INTELLIGENT GAIN-SCHEDULING CONTROL FOR MULTIVARIABLE DISCRETE LINEAR TIME VARYING SYSTEMS

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Abstract. *This paper proposes an Intelligent Linear Parameter Varying (ILPV) control approach for multivariable discrete Linear Time Varying (LTV) systems. An optimal linear quadratic closed loop control law is developed for each identified multivariable model so that the controlled system tracks a desired trajectory over the entire time interval. A gain scheduling adaptive control scheme based on neural networks is designed, by backpropagation algorithm, to tune on-line the optimal controllers.Simulation results are shown to demonstrate the efficiency of the proposed methodology for a multivariable plant with time varying eigenvalues, important in spacecraft and robot arms control applications, for instance.*

Keywords: *Gain-Scheduling Control, Neural Control, Time Variant System, Intelligent control.*

1. Introduction

The developmented of concepts and methods in Control Systems Theory and the new techniques in development in the Computational Intelligency field (Back et al., 1997; Sinha and Gupta, 1996; Liang-Hsuan and Cheng-Hsiung, 2003), as the neural networks and/or the genetic algorithms, can be conveniently combined for the Intelligent Control of complex dynamic systems in presence of uncertainty. The studies of (Narendra and Parthasarathy, 1990; Narendra, 1996) show that the use of neural networks can offer better solutions than the traditional techniques of identification and control. These works can be considered as the first important steps for identification and control using neural networks. According to (Harris, 1994), a small gain is obtained when intelligent control is used for time invariant linear systems. The same should not be said for the case of time varying linear systems, main objective of this work.

Intrinsically related to the identification problem is the *Adaptive Control* one, whose motivating idea is sufficiently attractive: a controller that modifies itself based on the controlled plant behavior, in order to satisfy some design specifications (Astrom and Wittenmark, 1995; Ioannou and Sun, 1996). The main element of this method of designing a controller is the mechanism for adjusting the parameters of the controller. Among several techniques for adjusting these parameters we can mention Gain Scheduling (GS), model reference based Adaptive Control, etc, (Bottura and Serra, 2004; Landau, 1979; Korba et al., 2003).

Adaptive Control is an important research area for several researchers: (Melin and Castillo, 2003; Miyasato, 2003; Ioannou and Sun, 1996) and have been used mainly to improve the online controllers performance. The development of Adaptive Control theory and its implementation with microprocessors led to several succesful applications in areas such as robotics and aircraft control.

A difficulty to design a control law for an aircraft automatic pilot, for instance, resides in how to obtain a controller able to self-tune to changes in the dynamic model of the airplane, to guarantee that an specified performance be achieved. Among the various control law design methods for such a problem there are: PID control law, intelligent control laws, Gain Scheduling (GS) control law and others adaptive control laws. Intelligent control was originally proposed by (Fu, 1971), and has been defined as an approach to generate control actions utilizing artificial intelligence, operations research and automatic control systems concepts and methods. It is an area of application of artificial intelligence to systems control, considered to succeed the 1970's adaptive control methodology. Strategies are defined and they intend to be able to search and keep the desired performance level, even under great uncertainty levels, for closed loop systems. For complex systems control, among the dificulties that appear, we highlight those classifiable in four categories: computational complexity, nonlinearity, unstationarity and uncertainty. To the control systems able to deal with such categories of dificulty employing computational intelligence we call intelligent control systems. The use of the terminology intelligent control groups several methodologies, combining conventional control theory with techniques of computational intelligence based on neural networks, fuzzy logic, expert systems, genetic algorithms and optimization techniques. If some controller parameters are conveniently corrected taking account of given operation points, the control method is called

Gain Scheduling (GS). A classical adaptive control system with GS presents two cycles: a feedback cycle composed by plant and controller, and another cycle for controller parameters adjustment based on the a priori knowledge about the plant operation points.

The Gain Scheduling approach has shown great utility in many engineering applications, for instance, for well behaved systems and for linear parameters varying (LPV) systems control, (Rugh and Shamma, 2000). Gain Scheduling control problems are the subject of important research both from the theoretical as from the practical point of view (Bendtsen and Trangbaek, 2002; Miyasato, 2003).

