QFT Parameter-Scheduling Control Design for Linear Time-Varying Systems Based on RBF Networks

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For most of linear time-varying (LTV) systems, it is difficult to design time-varying controllers in analytic way. Accordingly, by approximating LTV systems as uncertain linear time-invariant, control design approaches such as robust control have been applied to the resulting uncertain LTI systems. In particular, a robust control method such as quantitative feedback theory (QFT) has an advantage of guaranteeing the frozen-time stability and the performance specification against plant parameter uncertainties. However, if these methods are applied to the approximated linear time-invariant (LTI) plants with large uncertainty, the resulting control law becomes complicated and also may not become ineffective with faster dynamic behavior. In this paper, as a method to enhance the fast dynamic performance of LTV systems with bounded time-varying parameters, the approximated uncertainty of time-varying parameters are reduced by the proposed QFT parameter-scheduling control design based on radial basis function (RBF) networks.

Key Words : QFT (Quantitative Feedback Theory), Linear Time-Varying System, Parameter Scheduling, RBF (Radial Basis Function) Network

1. Introduction

There are many analysis and control methodologies for linear time-varying (LTV) systems based on the analytic solutions (Choi et al. 1999, 2001). However, generally, it is not easy to obtain the analytic solutions for LTV systems. Thus, to design controllers for LTV systems, robust control for uncertain linear time-invariant (LTI) systems have been used by approximating LTV systems as uncertain LTI systems. However, when the range of time-varying parameters becomes larger, these methods are not sufficient to reflect the fast dynamics of the original time-varying systems such as missiles and supersonic aircrafts. Thus, in this paper, the large uncertainties are divided into finite number of LTI sub-models with smaller uncertainties. Then, the finite number of control parameter designed by quantitative feedback theory (QFT) design will cover relatively small varying portion of time-varying parameters in each scheduling interval, where the parameter-scheduling control will guarantee the stability and the performance specifications in frozen time sense. Then, to schedule the designed control parameters, radial basis functions (RBF) neural networks are used. Nowadays, neural networks play a key role in many control design areas (Shin et al. 2000).

The designed QFT control parameters are used in the training of the RBF network. The proposed

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design method is applicable not only to nominal LTV systems but also to LTV systems with bounded time-invariant uncertainties.

This paper is organized as follows: In section 2, QFT and RBF network are overviewed briefly. Then, QFT parameter-scheduling control design for LTV systems is proposed in section 3. The proposed design method is illustrated by a numerical example in section 4, and conclusions with some future works are commented in section 5.

2. Preliminaries

2.1 QFT overview

QFT (Horowitz 1963, 1991; Houpis et al. 1994) is a frequency domain control design proposed by Isaac Horowitz. It is a design technique utilizing the Nichols chart (NC) to achieve a desired stability and performance tolerance over the specified region of plant parameter uncertainties (Chait 1991).

As depicted in Fig. 1, QFT control systems use 2 DOF control design including a prefilter $F(s)$ and a compensator $G(s)$, where $P(s)$ denotes an uncertain plant in a plant set $\mathcal{P}$. In QFT control system, $G(s)$ and $F(s)$ are designed to achieve the robustness against parameter uncertainties and the desired tracking performance, respectively. Robust stability and tracking performance for closed-loop SISO plant are given by

$$\left|\frac{P(j\omega)G(j\omega)}{1+P(j\omega)G(j\omega)}\right| \leq \gamma, \; all\ P\in\mathcal{P},\ \omega\in[0, \infty] \quad (1)$$

$$T_L(\omega) \leq \left|\frac{P(j\omega)G(j\omega)F(j\omega)}{1+P(j\omega)G(j\omega)}\right| \leq T_U(\omega), \quad (2)$$
$$all\ P\in\mathcal{P},\ \omega\in[0, \infty]$$

where γ, T_L and T_U denote the robust stability margin, lower and upper tracking performance bound, respectively. For an optimal design, the cost of feedback $L(s)=P(s)G(s)$ must be minimized, where the high-frequency gain of open loop transmission function.

