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H_∞ Model Predictive Controller as Power System Stabilizer

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SUMMARY

A robust feedback-control algorithm is proposed to control an unknown nonlinear system such as the power system. The design process is based on the model predictive control theory where only the past input-output observations of the system are available. This design approach consists of three steps: in step one, using the available time-series data the system dynamics is identified to form a model from the system; in step two, the obtained model is used to calculate the controller by the H_∞ optimal control theory; and finally, in step three, the real-time implementation of the feedback controller is performed. The system identification is the central part of the controller design since the controller can only be as good as the model that is used to design it. In order to improve the performance and robustness of the system identification, this paper proposes expert system supervised multiple system identifications. The role of the expert system is to periodically evaluate the estimated models and to propose one for the controller design. The conceptual framework behind this approach lies in the fact that it is impossible to define the best identification method because for different implementations the criterion for the "best" changes with the particular requirements for identification speed, expected noise level in the observation, and disturbances affecting the system. A system identification that uses many different models simultaneously dismisses the task of evaluating the best identification method for a particular implementation. Instead, an expert system is designed which, in real-time, selects the best identification method from a pool of methods running in parallel. Simulation results using a power system model demonstrate the effectiveness and robustness of the H_∞ model predictive controller.

KEYWORDS

Adaptive control, Adaptive signal processing, Digital control, Discrete time systems, H-infinity control, Industrial control, Linear systems, Power system control, Power system identification, Robustness

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1. Introduction

The future Power System Stabilizer (PSS) is required to be more reliable, autonomous, robust, and yet efficient. The emphasis of this research is to introduce a robust control algorithm definition that addresses the needs of non-linear power system environments. In the past, various feedback-control methods have been tested. Experiments with the direct non-linear controller implementation [1],[2] have not yet produced feasible controller implementation due to the complexity of required mathematics. Other methods, such as fuzzy controllers, despite their popularity over the last two decades, [3]-[5], did not gain a significant share in controller implementation.

This paper introduces a robust adaptive controller for a linearized system model. The proposed controller is based on an adaptive concept with a three-step approach, where in step three the real time implementation of the feedback-controller is performed using the principles of the model predictive controller. In step one, the system model is identified in a closed-loop by a robust technique [6]-[8]. In step two, the obtained system model from step one is used to formulate a robust controller [9]-[11]. If the controller is designed using a system model obtained by system identification, it can be described as a parameter-adaptive control. In this approach, the system parameters are estimated in real-time and used for the controller's on-line parameterization. This type of controller belongs to the family of Model Predictive Controller (MPC) [15]. The MPC is an optimal control-based strategy that uses the plant model, which is identified in an on-line process, to predict the effects of a control sequence on the evolving state of the plant. The control action of the MPC is calculated by minimizing an objective function over a finite horizon.

The system identification is the central part of the controller's design. In order to improve the performance and robustness of the system identification, this research proposes expert system supervised multiple system identifications. The role of the expert system is to periodically evaluate the estimated models and to propose one for the controller design. Generally, the criterion for the system identification is based on minimizing a particular norm of the error between the output from the estimated model and the observations. There are three dominant norms in the literature. The first norm is when a criterion is selected to minimize the average absolute value of the difference between the model and the observations. The second norm criterion is applied when the parameters for the model are selected in a way to minimize the average squares of the difference between the model and the observations. The third or infinity norm criterion is implemented when the goal is to minimize the single largest difference between the model and the observations. These three types of identification methods are the basis for the different types of algorithms.

The challenge of this approach is to define the best identification method due to the fact that for different implementations the criterion for the "best" method changes with the particular requirements. A system identification that uses many different models simultaneously dismisses the task of evaluating the best identification method for a particular implementation. Instead, an expert system is designed which, in real-time, selects the best identification method from a pool of methods running in parallel. This real-time multi model system identification is possible due to the advances in computation power.