2. Intelligent Control with GS of LPV System

By combining the basic idea of gain scheduling with that of model based adaptive control, in this work we are interested in proposing an optimal intelligent tracking control scheme with neural Gain Scheduling using a Multiple Layer Perceptron (MLP) neural network for multivariable discrete time systems models identified by a $MOESP$ (Mimo Output Error State sPace model identification) type algorithm (Verhaegen and Dewilde, 1992). The controller structure and the selected models will be later presented.

For this proposed adaptive scheme, the estimation of the unknown scheduled parameters is sucessively obtained through the method $MOESP\_VAR$ proposed and implemented in (Tamariz et al., 2005), and they feed the design algorithm that generates the controllers to stabilize the plant and to guarantee an adequate performance for this intelligent control system with neural gain scheduling. The $MOESP - VAR$ subspace identification algorithm is used for plant computational modelling from input-output data, and determines linear multivariable discrete time models at various operation points for a multivariable time varying plant. An optimal tracking feedback control law with gain scheduling is developed in section 2.1, such that the multivariable LPV system tracks a desired trajectory during a given time interval and in an intelligent form have an adequate performance for all of the operation region.

For design purposes, an alternative approach including random additive uncertainties in the identified dinamic models is proposed through a transformation based on Eq. (1), resulting on a suficiently robust controller able to stabilize the time varying plant. Consider the following LPV system:

$$\begin{cases} x_{k+1} &= A(\sigma)x_k + B(\sigma)u_k \\ y_k &= C(\sigma)x_k \end{cases} \tag{1}$$

where $x_k \in \Re^n$, $u_k \in \Re^m$, $y_k \in \Re^l$. The design with the gain scheduling methodology consists in selecting a finite subset with M points $\{\sigma = 1, 2, 3, \dots, M\}$, representative for the plant dynamics, from the set $\mathbf{I}$ of operation points and then design a linear time invariant controller for each of those M values on that subset of operation points. The design is such that at an operation point, the closed loop system has the specified performance properties for it. The linear controllers obtained in this way, for each operation point $r(\sigma), \sigma \in \mathbf{I}$, are then interpolated through a MLP neural network to cover all of the set $\mathbf{I}$. Artificial Neural Networks, due to their learning, adaptability, classification and functions aproximation properties, among others, have been very much studied and applied for signal processing and open loop systems identification. On the other hand, neural network applications for linear and nonlinear of dynamic systems closed loop control are greatly important due to their characteristics as universal approximators and their learning by training capability (Lau, 1991; Hornic et al., 1989; Lewis et al., 1999). Neural controllers are adaptive learning systems. It should be emphasized that neural controllers are able to present better results than conventional linear and nonlinear adaptive controllers concerning closed loop precision, accuracy and robustness.

The procedure to obtain the neural controller with Gain Scheduling is developed in the following steps:

- Determine the various operation points for the plant;
- Obtain linear time invariant models for the various operation points of the time varying plant via the $MOESP - VAR$ algorithm;
- Design linear controllers based upon the linear models obtained at each operation point using the optimal tracking controller design proposal presented at section 2.1;
- Train via backpropagation a neural controller with gain scheduling to substitute the linear controllers obtained at the corresponding operation points.
- Design an Intelligent controller with Gain Scheduling to online adjust and interpolate the optimal controllers designed above.

The Intelligent Linear Parameter Varying controller designed this way has the following properties:

- Improves loop performance;
- Works with an intelligent tuner;

- Updates all controllers for the LPV system;
- Provides smooth interpolation among operation points for the LPV system.