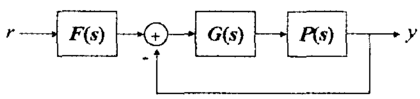

Fig. 1 A 2 DOF configuration of QFT control system

Based on Eqs. (1) and (2), the specified parameter uncertainties need to be transformed into NC(Nichols Chart) templates and all the given specifications into NC bounds in the design process for QFT design. Then, a control design can be found by loop-shaping (Horowitz 1992; Borghesani et al. 1994; Lin 1994; Halikias and Bryant 1995) to satisfy the specifications. In this paper, we design finite number of control systems by adopting general QFT design. The details of QFT design can be found in references (Horowitz 1963, 1991; Houpis et al. 1994).

2.2 RBF networks overview

An RBF network (Haykin 1994, Demuth and Beale et al. 1997; Jang et al. 1997) is composed of radial basis functions representing the locally receptive field units. The schematic diagram of 2-input and 1-output RBF network with four radial basis functions is depicted in Fig. 2.

The basis function of RBF network is given by

$$r_i(\mathbf{x}) = r_i(\|\mathbf{x}-\mathbf{u}_i\|) \quad (i=1, 2, \cdots, n) \quad (3)$$

where $\mathbf{x}$ is an input vector, $\mathbf{u}_i$ a center of i-th receptive field with the same dimension as $\mathbf{x}$, n the number of radial basis functions, and $r_i(\cdot)$ the i-th radial basis function with a single maximum at the origin. As depicted in Fig. 2, there are no weights connecting the input and the hidden layer. In general, $r_i(\cdot)$ is a gaussian function

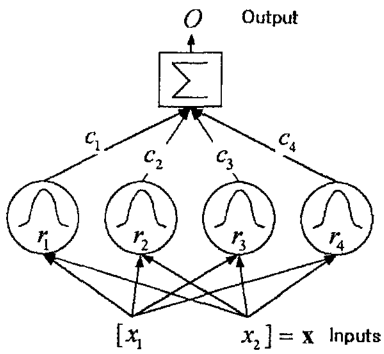

Fig. 2 An RBF network with four radial basis functions

$$r_i(\mathbf{x}) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{u}_i\|^2}{2\sigma^2}\right) \quad (4)$$

The output of RBF network can be formed in two ways. The simpler case is the weighted sum of each basis function output

$$O(\mathbf{x}) = \sum_{i=1}^{n} c_i r_i(\mathbf{x}) \quad (5)$$

where c_i is the connection weight between the output and the i-th basis function. The other case is the weighted average of each basis function output

$$O(\mathbf{x}) = \frac{\sum_{i=1}^{n} c_i r_i(\mathbf{x})}{\sum_{i=1}^{n} r_i(\mathbf{x})} \quad (6)$$

For the training of RBF networks, the following gradient-descent method is used to minimize the error function

$$\begin{aligned} E &= \frac{1}{2}\sum_{j=1}^{m}(e_j)^2 = \frac{1}{2}\sum_{j=1}^{m}(d_j - O(\mathbf{x}_j))^2 \\ &= \frac{1}{2}\sum_{j=1}^{m}\left(d_j - \sum_{i=1}^{n} c_i r_i(\mathbf{x}_j)\right)^2 \\ &= \frac{1}{2}\sum_{j=1}^{m}\left[d_j - \sum_{i=1}^{n} c_i \exp\left(-\frac{\|\mathbf{x}_j-\mathbf{u}_i\|^2}{2\sigma^2}\right)\right]^2 \end{aligned} \quad (7)$$

where m denotes the number of training patterns, n denotes the number of radial basis functions, $\mathbf{x}_j$ denotes the j-th input pattern, and d_j denotes the j-th target pattern. In Eq. (7), c_i and $\mathbf{u}_i$ are the parameters to be trained. The gradient-descent learning equations for these parameters are

$$\begin{aligned} &\frac{\partial E(n)}{\partial c_i(n)} = \sum_{j=1}^{m} e_j(n)\, r_i(\|\mathbf{x}_j - u_i(n)\|) \\ &c_i(n+1) = c_i(n) - \eta_1 \frac{\partial E(n)}{\partial c_i(n)}, \quad i=1, 2, \cdots, n \end{aligned} \quad (8)$$

$$\begin{aligned} &\frac{\partial E(n)}{\partial \mathbf{u}_i(n)} = 2c_i(n)\sum_{j=1}^{m} e_j(n)\, r_i'(\|\mathbf{x}_j - u_i(n)\|) \\ &\mathbf{u}_i(n+1) = \mathbf{u}_i(n) - \eta_2 \frac{\partial E(n)}{\partial \mathbf{u}_i(n)}, \quad i=1, 2, \cdots, n \end{aligned} \quad (9)$$

where e_j denotes the propagation error for the j-th training pattern in Eq. (7), η_1 the learning rate of parameters c_i, and η_2 the learning rate of parameters $\mathbf{u}_i$. In this paper, RBF network is adopted to generate continuous QFT parameter-scheduling functions.

