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A Study of a Gun-Turret Assembly in an Armored Tank using Model Predictive Control

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***Abstract*— Operation of the gun/turret system in a military tank is limited by several constraints some of which are posed by obstacles existing on the vehicle's own platform. These mechanical constraints acting as hard constraints can cause serious damage to the whole assembly if violated. A control strategy developed for such a system must avoid possible collision of the gun/turret system with these obstacles. We propose to use a MPC based control strategy, due to its inherent ability to handle constraints, for the deck clearance problem and evaluate its performance under operating conditions for a linear model of the tank. *Matlab*® based MPCtoolbox is used to set up the MPC calculations for the gun/turret system. Simulations are performed to investigate and compare the performance of the controller under various deck constraint limits. It is shown that MPC is effective in addressing both the stabilization and deck clearance objectives.**

I. Introduction

A key feature of a military tank is its ability to engage targets while on the move. Varying operational conditions pose significant challenges in maintaining a high level of accuracy which is an essential requirement for the operation of these tanks. Figure 1 depicts the tank elevation system and the related parameters defining its dynamics.

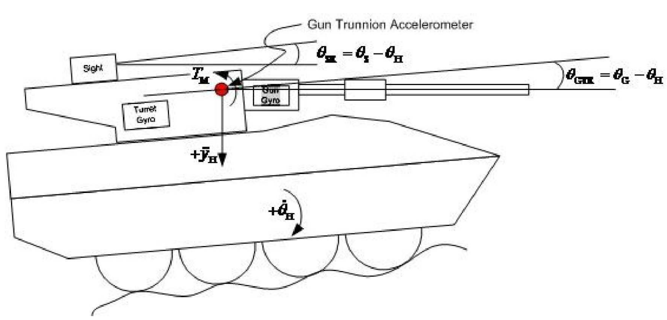

Fig. 1. Tank Elevation

TABLE I

Tank parameters

$\ddot{y}_H$	Vertical acceleration at gun trunnion
$\dot{\theta}_H$	Angular pitch velocity of hull
θ_G	Inertial angle of gun
θ_{GTR}	Relative angle at trunnion between gun and turret
θ_{SR}	Sight angle relative to turret
$\dot{\theta}_G$	Inertial angular rate of gun
$\dot{\theta}_M$	Inertial angular rate of motor
T_M	Elevation drive motor torque

An efficient control strategy must be employed to ensure precision pointing of the weapon according to the gunner's sighting system. It is essential that the control system implemented maintains this performance in the presence of large disturbances induced due to the movement of vehicle along the rough terrain. In addition the control system must account for the constraints posed by the obstacles present on the vehicle itself.

In spite of the interesting dynamics of this system, not many studies have been reported in the literature that discusses the weapon positioning problem. Recently, Feng et. al. [1] used sliding mode control combined with adaptive fuzzy control for tracking and disturbance rejection. Lewis et. al. [2] treated the gun turret assembly for a tank control system as a co-link robot arm and studied the problem from a robotics point of view where a minimum-time control law was designed. Kapoor et. al. [3] modeled the gun fire control system using an auto-regressive (AR) model based on velocity to predict the future position of the tank. It is important to note here that none of these approaches can handle constraints explicitly. Also, while the primary focus of [3] is modeling, they do not attempt precision tracking.

In this work, we study the disturbance rejection problem for a linear model of the weapon using Model Predictive Control due to its ability to handle the constraints. We use MPC as a tool to assist in the evaluation of our physical system. We show that MPC can be used as an effective control strategy for analyzing such a system which not only respects the hard constraints posed by the obstacles present on the vehicle but also shows a good potential to reject the disturbances. In section II, we formulate the problem. Next, we discuss our MPC setup for this control problem in section III and IV. We then present the simulation results using MPC and compare these results with μ-synthesis design in section V. We discuss the limitation of linear MPC design for our deck clearance problem in section VI which is followed by conclusions in section VII.