2.1 Optimal LPV Tracking Controller

Having identified the time varying plant through the algorithm $MOESP\_VAR$ and obtained a linear time invariant model plant for an operation point at the $\sigma - th$ time instant, we wish to determine an optimal tracking control scheme for this discrete time system. In other terms: we are interested in having the output tracking a desired known reference signal $r(\sigma)$, during a predefined time interval, using an optimal tracking closed loop control law. We want, for instance, to design an automatic pilot for a guided aeroespace launching vehicle. To design this, let us minimize the following quadratic performance criterium with fixed final state:

$$J(\sigma) = \frac{1}{2}(C(\sigma)x_N - r_N)^T L(C(\sigma)x_N - r_N) + \frac{1}{2}\sum_{k=0}^{N-1}[(C(\sigma)x_k - r_k)^T Q(C(\sigma)x_k - r_k) + u_k^T R u_k] \tag{2}$$

where $L \geq 0, Q \geq 0$ and $R > 0$ are known weighting symmetric positive definite matrices for a given σ. The solution to this optimal tracking control problem leads to the following equations set for the $\sigma - th$ instant:

$$\begin{aligned} &x_{k+1} = A(\sigma)x_k + B(\sigma)u_k; \\ &\lambda_k = A^T(\sigma)\lambda_{k+1} + C^T(\sigma)QC(\sigma)x_k - C^T(\sigma)Qr_k; \\ &0 = Ru_k + B^T(\sigma)\lambda_{k+1}; \\ &\lambda_N = C^T(\sigma)L(C(\sigma)x_N - r_N), \qquad x_0 \ \text{given} \end{aligned} \tag{3}$$

from which the resulting optimal control at the $\sigma - th$ instant is:

$$u_k(\sigma) \equiv \breve{u}_k \quad = -R^{-1}B^T(\sigma)\breve{\lambda}_{k+1} \ ; \tag{4}$$

For a given σ, in compact form, results the following Hamiltonian system:

$$\begin{bmatrix} x_{k+1} \\ \lambda_k \end{bmatrix}_\sigma = \begin{bmatrix} A(\sigma) & -B(\sigma)R^{-1}B^T(\sigma) \\ C^T(\sigma)QC(\sigma) & A^T(\sigma) \end{bmatrix} \begin{bmatrix} x_k \\ \lambda_{k+1} \end{bmatrix}_\sigma + \begin{bmatrix} 0 \\ -C^T(\sigma)Q \end{bmatrix} r(\sigma) \tag{5}$$

As this control problem has boundary conditions split between times $k = 0$ and $k = N$, to solve it let us express $\breve{u}_k$ as a linear combination of state variables plus a term depending on $r(\sigma)$, (Lewis and Syrmos, 1995). This term depends on the output $\breve{v}_k$ of the adjoint of the closed loop plant when driven by the reference to track $\breve{r}_k$. Thus, it is admitted that for all $k \leq N$, $\breve{\lambda}_k$, for a $\sigma - th$ instant, can be written as:

$$\breve{\lambda}_k = \breve{P}_k\breve{x}_k - \breve{v}_k \tag{6}$$

for an unknown auxiliary matrix sequence $\breve{P}_k \in \Re^{n\times n}$ and $\breve{v}_k \in \Re^n$, at the $\sigma - th$ instant.
Solving for $\breve{x}_k$ and $\breve{v}_k$ and using the matrix inversion lemma results

$$\begin{aligned} \breve{P}_k &= A^T(\sigma)[\breve{P}_{k+1} - \breve{P}_{k+1}B(\sigma)(B^T(\sigma)\breve{P}_{k+1}B(\sigma) + R)^{-1}B^T(\sigma)\breve{P}_{k+1}]A(\sigma) + C^T(\sigma)QC(\sigma) \\ \breve{v}_k &= [A(\sigma)^T - A^T(\sigma)\breve{P}_{k+1}B(\sigma)(B^T(\sigma)\breve{P}_{k+1}B(\sigma) + R)^{-1}B^T(\sigma)]\breve{v}_{k+1} + C^T(\sigma)Q\breve{r}_k \end{aligned} \tag{7}$$

where $\breve{P}_k$ is the solution of the recurrent discrete Riccati equation associated to the optimal tracking problem at the $\sigma - th$ instant. The boundary conditions for these recursions are seen to be:

$$\begin{aligned} &\breve{P}_N = \breve{C}^T L\breve{C} \\ &\breve{v}_N = \breve{C}^T L\breve{r}_N \end{aligned} \tag{8}$$