3. QFT Parameter-Scheduling Control Design for LTV Systems

3.1 Generalization of scheduling errors and uncertainties

Time-varying systems considered as nominal plants in this paper are given by

$$\begin{aligned} \dot{x}(t) &= A(t)x(t) + B(t)u(t) \\ y(t) &= C(t)x(t) + D(t)u(t) \end{aligned} \quad (10)$$

Assume that all the time-varying system parameters in (10) and their derivatives are continuous and bounded as

$$\begin{aligned} &(a_{ij})_{\min} < a_{ij}(t) < (a_{ij})_{\max},\ (b_{ij})_{\min} < b_{ij}(t) < (b_{ij})_{\max} \\ &(c_{ij})_{\min} < c_{ij}(t) < (c_{ij})_{\max},\ (d_{ij})_{\min} < d_{ij}(t) < (d_{ij})_{\max} \\ &(\bar{a}_{ij})_{\min} < \dot{a}_{ij}(t) < (\bar{a}_{ij})_{\max},\ (\bar{b}_{ij})_{\min} < \dot{b}_{ij}(t) < (\bar{b}_{ij})_{\max} \\ &(\bar{c}_{ij})_{\min} < \dot{c}_{ij}(t) < (\bar{c}_{ij})_{\max},\ (\bar{d}_{ij})_{\min} < \dot{d}_{ij}(t) < (\bar{d}_{ij})_{\max} \end{aligned} \quad (11)$$

where $a_{ij}(t)$, $b_{ij}(t)$, $c_{ij}(t)$ and $d_{ij}(t)$ are the time-varying elements of $A(t)$, $B(t)$, $C(t)$, and $D(t)$, respectively. In Fig. 3, an arbitrary time-varying parameter $v(t)$ is depicted by a solid line, where $v(t)$ satisfies $v_{\min} \le v(t) \le v_{\max}$ and $\bar{v}_{\min} \le \dot{v}(t) \le \bar{v}_{\max}$. LTV system parameters in Eq. (11) can be considered in the same way. If the parameter-scheduling interval is given by $T = 0.5$, nominal values of $v(t)$ in each scheduling interval can be chosen as $v(t) \to v_k = v(k \times T)$ ($k=0, 1, 2, \cdots$). For the first scheduling interval, $0.25 \le t < 0.75$, the upper and lower part of scheduling errors of v_1 is positive values δv_{1u} and δv_{1l}, respectively. The scheduling error is the deviation from the nominal parameter value mentioned above. In each time interval, the time-

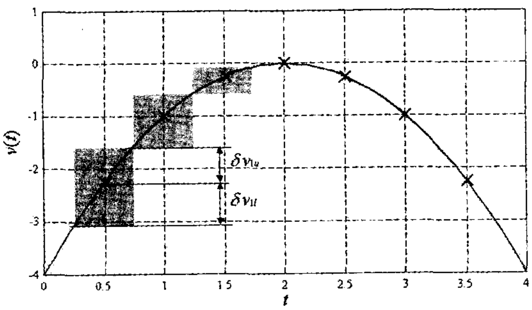

Fig. 3 Scheduling errors of a time-varying parameter ($\times$: v_k, $k=0, 1, 2, \cdots$)

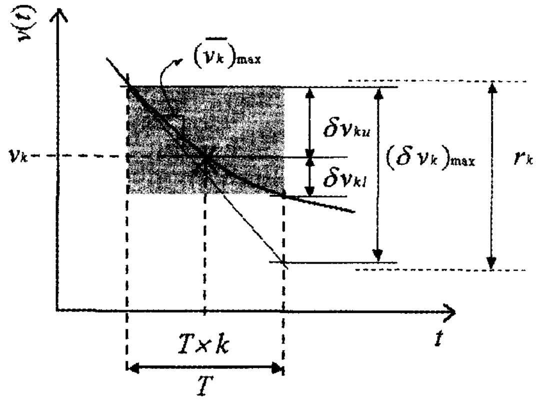

Fig. 4 Scheduling error in the k-th time interval

varying property of a system parameter can be regarded as small deviation.