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II. Problem Statement

During operation of the gun/turret system, it is critical that the gun be maneuvered to avoid any obstacles existing on the vehicle's own platform. Examples include antennas, open hatches, and the vehicle chassis itself. Due to such obstacles, it is possible to derive a constraint function, which defines the weapon elevation constraint as a function of the azimuth turret position. Consider Figure 2, where regions I to VI are defined. In general, the regions impose lower and upper elevation limits as follows:

$$L_i(\theta_{az}) < \theta_{GTR} < U_i(\theta_{az}) \quad i = 1,2,..6$$

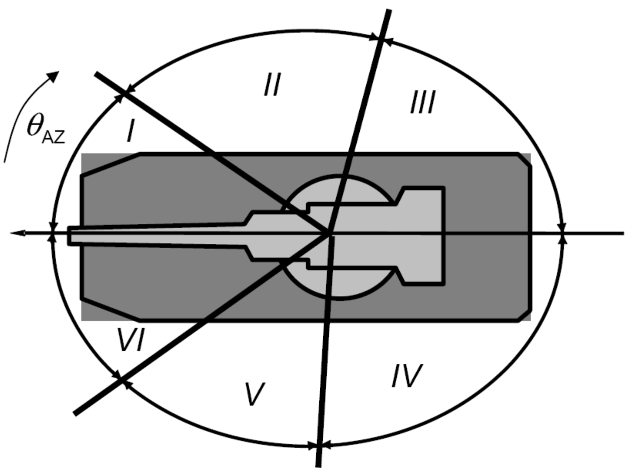

Fig. 2. Vehicle overhead view

It is necessary to identify, in real time, dynamic conditions which lead to a collision and employ an efficient control strategy that avoids such collision under different operating conditions. A control scheme designed for the gun/turret system must achieve the following, in order of priority:

1) Maintain θ_{GTR} within the constraints.
2) Minimize position error ($\theta_{SR} - \theta_{GTR}$) while rejecting disturbances.

III. Model Predictive Control

Model Predictive Control (MPC) is widely adopted as an effective means to deal with large multivariable constrained control problems in chemical engineering as well as other fields. A model of the plant is used by MPC for automation. The plant model is used for future prediction of the plant states. An online optimization problem is solved to compute the optimal control action over the control horizon. The MPC algorithm optimizes a pre-defined objective function over the prediction horizon while respecting the plant constraints. These constraints can include the actuator's physical limits, boundaries of safe operation and many other similar limits for operating conditions. Even though a sequence of current and future control moves is computed by the optimizer, only the first control move is implemented. At the next sampling time, new measurements are obtained. The prediction and control horizon are moved forward (Receding Horizon) by one step and the optimization is solved again using new measurements. The prediction and control horizon must be selected carefully as the performance of the MPC algorithm is significantly dependent on the size of these two horizons. Also, a meaningful objective function must be derived to accommodate the primary control task. A detailed discussion of the MPC algorithm and its different flavors can be found in [4]. A good discussion on handling constraints in linear stable and unstable system using MPC can be found in [5],[6],[7],[8],[9],[10]. Feasibility issues in non-square MPC has been described in [11]. Disturbance modeling for offset-free MPC is described in [12],[13],[14]. We chose to minimize the position error while respecting the elevation constraints.

IV. MPC Setup for Tank Elevation System

As mentioned in section I, very few contributions have been reported in the literature which concentrate on studying this problem from a control point of view. Furthermore, none of these contributions attempt to incorporate the physical constraints in the control design. This is mainly due to the inability of the control strategy to account for constraints. The ability of Model Predictive Control (MPC) to handle input/output constraints explicitly in an optimization framework makes it an ideal candidate for this problem. We used the MPC toolbox in Matlab for the deck clearance problem because of its relative ease of use.

