr>
<tr>
<td>Magnitude</td>
<td>( T_m/(2T_iK_p) )</td>
<td>( T_m )</td>
</tr>
<tr>
<td>ITAE</td>
<td>( 0.7T_m/(T_iK_p) )</td>
<td>( 3.76T_p )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>steady-state time, ( t_s )</th>
<th>overshoot, ( %\text{OS} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>16.5( T_m )</td>
<td>4.3</td>
</tr>
<tr>
<td>8.4( T_i )</td>
<td>4.3</td>
</tr>
<tr>
<td>3.6( T_m )</td>
<td>3</td>
</tr>
</tbody>
</table>

(\( XS \)) with the corresponding exponential membership functions [9]:

\[
\mu_{xs}(X) = \exp(-\frac{|X|}{\sigma_x}), \quad \mu_{xL}(X) = 1 - \exp(-\frac{|X|}{\sigma_x}),
\]

where \( \sigma_x \) is some positive constant. The following singletons are used for the output labels \( KL \) (\( K \) is large) and \( KS \) (\( K \) is small):

\[
\mu_{KL}(K) = \begin{cases} 1, & K = K_{\text{max}} \\ 0, & K \neq K_{\text{max}} \end{cases},
\mu_{KS}(K) = \begin{cases} 0, & K = K_{\text{min}} \\ 0, & K \neq K_{\text{min}} \end{cases},
\]

where \( K_{\text{max}} \) and \( K_{\text{min}} \) are the maximum and minimum values of \( K \). Engineering heuristics for tuning \( K \) with respect to \( X \) can be stated as

(i) If \( XS \) then \( KS \), If \( XL \) then \( KL \), or

(ii) If \( XS \) then \( KL \), If \( XL \) then \( KS \).

Using the centroid technique for defuzzification [5], the nonlinear relationship of \( K \) with respect to \( X \) can be found as

\[
K(X) = \frac{\mu_{xs}K_{\text{min}} + \mu_{xL}K_{\text{max}}}{\mu_{xs} + \mu_{xL}} \quad \text{for scheme (i)},
\]

\[
K(X) = \frac{\mu_{xs}K_{\text{max}} + \mu_{xL}K_{\text{min}}}{\mu_{xs} + \mu_{xL}} \quad \text{for scheme (ii)}.
\]

By analysing the frequency characteristics of the open-loop plant including the controller, it is required to increase the gain \( K_p \) and to decrease the time-constant \( T_i \) in order to reduce the control error and the system rise time. Thus, scheme (i) is proposed for tuning \( K_p \), and (ii) for \( T_i \) with respect to the control error \( e \). Taking into account the rate of change of error, the tuning process has a scaling factor, \( w_e \). The value of \( w_e \) is continuously changed by scheme (i) with respect to \( de(k) = e(k) - e(k-1) \), where \( k \) is discretised time [10]. By introducing the normalised error, \( e \), and change of error, \( \partial e \),

\[
e = \text{sat}\left(\frac{e}{e_{sat}}\right), \quad \partial e = \text{sat}\left(\frac{de(k)}{\partial e}\right),
\]

where

\[
\text{sat}(x) =\begin{cases} 1, & x \geq 1 \\ 0, & -1 \leq x \leq 1 \\ -1, & x \leq -1 \end{cases},
\]

and \( e_{sat} \) is the maximum magnitude of the error corresponding to saturation. Choosing the maximum and minimum values of \( K_p \), \( T_i \) and \( w_e \) (\( K_{p,\text{max}} \), \( K_{p,\text{min}} \), \( T_{i,\text{max}} \), \( T_{i,\text{min}} \), \( w_{e,\text{max}} \), and \( w_{e,\text{min}} \)), the tuning expressions for \( K_p \) and \( T_i \) are found as

\[
K_p = w_e[K_{p,\text{max}} - (K_{p,\text{max}} - K_{p,\text{min}})\exp(-\frac{|e|}{\sigma_e})],
\]

\[
T_i = w_e[T_{i,\text{min}} + (T_{i,\text{max}} - T_{i,\text{min}})\exp(-\frac{|e|}{\sigma_{te}})],
\]

where

\[
w_e = [w_{e,\text{max}} - (w_{e,\text{max}} - w_{e,\text{min}})\exp(-\frac{|\partial e|}{\sigma_{e}})]
\]

and \( \sigma_e \) and \( \sigma_{te} \) are some positive constants. At large values of \( T_m \), we have \( 1 + T_m s = T_m s \), from the closed loop characteristic equation for the system of Figure 1,