In Fig. 4, scheduling errors of are considered in detail.

In this figure, a maximum scheduling error of the k-th time interval is defined as

$$(\delta v_k)_{\max}=T\times(\bar{v}_k)_{\max}$$

where $(\delta\bar{v}_k)_{\max}=\max[|\dot{v}(t)|]$, $((k-0.5)T\leq t\leq(k+0.5)T)$, and $r_k(k=1,2,\cdots)$ is defined as an uncertainty range satisfying $r_k\geq(\delta v_k)_{\max}$. In this paper, r_k has the form as $r_k=\sqrt{((\delta v_k)_{\max})^2+1}$. As depicted in Fig. 3, the values of $(\delta v_k)_{\max}$ and r_k are varying with time. Thus, for a time-independent design, the generalized value of $(\delta v_k)_{\max}$ and r_k are necessary. Using the maximum gradient of the parameter, time-independent scheduling error E_v is defined as

$$E_v=T\times\max[|(\bar{v})_{\max}|,|(\bar{v})_{\max}|],\qquad(12)$$

and R_v, the generalized value of r_k, is defined as

$$\begin{aligned}R_v&=\max_k[r_k]\\&=T[1+\{\max[|(\bar{v})_{\min}|,|(\bar{v})_{\max}|]\}^2]^{\frac{1}{2}}\end{aligned}\qquad(13)$$

Thus, for an arbitrary $v(t)$ and in any time interval, E_v and R_v can be used as a generalized scheduling error and uncertainty range, respectively.

3.2 LTV systems approximation using finite number of uncertain LTI sub-models

In this section, the approximation of LTV systems is presented using finite number of uncertain

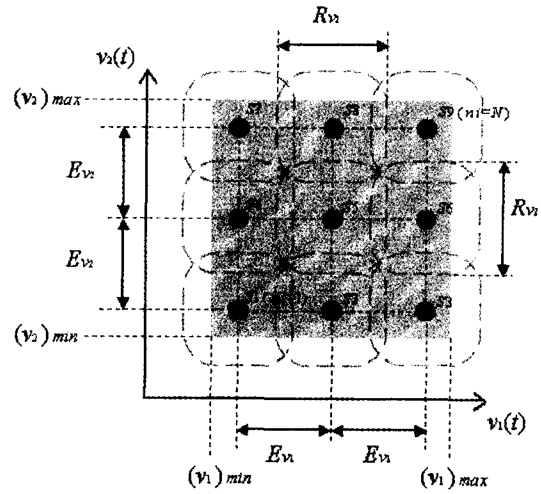

Fig. 5 Approximation of a LTV system with two time-varying parameters

LTI sub-models. The parameter uncertainty of the LTI sub-model is given by Eq. (13). By applying scheduling time interval, the system matrix $A(t)$ in Eq. (10) can be represented as

$$A(t)\rightarrow A_k=A(k\times T)\quad(k=1,2,\cdots),$$

and $B(t)$, $C(t)$, and $D(t)$ can be represented in the same manner. Then, taking Laplace transformation, the nominal system in k-th time interval can be described by the transfer matrix

$$P_k(s)=C_k[sI-A_k]^{-1}B_k+D_k.$$

For example, in the case of SISO plant or an element of $P_k(s)$, general n-th order transfer function becomes

$$p_k(s)=\frac{(b_m)_k s^m+(b_{m-1})_k s^{m-1}+\cdots+(b_o)_k}{s^n+(a_{n-1})_k s^{n-1}+\cdots+(a_o)_k}\quad(m\leq n).\quad(14)$$

Since the frequency domain parameters $(a_{n-1})_k$, $\cdots$, $(a_o)_k$ and $(b_m)_k$, $\cdots$, $(b_o)_k$ are determined by the time domain parameters in A_k, B_k, C_k, and D_k, their uncertainty bounds have the same relation. Thus, if the finite number of uncertain LTI sub-models can cover the variation of original model in the time domain, the sub-models are also able to cover the original model in the frequency domain. The method of selection of finite number of LTI sub-systems to approximate a LTV system is shown in Fig. 5. In this figure, the LTV system has two time-varying parameters