After some algebric manipulations, this two-point boundary value problem leads to the following set of equations for the closed loop

$$\breve{u}_k \quad = -\breve{K}_k\breve{x}_k + \breve{K}_k^v\breve{v}_{k+1} \tag{9}$$

$$\begin{aligned} \breve{P}_k &= A^T(\sigma)\breve{P}_{k+1}(A(\sigma) - B(\sigma)\breve{K}_k) + C^T(\sigma)QC(\sigma) \\ \breve{v}_k &= (A(\sigma) - B(\sigma)\breve{K}_k)^T\breve{v}_{k+1} + C^T(\sigma)Q\breve{r}_k \end{aligned} \tag{10}$$

$$\breve{x}_k + 1 = (A(\sigma) - B(\sigma)\breve{K}_k)\breve{x}_k + B(\sigma)\breve{K}_k^v\breve{v}_{k+1} \tag{11}$$

where the LPV controller gains are:

$$\begin{aligned} \breve{K}_k &= (B^T(\sigma)\breve{P}_{k+1}B(\sigma) + R)^{-1}B^T(\sigma)\breve{P}_{k+1}A(\sigma) \\ \breve{K}_k^v &= (B^T(\sigma)\breve{P}_{k+1}B(\sigma) + R)^{-1}B^T(\sigma) \end{aligned} \tag{12}$$

Thus, this design problem, for a given σ, can be reduced to the problem of obtaining a recursive positive definite solution $\breve{P}_k$ of a discrete Riccati equation for that σ.

2.2 Neural Gain Scheduling

In this section, neural network learning functions are employed to design an intelligent controller with gain scheduling based on self-tuned tracking control designs. The schematic structure of this ILPV controller consists of:

- Neural GS controller (NGSC),
- Optimal Tracker Controller algorithm.

The training scheme for the neural gain scheduler is presented in Fig. 1. For this scheme, the training is made in the usual form, based on the set of M chosen operation points $r_\sigma, \sigma \in I$, that constitute the columns of the reference matrix W:

$$W = \begin{bmatrix} r_1 & \dots & r_M \end{bmatrix} \tag{13}$$

and on the corresponding set of M optimal controllers that constitute the M rows of the optimal controllers matrix K, called targets, given as inputs to the net. After, a simulation is made, and a matrix of neural gains G is obtained. For the obtained results a verification is made to check if the resulting error is minimized, that is to say, if this neural network obtains neural gain matrices similar to the ones offered by matrix K, corresponding to the optimal controllers obtained for each identified time invariant model at the respective analised operation point.

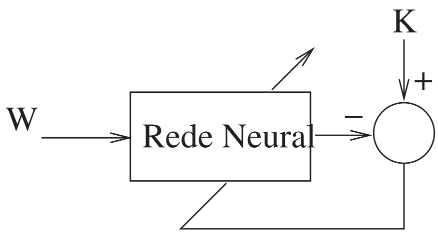

Figure 1. Learning scheme of the ILPV Controller

2.3 ILPV Controller Design

To design the neural controller with gain scheduling, intelligent controller, an identified model is chosen among the M obtained models and for a new reference matrix $\bar{W}_{m\times p}$:

$$\bar{W}_{m\times p} = \begin{bmatrix} r_1 & \dots & r_p \end{bmatrix}, \tag{14}$$

an optimal tracking control law is designed for assuring the desired performance as well as systems stability. This new reference matrix expresses the objective that at every M/p points the system tracks each one of the p values expressed by the columns of $\bar{W}_j$ starting from the first reference r_1, after M/p points, the reference r_2 and so on.

The value of $\breve{v}_{\bar{W}}$, according to Eq. (8), is computed as $\breve{v}_{\bar{W}} = C_m^T L\bar{W}$; for the $k-th$ instant, a time varying matrix A_k is determined. An online tuning of the controller parameters for all of the set **I** is made via neural simulations with the net generated during the identification, with the new reference matrix $\bar{W}$.

Hence, due to the neural controller with GS generalization capability, the output tuning, for any offered reference is materialized.

An alternative approach including a random additive uncertainty on the dynamical matrices for the identified models is proposed as:

$$\breve{v}_k \quad = [A_m + (diag(eig(A)) - A_m) * 0.01 * randn] - B_m\breve{K}_k)^T\breve{v}_{k+1} + C_m^T Q\bar{W} \tag{15}$$

from which results a sufficiently robust controller to stabilize the time varying plant, where A_m, B_m, C_m denote the identified matrices.