The robust controller is formulated by the H_∞ (sub)optimal design procedure [12]-[14] using the proposed system model. The idea behind this controller design technique is to combine an on-line identification algorithm with a control design method that yields a time-varying controller, which follows the changes in the power system operations. In the game theoretical framework, the H_∞ control problem can be regarded as a game where nature (the opponent) has access to the unknown exogenous input and the designer has a choice for the controller. The objective in selecting the controller is to obtain a design that minimizes a given performance index under the worst possible disturbances or parameter variations in the plant model. At the same time, nature (the opponent) has the objective to maximize the same performance index by controlling the exogenous input by selecting the worst possible disturbances. In literature, this is described as the two-player zero-sum game between nature - the maximizing player, and controller - the minimizing player.

The effectiveness of the proposed H_∞ MPC as a PSS is demonstrated by simulation and experimental tests. Through the implementation process, the H_∞ MPC is examined to determine how well it handles model uncertainty, disturbances and measurement noise. The results are compared to that of a Conventional Power System Stabilizer (CPSS) on the same benchmark power system model realized in software and on a scaled physical model using the micro-synchronous generator at the University of Calgary.

2. Robust System Identification

The system identification is a process where a model is constructed from the observed input and output data from the system, $G(t)$, using no physical insight whatsoever. The model parameters are simply knobs that can be adjusted to optimize the model fit. Despite the simplistic nature of the system identification, compared to the models constructed based on physical laws governing the behavior of the system, it is very efficient for modelling dynamic systems and requires less engineering time [16].

The model in system identification can be linear or nonlinear. System identification of general nonlinear structures is quite demanding in the estimation mathematical procedures as well as in the observed data quality and quantity. The well-practiced solution for this problem is the linearization of the nonlinear system around a certain trajectory, using the fact that the controller in closed-loop system identification can linearize the non-linear system behavior on a relevant operating point. This trajectory will be a time varying function of the non-linear system's operating point, with a linear model $G(\theta_n, T_s)$ using a time varying parameter vector θ_n. The shortcoming of the closed-loop permanent system identification is that after a major system perturbation, the identified model will be perturbed as well for a period. In order to improve the system identification during and after major system disturbances a multiple-model based system identification is proposed [17][18], which is further extended in this research by using multiple different system identification techniques, as presented ine Figure 1.