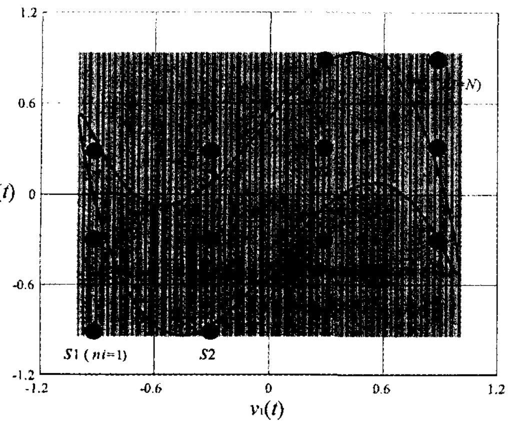

Fig. 6 Approximation of a LTV system with periodically varying parameters

$v_1(t)$ and $v_2(t)$.

The parameter varying range of LTV system is depicted by the area filled with gray color, and the selected LTI sub-systems $s_{ni}(ni=1, 2, \cdots, N)$ are depicted with ' '. Each dashed-box represents the uncertainty region that should be covered by the sub-system located at the center. To determine the number and the nominal parameter values of LTI sub-models, the parameter varying range is divided by E_{v_1} and E_{v_2}. In this manner, the wider range of varying parameters of the LTV system can be covered by the finite number of sub-systems having smaller region of uncertainty in the frozen time sense. The number of the selected sub-systems is determined as

$$N=\prod_{p=1}^{q}\left[\mathrm{int}\left(\frac{(v_p)_{\max}-(v_p)_{\min}}{E_{v_p}}\right)+1\right] \quad (15)$$

where q denotes the number of time-varying system parameter ($q=2$ in case of Fig. 5), v_p the p-th time-varying parameter of the system, E_{v_p} the generalized scheduling error of v_p, and $(v_p)_{\max(\min)}$ the maximum(minimum) value of v_p. If the parameters are periodically varying, N will be a smaller value. For example, the approximation of LTV systems with periodically varying parameters $v_1(t)=\sin t$ and $v_2(t)=(\sin(3t)+\cos t)/2$ is considered in Fig. 6.

3.3 QFT parameter-scheduling function generation using RBF network

In this section, the QFT control design is considered for the selected sub-models and the QFT parameter-scheduling function generation. As mentioned in the previous sections, R_v is used as an uncertainty size of parameter $v(t)$. Then, the uncertainty of $v(t)$ for the ni-th sub-model is

$$-\frac{R_v}{2}\leq\Delta v_{ni}\leq\frac{R_v}{2}\ \ (ni=1, \cdots, N) \quad (16)$$

For LTV systems with time-invariant parameter uncertainty, there is a need to modify the uncertainty size. The state equation of uncertain LTV system is as follows:

$$\begin{aligned}\dot{x}(t)&=(A(t)+\Delta A)x(t)+(B(t)+\Delta B)u(t)\\ y(t)&=(C(t)+\Delta C)x(t)+(D(t)+\Delta D)u(t)\\ &(\Delta a_{ij})_{\min}\leq\Delta a_{ij}\leq(\Delta a_{ij})_{\max},\ (\Delta b_{ij})_{\min}\leq\Delta b_{ij}\leq(\Delta b_{ij})_{\max}\\ &(\Delta c_{ij})_{\min}\leq\Delta c_{ij}\leq(\Delta c_{ij})_{\max},\ (\Delta d_{ij})_{\min}\leq\Delta d_{ij}\leq(\Delta d_{ij})_{\max}\end{aligned} \quad (17)$$

For the time-varying parameter $v(t)$ with uncertainty $(\Delta v)_{\min}\leq\Delta v\leq(\Delta v)_{\max}$, the uncertainty specification for QFT design can be modified as

$$-\frac{R_v}{2}+(\Delta v)_{\min}\leq\Delta v_{ni}\leq\frac{R_v}{2}+(\Delta v)_{\max}\quad (ni=1, \cdots, N) \quad (18)$$