3. Experimentation and Results

At the level of the numerical algorithms, for a finite number M of adaptivelly controlled operation points, different sets of systems matrices are identified. Thus the algorithm $MOESP\_VAR$ (Tamariz et al., 2005) will be executed M times to determine the set of systems matrices for these M operation points. For each of this operation points, a linear controller will be optimally designed. In this section, some experiments are made to determine these linear controllers. Thence these results are generalized by a gain scheduling neural controller for any reference point in the operation region of the system. A MLP neural network for implementing the gain scheduling controllers for MIMO linear plants is utilized.

Various operation points are selected to cover all of the plant operation region. These operation points are determined by the reference values. For a finite number M of operation points, the time varying plant is computacionally modeled in the state space. The set of matrices $A_(\sigma), B_(\sigma), C_(\sigma), \sigma \in N$ constituting time invariant approximations for a finite set of time instants is obtained. Then the gain matrices $\breve{K}_k$ and $\breve{K}^v_k$ are computed and finally the corresponding optimal controllers are determined for these operation points. For the linear discrete time varying plant

$$x_{k+1} = A_k x_k + B_k u_k \tag{16}$$

$$y_k = C_k x_k \tag{17}$$

with

$$A_k = \begin{bmatrix} a1 & 0 \\ 0 & a2_k \end{bmatrix} \tag{18}$$

where

$$\begin{aligned} a1 &= -0.3 \\ a2_k &= -1/3 - 0.1 sen(2\pi k/400) \end{aligned} \tag{19}$$

we take $M = 150$ different points, $k = 1, 2, \ldots, 150$. For this M systems we determine x_k and y_k in response to randomly generated values of u_k. In Fig. 2 the trajectory of the output y_k is presented.

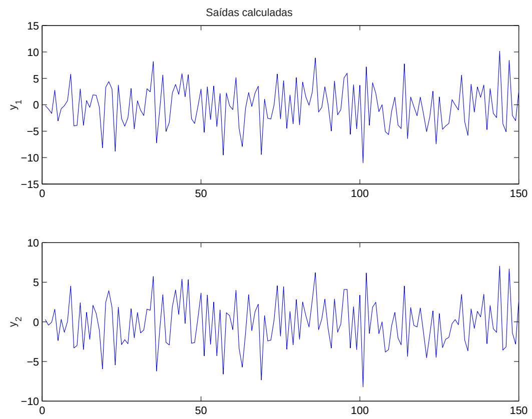

Figure 2. Trajectory of the y_k output

For this set of input-output vectors, the state space identification of the time varying plant is made. After some transformation, the modified identified matrices are:

$$\begin{aligned} Am(\sigma) &= \begin{bmatrix} -0.4102 & 0 \\ 0 & -0.3000 \end{bmatrix}; \quad Bm(\sigma) = \begin{bmatrix} 3.8107 & 3.9707 \\ -2.8583 & 1.4129 \end{bmatrix} \\ Cm(\sigma) &= \begin{bmatrix} 0.7698 & 0.6728 \\ 0.5132 & 0.6817 \end{bmatrix}; \quad Dm(\sigma) = \begin{bmatrix} -0.0232 & -0.0047 \\ -0.0151 & -0.0029 \end{bmatrix} \end{aligned} \tag{20}$$

Figure 3 shows the output values ym_k obtained after the transformation on the identified model. Figure 2 and Fig. 3 show that the benchmark output y_k and ym_k are coincident for all of the time interval under consideration.

All of this procedure is repeated for 9 different references, represented by the columns of the matrix

$$W = \begin{bmatrix} 1 & 1 & 1 & 3 & 3 & 3 & 5 & 5 & 5 \\ 1 & 3 & 5 & 1 & 3 & 5 & 1 & 3 & 5 \end{bmatrix} \tag{21}$$

For each one of this operation points, the identified model whose matrices $A_m(\sigma), B_m(\sigma), C_m(\sigma)$ satisfy the original time varying system, is obtained, and the respective gain matrices $\breve{K}_k, \breve{K}^v_k$ are obtained. For example, for three of the operation points we obtained the following gains:

- For Operating Point 1:

$$\breve{K}_k = \begin{bmatrix} -0.0351 & 0.0655 \\ -0.0690 & -0.0683 \end{bmatrix} \quad \breve{K}^v_k = \begin{bmatrix} 0.1242 & -0.1166 \\ -0.0155 & 0.0175 \end{bmatrix} \tag{22}$$

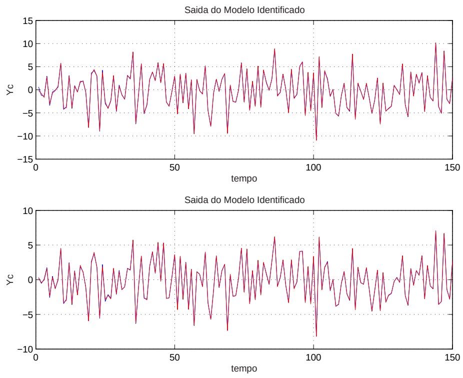

Figure 3. ym_k output

- For Operating Point 5:

$$\breve{K}_k = \begin{bmatrix} -0.0351 & 0.0628 \\ -0.0695 & -0.0671 \end{bmatrix} \quad \breve{K}_k^v = \begin{bmatrix} 0.1291 & -0.1212 \\ -0.0152 & 0.0172 \end{bmatrix} \tag{23}$$

- For Operating Point 9:

$$\breve{K}_k = \begin{bmatrix} -0.0352 & 0.0686 \\ -0.0706 & -0.0678 \end{bmatrix} \quad \breve{K}_k^v = \begin{bmatrix} 0.1215 & -0.1136 \\ -0.0141 & 0.0161 \end{bmatrix} \tag{24}$$

For each one of these operation points the corresponding linear optimal tracking controller is designed. A feedforward MLP neural network is trained to 100 epochs with a reference matrix W and a controller K matrix, constituted by the corresponding optimal controllers, here called targets, offered as inputs to the net. Figure 4 shows the neural network training performance, using the backpropagation algorithm, when mapping operation points and optimal tracking controllers. The mean square error was reduced from 7.98622 to $5.67857e^{-7}$ within 7 epochs.

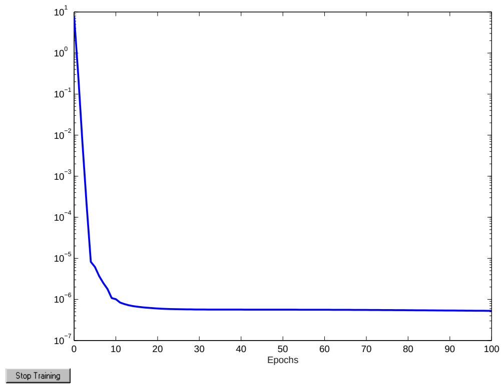

Figure 4. Neural Training by Backpropagation

To design the ILPV controller, we selected one identified model among the nine ones:

$$Am = \begin{bmatrix} -0.4010 & 0 \\ 0 & -0.3000 \end{bmatrix} \quad Bm = \begin{bmatrix} 3.9588 & 3.7956 \\ -2.9939 & 1.5231 \end{bmatrix} \quad Cm = \begin{bmatrix} 0.7723 & 0.6795 \\ 0.5148 & 0.6750 \end{bmatrix} \tag{25}$$

and defined a new reference matrix:

$$\bar{W} = \begin{bmatrix} 5 & 20 & 35 & 25 & 15 & 1 \\ 5 & 20 & 35 & 25 & 15 & 1 \end{bmatrix} \tag{26}$$

for which we designed an optimal tracking control law. With this new reference matrix we are interested in that at each of $\frac{M}{6}$ points the systems tracks each one of the reference values of this matrix starting from the first one; so, firstly $[5, 5]^T$, after $\frac{M}{6}$ points, the reference $[20, 20]^T$, and so on.