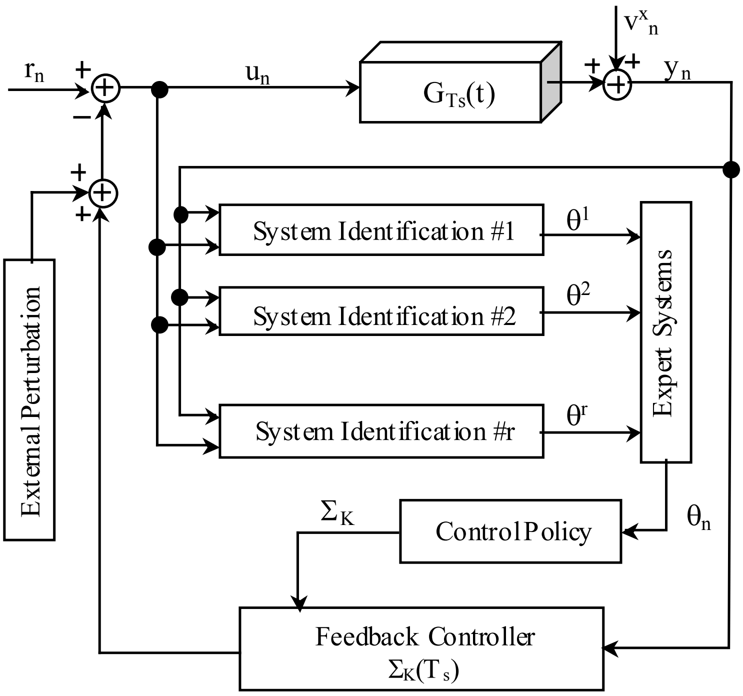

Figure 1 Control oriented system identification

The use of diversified parameter estimation techniques will guarantee better-estimated parameter accuracy and stability. This diversification of parameter estimation is made possible by techniques such as H_2, H_∞, Kalman Filter, Worst-Case Estimation, etc. These different system identification techniques are concurrently calculating the system models and these models form the model set M, while an expert system selects the "best" one, θ_n^S, which is used to formulate a model based feedback controller. In order to obtain the model, which can best represent the system to be controlled, the expert system solves the following optimization equation

$$J_n(\theta_n) = \min_{\theta_n^k \in M} \left[L_n^k(\theta_n^k, \phi_n) \right] \rightarrow \theta_n^S \qquad (1)$$

where $L_n^k(\theta_n^k, \phi_n)$ is the performance index defined for model validation and selection and ϕ_n is the observation from the system. The performance index, L^k, can be selected in many different ways as described in [19]. The goal is to predict the future behavior of the system dynamics by selecting the best available model from the system. One commonly used measure of the model quality is the residual, which is used to characterize the error in modeling. The residuals, $v_n^k = y_n - \hat{y}_n^k$, for the k^{th} model are defined as the difference between the plant output and the output predicted by the k^{th} model. To accomplish this goal, the performance index should be determined by the analysis of residuals

$$L_n^k(\theta_n^k, \phi_n) = \kappa_2 \|v_n\|_2 + \kappa_\infty \|v_n\|_\infty + \kappa_\Sigma L_\Sigma^k \qquad (2)$$

where κ_2, κ_∞, and κ_∞ are positive weighting coefficients, the 2[nd] and the infinity norm are calculated by $\|v_n\|_2 = \frac{1}{N}\sum_{i=1}^{N} v_{n-i}^2$ and $\|v_n\|_\infty = \max_{1 \le i \le N} |v_{n-i}|$, while L_Σ^k stands for the reminiscence of the k^{th} adaptive algorithm from the past. In the decision process the function of the reminiscence is based on the general observation that the model with a continuous good performance has the most chance to perform well in the next decision interval. The reminiscence function can be selected as

$L_\Sigma^k = \frac{1}{N_R}\sum_{i=1}^{N_R} L_{n-i}^k \lambda^{-i}$, where N_R is the number of the decision intervals included in reminiscence calculation, which corresponds to $T_S N_R$ time interval, and $0 << \lambda \le 1$ is the reminiscent weighting factor. If the reminiscent weighting factor is selected as $\lambda = 1$, it has a uniform weighting on the data in the decision process. Accordingly, if it is selected as $\lambda = 1$, the recent performance of the estimation algorithm has more influence on the decision-making. An effective implementation of (2) is to use the exponentially weighted moving average in recursive calculation

$$L_n^k = \rho L_{n-1}^k + (1-\rho)(\kappa_2 \|v_n\|_2 + \kappa_\infty \|v_n\|_\infty) \qquad (3)$$

where $0 < \rho < 1$ is the reminiscence factor. If the reminiscence factor is selected such that $\rho \rightarrow 1$ then the decision is primarily based on the past system identification performance. Accordingly, if it is selected as $\rho \rightarrow 0$, then the recent performance of the estimation algorithm has more influence on the decision-making.

The above theory, as presented in Figure 1, suggests that it implements *r* different algorithms. These algorithms should be selected in such a way to differ from each other in tolerance for robustness, identification speed, etc. For example, these algorithms can be developed to minimize the l_1, l_2, or l_∞, norms of the residuals in system identification. The resulting algorithms will result in different behavior. The l_1 norm criterion has the ability to ignore a few bad data points, while emphasizing the majority of data points which more properly reflect the true nature of the data [8]. The l_∞ norm is preferred when the goal is to minimize the largest error magnitude in the residuals during system identification. In general, the algorithms developed by minimizing the l_2 norm of the residuals, lead to the most accurate solution if the perturbing forces affecting the plant to be modeled and consequently the residuals are characterized by Gaussian distribution. If this condition is not satisfied, the l_2 algorithm could be unstable. Due to the limited space available for this paper, the different algorithms cannot be specified, rather [20] and the literature there is suggested.