For each sub-model, pre-filter transfer matrices $F(s)_{ni}$ and compensator transfer matrices $G(s)_{ni}$ can be designed to satisfy the frozen time stability and performance specifications by adopting QFT control design. In this paper, it is assumed that all the elements of $F(s)_{ni}$ and $G(s)_{ni}$ can have the same structure. The controllers for these structures can be designed by automatic loop-shaping methods based on the evolutionary algorithm (Chen et al. 1999; Gu et al. 1999), the optimal loop-shaping (Halikias and Bryant 1995), and so on. In this paper, RBF networks are adopted for the generation of a scheduling function. The structure of the neural network used in this work is presented in Fig. 7. The whole network is composed of multi input-single output RBF sub-networks. The number of sub-network is the same as QFT parameters. Each RBF sub-network is trained to learn the relation among all the plant parameters and each one of QFT control parameters, and these RBF sub-networks are combined in parallel form. To train the parameter relation into RBF network by gradient-descent training, the nominal values of time-varying parameter sets are used as input patterns and the corresponding control parameter sets are used as target patterns.

Thus, the number of selected sub-model and the training patterns are the same. The input and target patterns of the k-th ($k=1, 2, \cdots, n$) RBF network is

$$\mathbf{x}_j=\mathbf{v}_j=[v_{1j} \cdots v_{mj}]$$
$$d_j=q_{jk} \quad (j=1, \cdots, N)$$

where $\mathbf{v}_j$ is the parameter vector of the j-th selected sub-model, m the number of time-varying parameters of the plant, N the number of sub-models, and q_{jk} the k-th QFT parameter for the j-th selected sub-model. For the k-th RBF network, the center $\mathbf{u}_j$ and the connection weight c_j of the basis function r_j can be initialized as follows:

$$\mathbf{u}_j=\mathbf{v}_j+\Delta_j=[v_{1j}+\varepsilon_{1j} \cdots v_{mj}+\varepsilon_{mj}]$$
$$c_j=q_{jk}+\varepsilon_j \quad (j=1, \cdots, N)$$

where $\varepsilon_{ij}(i=1, \cdots, m)$ and ε_i are relatively small random values to perturb the initialization values.

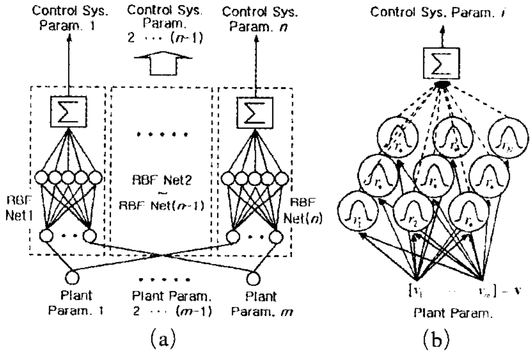

Fig. 7 RBF network structures of the parameter scheduler

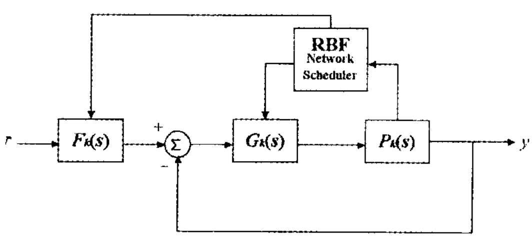

Fig. 8 Block diagram of QFT parameter-scheduling control system

Using properly trained RBF networks as a scheduler, the whole QFT parameter-scheduling control system can be constructed as Fig. 8.

4. A Numerical Example

In this section, the proposed parameter-scheduling control design is illustrated by a numerical example. A time-varying mass-spring-damper (MSD) model depicted in Fig. 9.

The dynamic equation of the MSD model is given by

$$\ddot{x}=-\frac{k(t)}{m(t)}x(t)-\frac{c(t)+\dot{m}(t)}{m(t)}\dot{x}(t)+\frac{1}{m(t)}u(t)$$
$$=-4x(t)-a(t)\dot{x}(t)+a(t)K(t)u(t)$$

where the time-varying parameters $a(t)$ and $K(t)$ are given by

$$a(t)=5\sin t+8(3\leq a(t)\leq 13)$$
$$K(t)=5\cos t+8(3\leq K(t)\leq 13)$$

In the above model equation, time-varying MSD model is similar in forms to general LTI SISO 2nd order model except that the parameters are time-varying. Thus, we can use this model as a general LTV SISO 2nd order model to apply the proposed control design scheme.