\[
T_m s^3 + T_m T_s^2 + K_0 K_p T_m s + K_0 K_p = 0,
\]

the stability condition can be derived as \( T_i > T_m \). Thus, with fuzzy tuning the overall system is stable if

\[
T_{i,\text{min}} > T_{p,\text{max}}.
\]
The simulation parameters of the system $K_0$, $T_m$, and $T_i$ in Figure 1 are given in Table II. The values of $T_{i,\text{nom}}$ and $K_{p,\text{nom}}$ are calculated from the values $K_{0,\text{nom}}, T_m,\text{nom}$, and $T_{i,\text{nom}}$ using the symmetrical optimum given in Table I. The prefilter time constant $T_f$ is set at $T_{i,\text{nom}}$. Choosing the minimum and maximum values for $K_p$, $T_i$, and $w_c$ as shown in Table II, and the coefficients $\sigma_c = \sigma_{b,c} = 0.01$, the controller parameters are on-line tuned by the following forms

$$K_p = [2 - 1.5 \exp(-100|\delta|)][8 - 6 \exp(-100|\delta|)],$$
$$T_i = [2 - 1.5 \exp(-100|\delta|)][0.1 + 0.3 \exp(-100|\delta|)].$$

The unit step reference response is shown in Figure 2(a) for the nominal case (solid lines) ($K_0 = K_{0,\text{nom}}, T_m = T_{m,\text{nom}}$, and $T_i = T_{i,\text{nom}}$) and for a critical case of changing parameters (dash-dotted lines) ($K_0 = 0.5 K_{0,\text{nom}}, T_m = 2 T_{m,\text{nom}}$ and $T_i = 2 T_{i,\text{nom}}$), with fuzzy tuning (curves 1) and without fuzzy tuning (curves 2). The unit step disturbance response is shown in Figure 2(b) under the same conditions. A well-damped response with adequately fast dynamics is observed even in the case of parameter variations. With fuzzy tuning the disturbance response exhibits a reduction of about 50% of the maximum deviation. Simulations indicate that transient performance and disturbance rejection capability are significantly improved with any set of parameters $K_0$, $T_m$, and $T_i$ given in Table II. The values of $T_{i,\text{min}}, T_{i,\text{max}}, w_{c,\text{min}}, \text{and} w_{c,\text{max}}$ are chosen depending on the range of changes of these system parameters. After adjusting $\sigma_c$ and $\sigma_{b,c}$ the expressions (9) for $K_p$ and $T_i$ are obtained explicitly. Thus, the computational cost for the scheme implementation is low.

$$x(k+1) = Ax(k) + Bu(k) + Dv(k),$$
$$y(k) = (I_m \ 0)x(k),$$

where $x(k) \in \mathbb{R}^n$ is the state vector, $u(k) \in \mathbb{R}$ is the control signal, $v(k) \in \mathbb{R}^q$ is the unknown external disturbance vector, $y(k) \in \mathbb{R}^m$ is the output vector, $I_m$ is the $m \times m$ unity matrix, $A$, $B$, $D$ are constant matrices of the dimensions $n \times n$, $n \times 1$, $n \times q$, respectively. The first step in the design procedure is to obtain the augmented form from the state equation (11):

![Figure 2](image-url)
where \( x_1(k) \in \mathbb{R}^m \) is the vector of measurable state variables, \( x_2(k) \in \mathbb{R}^{n-m} \) is the vector of the state variables, \( A, B, D \) \((j,h=1,2)\) are matrices of corresponding dimensions, partitioned from \( A, B, D \); \( \Gamma = \text{diag}(\gamma_m) \) is the diagonal matrix of predictive coefficients \( \gamma_m \in (-1,1), \ i=1,2,\ldots,q \). The next step is to construct a reduced-order Luenberger observer on the basis of the measurable state \( x_1(k) \) [13]

\[
\begin{align*}
(x_{k+1}) & = \begin{pmatrix} A_{11} & A_{12} & D_1 \\ A_{21} & A_{22} & D_2 \\ 0 & 0 & I + \Gamma \end{pmatrix} x_1(k) + \begin{pmatrix} B_1 & 0 \\ 0 & 0 \end{pmatrix} u(k), \\
(y_{k+1}) & = \begin{pmatrix} 0 & 0 \end{pmatrix} x_2(k) + \begin{pmatrix} 0 & 0 \end{pmatrix} v(k),
\end{align*}
\]

(12a)

\[
y(k) = (I_n \ 0 \ 0) x_2(k),
\]