3. Model Predictive Controller

The robust system identification produces a model from the system in real-time. This model is used thereafter to formulate a controller for the system also in real-time. This process of parameter-adaptive controller formulation in real-time is known as Model Predictive Controller (MPC). When the MPC is formulated following the H_∞ optimization procedure, the obtained H_∞MPC will be robust for external disturbances and inaccuracies in system identification.

The optimal control problem, when calculated at each sampling time, is referred to as the point-wise strategy. The terminal point in this control is of fixed-length, $N_T T_S$, where the finite cost horizon continuously recedes at each time instance [21]. The implementation of the point-wise strategy requires processing power, which is capable of calculating the optimal strategy in real time. This calculation must be performed in less time than the sampling interval, T_S. In most industrial control systems, the processing power presently available is not sufficient for the implementation of the H_∞ optimal control algorithm. In ten to fifteen years, there will probably be computers on the market with sufficient processing power to allow the implementation of the point-wise strategy. Until then, the interval-wise strategy shell be used for implementation.

In the interval-wise strategy, the terminal point $N_T T_S$ is kept fixed for the finite cost horizon and after an interval of NT_S, the terminal point moves by NT_S and the strategy is fixed for the next NT_S period, as presented in Figure 2.

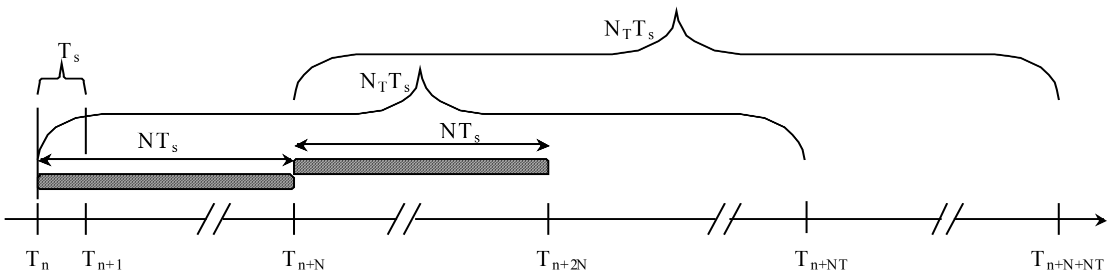

Figure 2 Interval-wise model predictive control strategy

The required NT_S period can be determined from the following inequality

$$T_{SI} + T_{CA} + \varepsilon < T_S \qquad (4)$$

where, T_{SI} is the calculation time of the system identification, T_{CO} is the calculation time of the real time feedback control, ε is the calculation time which can be spread over an interval and can be determined by

$$\varepsilon = T_{ES} + T_{CO} + T_{CS} \qquad (5)$$

where, T_{ES} is the required processing time for the expert system to select a model, T_{CO} is the time required to perform the H_∞ optimization for controller formulation, and T_{CS} is the time required to switch to the newly obtained controller, which includes the retroactive state estimation for a smooth transition.

A step-by-step implementation algorithm for the H_∞MPC can be found in [20].

4. Simulation Results

To validate the proposed H_∞MPC theory as a feasible control method, it was tested on a power system model. The power systems are non-linear time varying systems that are subject to unpredictable disturbances, such as load changes, operating point changes and faults. In the simulation studies, a synchronous generator connected to an infinite bus through a double-circuit transmission line was used [20].