A. Plant Model

For this study we used a linear model of the tank elevation dynamics coupled with a nonlinear friction block. The nonlinear friction block consists of diagonally arranged saturation functions. This model was derived for this feasibility study to closely represent the dynamics of the tank system while avoiding disclosure of proprietary information. The terrain disturbances were modeled as sinusoidal moguls (Figure 4) giving a good approximation of the variations in terrain profile over a long distance. A schematic of the closed loop system is given in Figure 3.:

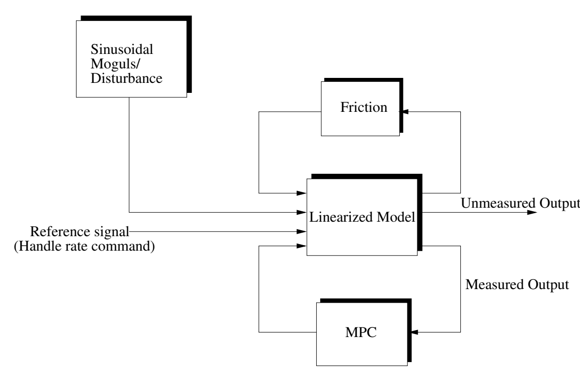

Fig. 3. A schematic of the plant model with controller

TABLE II

INPUT/OUTPUT VARIABLE TYPE FOR GUN/TURRET SYSTEM

Type of signal	Variables
Manipulated variable	T_M
Measured disturbance	θ_{SR}, $\dot{\theta}_H$, $\ddot{y}_H$
Measured output	θ_{GTR}, $\theta_{SR}-\theta_{GTR}$

B. MPC Setup

We used the MPC toolbox Graphical User Interface (GUI) in Matlab [15] to design a MPC algorithm for this gun/turret system. A typical control structure of MPC in Matlab consists of signals defining manipulated variables, measured/unmeasured disturbances, measured/unmeasured outputs, unmeasured disturbance model, output disturbance model and output measurement disturbance model. For the gun/turret system, the important input and output variables can be categorized as in Table II

For this study we used the Matlab default models for the unmeasured input disturbance, output disturbance and output measurement disturbance which is a white noise signal. With any MPC implementation it is very important that an appropriate sampling interval is chosen which is also the frequency of control action execution period. This may vary for different systems and for different control goals. A poor choice of sampling period may lead to poor performance of the controller. After careful study of the dynamics of the system, we chose a sampling period of 0.0125 time units for simulation studies.

Also, as commonly seen with any MPC based control algorithm, the performance of the controller is dependent on the choice of control and prediction horizon. A longer control horizon leads to improved controller performance. However this results in an increased computational cost. We used a prediction horizon of 50 and a control horizon of 20 for the simulation studies.

Next, we tuned the MPC algorithm using output and input weights. Depending on the control goal, an appropriate selection of these weights is necessary to provide acceptable controller performance. Specifically, Table III shows the weights chosen to provide good performance for the unconstrained and constrained cases. To evaluate stabilization performance due to rough terrain, the disturbance inputs, hull pitch rate and hull vertical acceleration, were derived by modeling the effect of traversing large sinusoidal moguls. These disturbances are shown in Figure 4. Figure 5 shows the stabilization performance via the position error (measured via θ_{SR} - θ_{GTR}), for each control design operating without constraints. Note a key MPC trade-off is evident here in that it is necessary to give up nominal unconstrained performance in order for the MPC optimization to accommodate the deck clearance constraints.