If the parameter-scheduling interval is set as $T=0.4$ sec, the generalized scheduling error and uncertainty can be determined as $E_a=E_k=1$, $R_a=R_k\approx 1$. Then, using E_a and E_k, the nominal plant parameter sets can be constructed as $a_{ni}\in\{3, 5, 7, 9, 11, 13\}$ and $k_{ni}\in\{3, 5, 7, 9, 11, 13\}$. Since all the given time-varying parameters are periodic functions, the number N of LTI sub-models can be smaller than that of Eq. (15). Thus, the uncertainty bounds of each sub-model for QFT design are given as

$$-1\leq\Delta a_{ij}\leq 1$$
$$-1\leq\Delta k_{ij}\leq 1 \quad (ni=1, \cdots, 20)$$

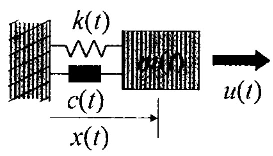

Fig. 9 Time-varying MSD model

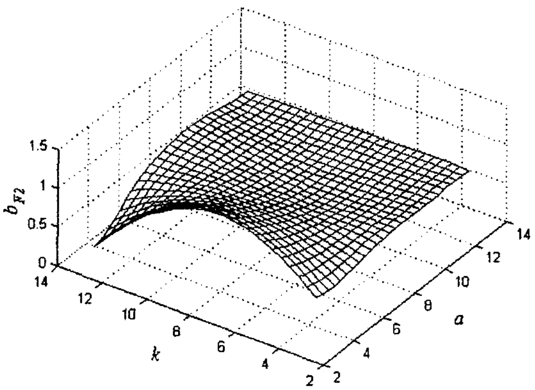

Fig. 10 Mapping result of parameter b_{F2}

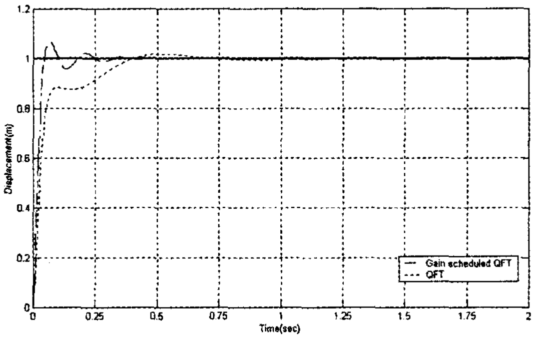

Fig. 11 Step input response

and the ni-th selected sub-model has a form as

$$s_{ni}(s)=\frac{(k_{ni}+\Delta k)(a_{ni}+\Delta a)}{s^2+(a_{ni}+\Delta a)s+4}\quad(ni=1,\ 2,\ \cdots,\ 20)$$

Then, the structure of the pre-filter and compensator transfer functions are formed as

$$F_{ni}(s)=\frac{b_{F2}s^2+b_{F1}s+b_{F0}}{s^3+a_{F2}s^2+a_{F1}s+a_{F0}}$$

$$G_{ni}(s)=\frac{b_{G1}s+b_{G0}}{s^2+a_{G1}s+a_{G0}}$$

With parameter values $\{a_{F2},\ a_{F1}\ a_{F0},\ b_{F2},\ b_{F1},\ b_{F0},\ a_{G1},\ a_{G0},\ b_{G1},\ b_{G0}\}_{ni}$ $(ni=1,\ 2,\ \cdots,\ 20)$, QFT control design can be performed for the ni-th selected sub-models. The plant parameter set, a and k, of a sub-model is used as an input pattern $\mathbf{v}_j(j=1,\ 2,\ \cdots,\ 20)$, and the designed QFT parameter set is used as a corresponding output pattern d_j. In Fig. 10, the parameter mapping among b_{F2} and two time-varying plant parameters is depicted.