In the studies described in this paper, the generator rotational speed deviation, $\nabla\omega = \omega - \omega_0$, is sampled as the system output to be stabilized, where ω_0 is the rotational speed of the infinite bus and ω is the rotational speed of the generator to be controlled. The signal, $\nabla\omega$, has zero mean value when the system is under steady state. When the system is disturbed, it is required to provide control to maintain the zero mean value. The disturbances are manifested as oscillations of the $\nabla\omega$ signal. In order to analyze the response of the proposed controller, it was compared to that of a widely used lead-lag controller IEEE Standard P421.5/D15 (CPSS) [20].

In these tests, the generator of the single machine infinite bus system is operating under a full load condition, P = 0.97 pu and pf = 0.97 lag [20]. To demonstrate the control action, three characteristic examples are shown for small, medium and large disturbance in sections 4.1 to 4.3 respectively. Each figure shows three test results. A doted line represents the NoC test situation, where the generator in not equipped with the supplementary controller. The CPSS, represented with a thin line, is a test situation where the generator is equipped with the widely used CPSS. Lastly, the bold line symbolizes the test situation with the proposed MPC.

4.1. Test-1

In Test-1, the generator's rotational speed deviation and control action is presented at the exciter voltage reference change of -0.015 pu, -0.015 pu and 0.03 pu, at 0.5 s, 2.8 s and 5 s respectively.

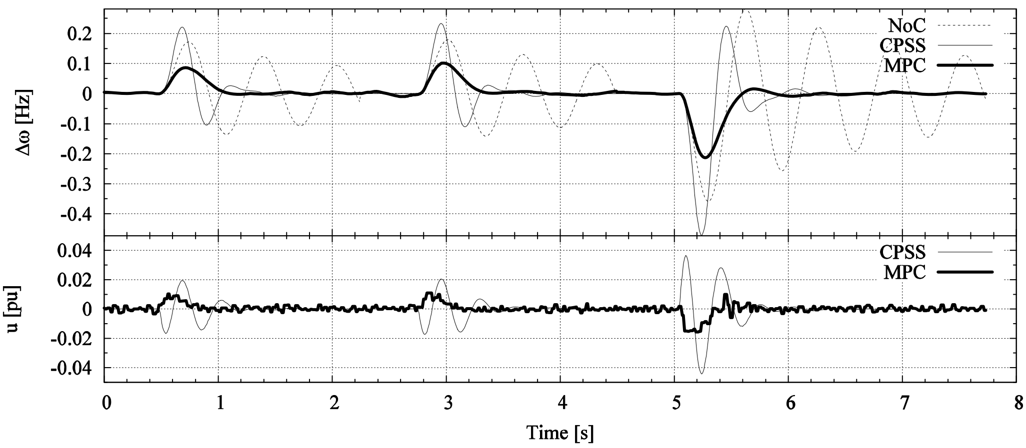

Figure 3 Speed deviation and control action for a small disturbance

Figure 3 demonstrates the effectiveness of the MPC controller, which significantly reduces the peak of the generator's rotational speed deviation. Contrary to this, the initial response of the CPSS to these smaller disturbances is less satisfactory.

4.2. Test-2

In Test-2, a $\Delta P = 0.15$ pu step increase and decrease in input mechanical torque is applied at 1 s and 5 s respectively, to analyze the generator's rotational speed deviation and control action. Test results verify that both the CPSS and MPC perform very well. The difference in performance goes in favour of the MPC with smaller amplitudes in post-disturbance oscillations. However, the over-conservative behavior of the H_∞ controller can be observed in Figure 4, where the effects of disturbances with highest magnitudes are reduced, while the small oscillations remain uncontrolled.