In Fig. 5 the performance of the output of the time varying plant intelligently controlled by a neural optimal controller with GS tracking the reference matrix $\bar{W}$ in presence of plant output noise (mean=0, variance = 0.1) and with an online tuning mechanism for the controller parameters $\breve{K}_k$ and $\breve{K}_k^v$ is shown. In Fig. 6 the intelligent control signal for the

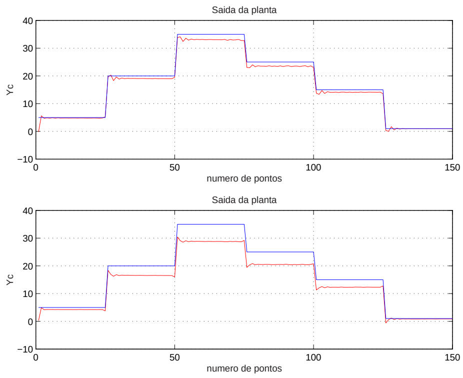

Figure 5. Output of the Intelligent Control System

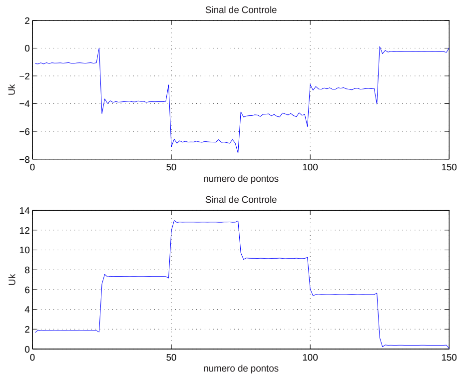

Figure 6. Intelligent Control Signal

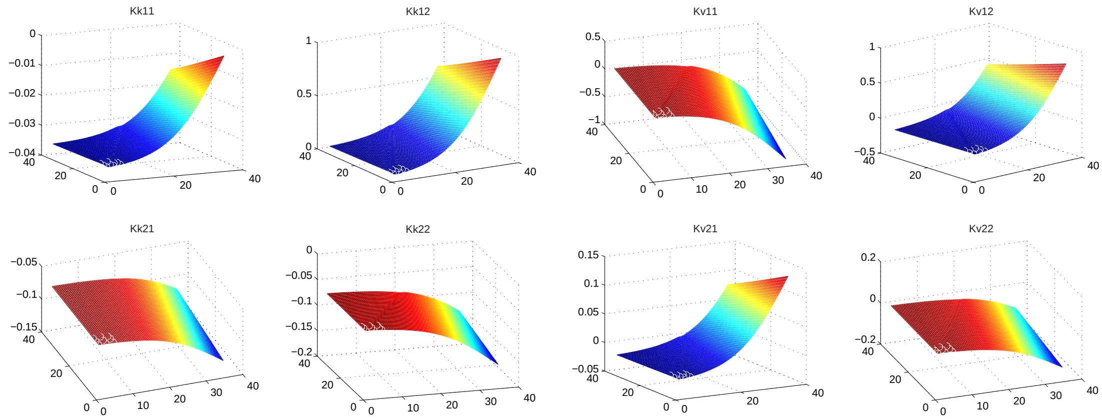

Figure 7. Gain Scheduled Surface for a set of reference points

same reference matrix is shown. In Fig. 7 neural gain surfaces for the designed intelligent gain scheduler controller for the MIMO discrete time varying plant here considered is shown. For each operation point the neural network output is plotted for a references grid with dimensions $[40, 0] \times [40, 0]$. We can observe the smooth transitions among the intelligent controller gains for the different operation points, expliciting the generalization property the neural network has. Indeed this is even more explicited when one considers the reference matrix W used for training and the results presented in Figs.5 - 7. Thus, from these results we can conclude that the proposed intelligent controller structure provides a smooth controller parameters interpolation for its various operation points and it is able to generalize for a wide operation range, the training done on a reletively narrow range.

4. Conclusion

The proposed and implemented intelligent control architecture to create an ILPV control scheme for linear multivariable time varying plants was succesfull in addition to beeing original in its conception and structure. Further studies, analysis and applications are natural and necessary developments for this study. From the results shown for this intelligent control system we can state that:

- it improves the loop performance because of the optimization;
- it works as an intelligent tuner updating all eight(8) tuning parameters and providing interpolation among operating conditions because of the neural gain scheduler;
- it achieves trajectory tracking in spite of noise and is efficient in the control of linear time variant linear plants.

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