(12b)

\[
\begin{align*}
\hat{x}_2(k) & = (z(k)) + (L_1) v(k), \\
\hat{v}(k) & = (w(k)) + (L_2) y(k),
\end{align*}
\]

(13c)

where \( x_1(k) \in \mathbb{R}^m \) and \( w(k) \in \mathbb{R}^q \) are observer state variables, \( L_1 \in \mathbb{R}^{(m-n)xm} \) and \( L_2 \in \mathbb{R}^{nxm} \) are observer matrix gains, \( \hat{x}_2 \) and \( \hat{v} \) are the estimates of \( x_2 \) and \( v \). In order to improve the observer robustness, the predictive coefficients \( \gamma_m \) can be made continuously changeable by the use of fuzzy logic with respect to the rate of change of \( \psi_i \). By defining

\[
\tau_i(k) = \begin{cases} 
\text{sign}(-\hat{\psi}_i(k-1)) & \text{if } \hat{\psi}_i(k) = 0 \\
\text{sat}
\left(\frac{\hat{\psi}_i(k) - \hat{\psi}_i(k-1)}{\psi_i(k)}\right) & \text{if } \hat{\psi}_i(k) \neq 0,
\end{cases}
\]

(14)

the fuzzy scheme (ii) is applied to tune \( \gamma_m \) according to the value of \( \tau_i(k) \). The expression for \( \gamma_m \) can then be found as

\[
\gamma_m = \gamma_{m,0} \exp\left(-\frac{\left|\tau_i\right|}{\sigma_{\psi}}\right),
\]

(15)

using the exponential membership function for \( \tau_i(k) \) and singleton for \( \gamma_{m,0} \), where \( \gamma_{m,0} \) is some constant and \( \sigma_{\psi} \) is positive. The observer capability of providing correct estimates of the time-varying unknown inputs in the presence of parameter uncertainty is demonstrated through the estimation of a disturbance torque \( T_L \), load speed \( \omega_2 \) and elastic torque \( T_E \) of a two-mass servo drive [14]. The plant block diagram is shown in Figure 3 with the specifications given in Table III. The actual and estimated load torque \( T_L \) is shown in Figure 4(a) with fuzzy tuning of the predictive coefficient and Figure 4(b) without fuzzy tuning, when \( T_L \) varies stepwise and the load moment of inertia \( J_2 \) increases to 500% of its nominal value.

The proposed observer can be used with a feedforward controller or a robust modal controller to suppress vibration, reject load disturbance influences, and improve parameter-insensitivity in multi-mass servo drives. It can also be applied in incipient fault detection of dynamic systems [15].

### 4 Dynamic Feedforward Controller with Fuzzy Tuning

In servo drive applications, any variation in the motor torque, moment of inertia, or friction can be considered as
Table III. System nominal parameters.

<table>
<thead>
<tr>
<th>Nominations</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply amplifier gain, $K_p$</td>
<td>25</td>
</tr>
<tr>
<td>Supply amplifier time constant, $T_p$</td>
<td>0.01 (sec)</td>
</tr>
<tr>
<td>Armature resistance, $R_a$</td>
<td>0.3 (ohm)</td>
</tr>
<tr>
<td>Electromagnetic time constant, $T_a$</td>
<td>0.03 (sec)</td>
</tr>
<tr>
<td>Back-EMF constant, $K_b$</td>
<td>1.5 ($V/\text{sec}^{-1}$)</td>
</tr>
<tr>
<td>Torque constant, $K_t$</td>
<td>1.5 ($Nm/\text{A}$)</td>
</tr>
<tr>
<td>Motor moment of inertia, $J_i$</td>
<td>0.814 ($kg.m^2$)</td>
</tr>
<tr>
<td>Electromechanical time constant, $T_{m_1}$</td>
<td>0.116 (sec)</td>
</tr>
<tr>
<td>Coupling rigidity modulus, $C_{12}$</td>
<td>0.21 ($Nm/\text{rad}$)</td>
</tr>
<tr>
<td>Coupling viscous friction, $B_{12}$</td>
<td>6.3.10^{-5} ($Nm/\text{sec}^{-1}$)</td>
</tr>
<tr>
<td>Load moment of inertia, $J_L$</td>
<td>0.012 ($kg.m^2$)</td>
</tr>
<tr>
<td>Speed reduction ratio, $i$</td>
<td>1:66</td>
</tr>
</tbody>
</table>