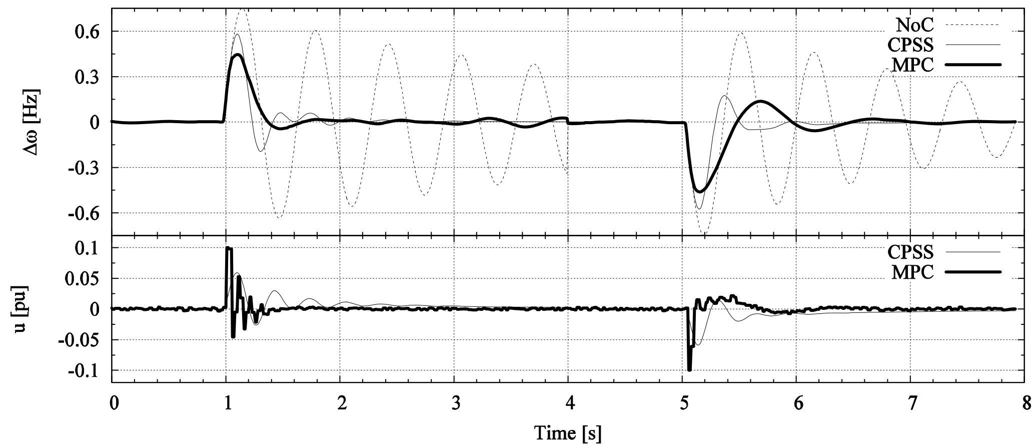

Figure 4 Speed deviation and control action for an average disturbance

4.3. Test-3

In Test-3 to demonstrate the speed deviation and control action of a generator for a large disturbance, a three phases to ground fault test of 100 ms length on generator bus has been performed at 1 s.

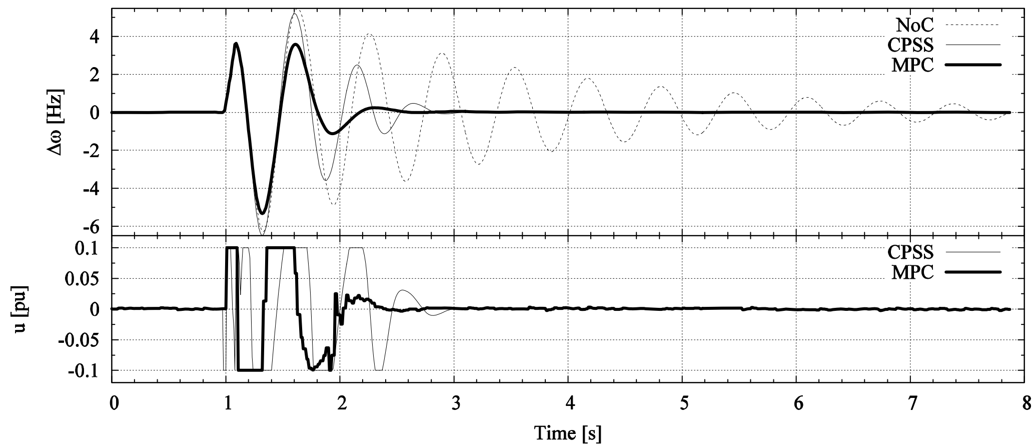

Figure 5 Speed deviation and control action for a large disturbance

Test results demonstrate the superior behavior of the MPC. This controller minimizes the peak of the generator's rotational speed deviation after the fault and helps the system return to its normal operating condition faster than the CPSS.

5. Conclusion

An H_∞MPC as power system stabiliser is briefly described in this paper. From the presented test results as well as from the experimental results offered in [20], the following can be concluded:

For real-time control of a non-linear system affected by strong disturbances, multiple-model based system identification will produce a stable and accurate system model.

The proposed H_∞ optimized controller provides excellent robustness in system performance.

The test results for various conditions concur that the proposed adaptive stabilizer can provide good damping over a wide operating range and it can improve the dynamic performance of the power system.

BIBLIOGRAPHY

[1] M.A. Henson and D.E. Seborg, “Nonlinear Process Control”, Prentice Hall PTR, Upper Saddle River. New Jersey, 1997.