Simulations results are depicted in Figs. 11 and

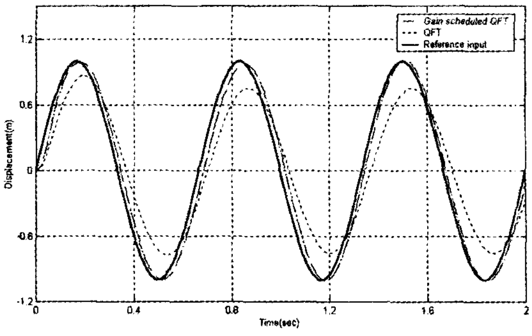

Fig. 12 Sinusoidal input response

12. In the case of the step input, the two responses are shown to have similar tracking performances. However, for a sinusoidal input, QFT parameter-scheduling control shows more improved tracking performance than the existing QFT control.

5. Conclusions

In this paper, we propose a method, QFT parameter-scheduling control, to design the control system of LTV systems. The design procedures are illustrated by a numerical example. The proposed design method combine QFT controller and RBF neural networks to enhance the controlled performance of LTV systems. In the design procedure, QFT control design specifications are derived for LTV systems, and the resulting QFT control parameters are mapped into the RBF networks to construct control parameter scheduling system.

The proposed method can be applied to LTV systems with time-invariant parameter uncertainties. The simulation results of time-varying MSD model show that the QFT parameter-scheduling control makes the controlled performance improved for systems with faster dynamics and highly time-varying command inputs.

The following two points can be pursued as future works. One is to adopt an on-line learning RBF network since it can eliminate some trial and error procedure in the off-line learning neural network. The other is the stability analysis of the whole control system including neural network, which may require the extension of stability analysis method for neural network control systems and hybrid system.

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References

Borghesani, C., Yaniv, O., and Chait, Y., 1994, *Quantitative Feedback Theory Toolbox User's Guide*, The Mathworks, Inc..

Chait, Y., 1991, "Robust Internal Stability in Multi Input-Output Quantitative Feedback Theory," *Proceedings of the 30th Conference on Decision and Control*, pp. 2970~2971.

Chen, W. H., Ballance, D. J., Feng, W., and Li, Y., 1999, "Genetic Algorithm Enabled Computer-Automated Design of QFT Control System," *Proceedings of the IEEE International Symposium on Computer Aided Control System Design*, pp. 492~497.

Choi, J. W., Lee, H. C., and Yoo, W. S., 1999, "Eigenstrwcture Assignment for Lirear Time-Voring Systems via Differential Sylvester Equortion," *KSME International Journal*, Vol. 13, pp. 609~619.

Choi, J. W., Lee, H. C., and Zhu, J. J., 2001, "Decoupling and Tracking Control Vsing Eigenstrwcture Assignment for Lirear Time-Voring Systems," *KSME International Journal of Control*, Vol. 74, pp. 453~464.

Demuth, H., and Beale, M., 1997, *Neural Network Toolbox User's Guide*, The Mathworks, Inc..

Gu, J., Shen, J., and Chen, L., 1999, "The QFT Control Design via Genetic Algorithms and Application," *Proceedings of the 14th Triennial World Congress of IFAC*, pp. 103~108.

Halikias, G. D., and Bryant, G. F., 1995, "Optimal Loop-Shaping for Systems with Large Parameter Uncertainty via Linear Programming," *International Journal of Control*, Vol. 62, pp. 557~568.

Haykin, S., 1994, *Neural Networks : A Comprehensive Foundation*, Macmillan College Publishing.

Horowitz, I. M., 1963, *Synthesis of feedback systems*, Academic Press.

Horowitz, I. M., 1991, "Survey of Quantitative Feedback Theory," *International Journal of Control*, Vol. 53, pp. 255~291.

Horowitz, I. M., 1992, *Quantitative Feedback Theory (QFT)*, QFT Publications.

Houpis, C. H., Sating, R. R., Rasmussen, S., and Sheldon, S., 1994, "Quantitative Feedback Theory Technique and Applications," *International Journal of Control*, Vol. 59, pp. 39~70.

Jang, J.-S. R., Sun, C.-T., and Mizutani, E., 1997, *Neuro-Fuzzy and Soft Computing*, Prentice Hall.

Lin, C. F., 1994, Advanced Control Systems Design, Prentice Hall.

Shin, B. K., Hahn, O. J., Yi, K. S., and Lee, K. I., 2000, "A Supervisor-Based Neural-Adaptive Shift Controller for Automatic Transmissions Considering Throttle Opening and Driving Load," *KSME International Journal*, Vol. 14, pp. 418~425.