equivalent to an uncertain disturbance change. Disturbance rejection for improving accuracy and system robustness can be accomplished by feedforward compensation from the estimated load torque $T_L$ using observers [12,16,17]. In these observer-based controllers, the load torque $T_L$ was assumed to be constant. In order to make the system more robust against any perturbations, dynamic feedforward controller is introduced to compensate for the load torque and its rate of change, which can be estimated using a DPO described above. The discrete-time control signal $u(k)$ with full state feedback and feedforward compensation is written as

$$u(k) = U_{ref} + u_m(k) + u_f(k),$$

where $U_{ref}$ is the reference input which is a step value as in a tracking servo problem, $u_m(k) = -K_m x(k)$ is the feedback (modal) signal from the drive state $x(k)$, and $u_f(k)$ is the feedforward compensation signal. An unknown load torque $T_L$ in general can be considered as a combination of a slowly time-varying component $T_{m_1}$ and a perturbation component $T_{k}kT$ dependent on its time derivative $T_{k}$ ($T$ is the sampling period). The feedforward signal will then consist of a static signal $u_{s}$ and dynamic signal $u_{f}$

$$u_f(k) = u_s(k) + u_d(k) = K_{s} T_{k} + K_{d} dT_{k}(k),$$

where $K_s$ and $K_d$ are found from the condition of zero steady state error with respect to a constant and a ramp disturbance input, $T_{k}(k)$ is the estimate of the load torque obtained from a disturbance observer, and $dT_{k}(k) = T_{k}(k) - T_{k}(k-1)$ [18]. The dynamic feedforward coefficients will be tuned according to knowledge of the control error and the estimated load torque. Using the normalised control error (3), the following conditional scheme is provided for continuously changing the dynamic feedforward gain, dependent on the signs of $e(k)$ and $dT_{k}(k)$:

(iii) If SDTESE and EL then KDL, If SDTESE and ES then KDS,
(iv) If SDTNESE and ES then KDZ, If SDTNESE and EL then KDN,

where the labels EL, ES, KDL, KDS, KDZ, KDN, SDTESE, and SDTNESE mean $e(k)$ is large, $e(k)$ is small, $K_d$ is large, $K_d$ is small, $K_d$ is zero, $K_d$ is
negative, \( \text{sign}(d\hat{T}_L) = \text{sign}(e) \), and \( \text{sign}(d\hat{T}_L) \neq \text{sign}(e) \), respectively. By defining the corresponding singletons \([19]\)

\[
\mu_{KDL} = \begin{cases} 
1, & K_{\mu} = 2K_{d0} \\
0, & K_{\mu} \neq 2K_{d0}
\end{cases}, \quad \mu_{KDN} = \begin{cases} 
1, & K_{\mu} = -K_{d0} \\
0, & K_{\mu} \neq -K_{d0}
\end{cases}
\]

\[
\mu_{S_DTESE} = \begin{cases} 
1, & \text{sign}(d\hat{T}_e) = \text{sign}(e) \\
0, & \text{sign}(d\hat{T}_e) \neq \text{sign}(e)
\end{cases}, \quad \mu_{S_DTPSE} = \begin{cases} 
1, & \text{sign}(d\hat{T}_e) \neq \text{sign}(e) \\
0, & \text{sign}(d\hat{T}_e) = \text{sign}(e)
\end{cases}
\]

the value of \( K_{\mu} \) is found by the max-min inference and centroid method as:

\[
K_{\mu} = \begin{cases} 
K_{d0} \left( 2 - \exp\left(-\frac{|e|}{\sigma_e}\right) \right), & \text{sign}(d\hat{T}_L) = \text{sign}(e) \\
-K_{d0} \left( 1 - \exp\left(-\frac{|e|}{\sigma_e}\right) \right), & \text{sign}(d\hat{T}_L) \neq \text{sign}(e)
\end{cases}
\]

where \( K_{d0} \) is the time-invariant component of \( K_{\mu} \) \([18]\).