[2] J.J. Slotine ant W. Li, “Applied Nonlinear Control”, Prentice Hall PTR, Upper Saddle River. New Jersey, 1991.

[3] P. Odry, Sz. Divéki, N. Burány and L. Gyantár, “Fuzzy control of brush motor - problems of computing”, SISY, Subotica, 2004, pp. 37-46

[4] P. Odry, Sz. Divéki, A. Császnyi, N. Burány, “Fuzzy Logic Motor Control with MSP430x14x”, Texas Instruments Application Report SLAA 235, February 2005.

[5] G. Ramakrishna, O.P. Malik, Radial Basis Function Identifier and Pole-Shift Controller for Power System Stabilizer Application, IEEE Transactions on Energy Conversion, vol. 19 no. 4, ISSN 0885-8969, December 2004, pp. 663-670.

[6] R. A. de Callafon, “Feedback oriented identification for enhanced and robust control,” Ph.D. dissertation, Delft University of Technology, Delft, The Netherlands, 1998.

[7] L. Ljung, System Identification: Theory for the User, 2nd ed., ser. nformation and System Science Series. Upper Saddle River, New Jersey: Prentice Hall, 1999.

[8] J. A. Cadzow, “Minimum l_1, l_2 and l_∞ norm approximate solutions to an overdetermined system of linear equations, ”Digital Signal Processing, vol. 12, no. 4, pp. 524–560, October 2002.

[9] I. D. Landau, “From robust control to adaptive control,” Control Engineering Practice, vol. 7, no. 9, pp. 1113–1124, September 1999.

[10] K. Narendra and C. Xiang, “Adaptive control of discrete-time systems using multiple models,” IEEE Transactions on Automatic Control, vol. 45, no. 9, pp. 1669–1686, September 2000.

[11] S.Fekri, M.Athatns, and A.Pascoal, “Rmmac: A novel robust adaptive control scheme-part i: Architecture,” Proc. 43rd IEEE Conference on Decision and Control, pp. 1134–1139, December 2004.

[12] A. A. Stoorvogel, The H∞ Control Problem: A State Space Approach. New York: Prentice Hall, 1992.

[13] T. Basar and B. P., H∞ - Optimal Control and Related Minimax Design Problems - A Dynamic Game Approach, 2nd ed. Boston: Birkhauser, 1995.

[14] M. Green and D. J. N. Limebeer, Linear Robust Control. Englewood Cliffs, New Jersey: Prentice-Hall, 1995.

[15] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. M. Scokaert, “Constrained model predictive control: stability and optimality,” Automatica, vol. 36, no. 6, pp. 789–814, June 2000.

[16] Forssell, U., “Closed-loop Identification – Methods, Theory, and Applications”, PhD Thesis, Linkoping University, Linkoping, Sweden, 1999.

[17] Landau, I. D., “Identification in closed loop: a powerful design tool (better design models, simpler controllers)”, Control Engineering Practice, Vol. 9, No. 1, January, 2001, pp. 51-65

[18] Narendra, K., and Cheng Xiang, “Adaptive Control of Discrete-Time Systems Using Multiple Models”, IEEE Transactions on Automatic Control, Vol. 45. No. 9, September, 2000, pp. 1669-1686.

[19] Ninness, B., and Goodwin, G., “Estimation of Model Quality”, System Identification (SYSID 1994), A Postprint Volume from the IFAC Symposium, Vol. 1, 1995, pp. 25-44.

[20] Antal Soos, " H_∞ Model Predictive Control - Theory and Application", PhD thesis, University of Calgary, Calgary, Canada, 2005. www.asoos.com

[21] Ki Baek Kim, Jae-Won Lee, and Wook Hyun Kwon, “Intervalwise receding horizon H_inf-tracking control for discrete linear periodic systems”, IEEE Transactions on Automatic Control, Vol. 45, No. 4, April, 2000, pp. 747-752.