Consider the two-mass position drive of Figure 3. The position step response of the system controlled by an observer-based state feedback and feedforward compensation at \( J_2 = 1.33J_{2,\text{nom}} \) and \( T_L = 0.5(1+\text{sint})T_{\text{nom}} \), is shown in Figure 5(a) with fuzzy tuning and in Figure 5(b) without tuning. It is observed that the accuracy and mechanical vibration suppression capability are improved due to fuzzy tuning of the compensation signal. An overshoot due to parameter changes can be eliminated with a robust feedback as discussed in the following section.

\[ u(k) = U_{\text{ref}} + u_a(k) + u_f(k) + u_r(k). \]

When the system uncertainties satisfy some matching conditions, the robust feedback control signal \( u_r(k) \) can be calculated by \([20]\):

\[
u_r(k) = -K_r x(k) = \frac{B^T_m P A_m}{B^T_0 B_0} x(k),
\]

where \( A_m = A_0 - B_m K_m; \) \( A_0, B_0 \) are matrices of the state equation \((10)\) with system nominal parameters; and \( P \) is the positive-definite symmetric matrix solving for the Liapunov equation

\[
A_n^T P A_m - P + Q = 0,
\]

where \( Q \) is a given positive-definite matrix satisfying the system asymptotic stability condition \([21]\). For improving robustness to time-varying parameters, a weighting factor \( w_r, 0 \leq w_r \leq 1, \) is introduced to tune the gain \( K_r \) defined in \((21)\). The robust control signal then becomes

**Figure 5.** Feedforward controlled step response at \( J = 1.33J_{2,\text{nom}} \) and \( T_L = 0.5(1+\text{sint})T_{\text{nom}} \).

(a) with fuzzy tuning, and (b) without fuzzy tuning.
where $\Delta K_r = w_r K_r$ is the robust feedback gain. Control engineering knowledge indicates that in the case of large overshoot or undershoot, it is required to increase feedback gain or, in this case, weighting factor $w_r$. This implies that $w_r$ depends not only on the error $e(k)$ but also on $\text{sign}(e)$ and $\text{sign}(de)$. The following fuzzy scheme is proposed:

(v) If $EL$ or $SE SDE$ then $WL$, \\
If $ES$ or $SENESDE$ then $WS$,

where $EL$, $ES$, and $WL$, $WS$ mean that $e$ is large, $e$ is small, and $w_r$ is large, $w_r$ is small with the corresponding exponential membership function (1) and singleton (2), respectively [22]. The labels $SE SDE$ and $SENESDE$ mean $\text{sign}(e) = \text{sign}(de)$ and $\text{sign}(e) \neq \text{sign}(de)$ with the following membership functions

\[
\mu_{SE SDE} = \begin{cases} 
1, & \text{sign}(e) = \text{sign}(de) \\
0, & \text{sign}(e) \neq \text{sign}(de) 
\end{cases} \\
\mu_{SENESDE} = \begin{cases} 
1, & \text{sign}(e) \neq \text{sign}(de) \\
0, & \text{sign}(e) = \text{sign}(de) 
\end{cases}
\]  

Using the max-min inference rule and centroid method, the weighting factor $w_r$ can be found as follows [22]

\[
w_r = \frac{\mu_{SE SDE} \cdot w_0 + \mu_{ES} \cdot 0}{\mu_{SE SDE} + \mu_{ES}} = \frac{w_0}{1 + \exp\left(-\frac{|e|}{\sigma_e}\right)} \cdot \text{sign}(de) \\
\mu_{SENESDE} \cdot w_0 + \mu_{SENESDE} \cdot 0}{\mu_{SENESDE} + \mu_{SENESDE}} = \frac{w_0}{1 - \exp\left(-\frac{|e|}{\sigma_e}\right)} \cdot \text{sign}(e) \neq \text{sign}(de) \\
\]  

where $w_0$ is the maximal value of the weighting factor.

The RMC step response of the two-mass at $J_2 = 2 J_2^{\text{nom}}$ and $T_L = 0.5 T_L^{\text{nom}}(1 + \sin 0.3t)$ is shown in Figure 6(a) with fuzzy tuning and in Figure 6(b) without tuning. As can be seen fuzzy tuning makes the system more robust to load and parameter variations. The same results can be obtained with the position control of an overhead crane model [23].

6 Conclusion

A methodology applying fuzzy logic to tune the parameters of servo motion controllers to improve the system robustness has been presented. Expert engineering experience is heuristically reflected in the tuning schemes. The controller can adjust parameters on-line to adapt to any disturbances or parameter variation. The explicit forms of the tuning expressions allow a cheap computational implementation and make it easy to change continuously the controller parameters to cope well with uncertainties.

Simulation results indicate that fuzzy tuning can be applied to the conventional cascade control or to robust modal control of electromechanical systems to address the problem of intelligence and robustness. Servo drives are simulated, however, the proposed approach can be applied to other linearised dynamic systems suffering from parameter variation or changing environments. Further research may also focus on the stability condition of the overall system and the application of fuzzy tuning for plants with severe nonlinearities.

References