V. SIMULATION STUDY AND RESULTS

We study the performance of the gun-turret assembly. As part of this study, we considered the following control scenarios:

TABLE III

WEIGHTS USED FOR KEY INPUT AND OUTPUT VARIABLES FOR MPC CASE STUDY

Variable	Weight 1	Weight 2
T_M	0	0
$\dot{T}_M$	0.00001	0.01
θ_{GTR}	0.0001	10
$\theta_{SR}-\theta_{GTR}$	1000	100

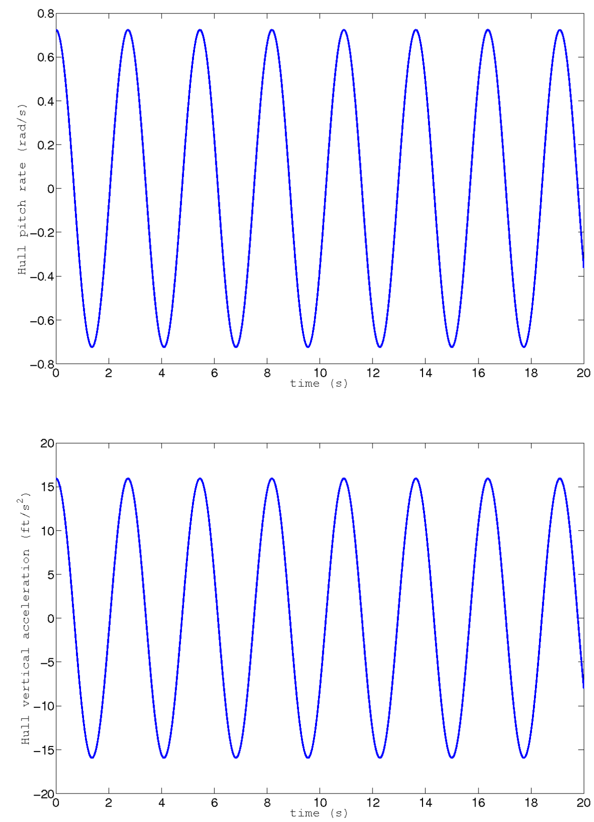

Fig. 4. Sinusoidal moguls approximating terrain disturbances

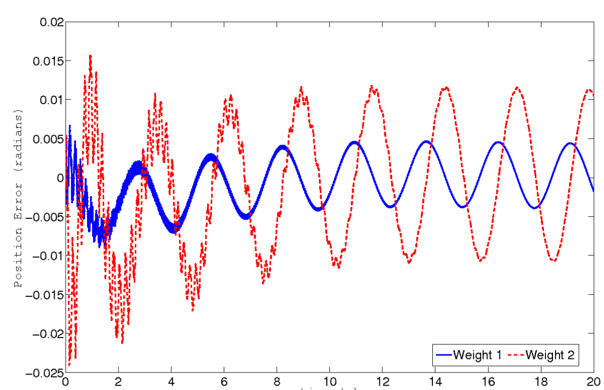

Fig. 5. Unconstrained MPC performance for two different set of weights

- Comparison of linear unconstrained MPC with μ-synthesis design.
- Comparison of linear constrained and unconstrained MPC design.
- Comparison of linear MPC design for various constraint bounds.
- Comparison of linear unconstrained MPC and μ-synthesis designs, tested on the non-linear model.

Linear MPC design refers to the system without the non-linear friction block. The following constraint was enforced on 'θ_{GTR}'

$$-5^\circ \leq \theta_{GTR} \leq 5^\circ$$

We study various cases for each scenario mentioned above to understand more closely the effect of these variations on the performance of the MPC implementation. We compare our results with performance of the μ-synthesis controller being studied at General Dynamics Land Systems (*GDLS*) for the same problem.

1) Comparison of linear unconstrained MPC with μ-synthesis design: The performance of MPC with respect to μ-synthesis in the absence of constraints is reported in Figure 6. We use Weight 1 from Table III for linear MPC design. It is observed that θ_{GTR} is nearly identical for both designs and even though the MPC position error performance is somewhat degraded with respect to the μ-synthesis design, the two designs are sufficiently comparable for our purposes.

2) Comparison of linear constrained and unconstrained MPC design: Figure 7 shows a comparison of the performance of MPC for the constrained and unconstrained system. We use Weight 2 from Table III for linear MPC design. It is observed that MPC respects the constraints imposed on the system. In contrast to μ-synthesis, this illustrates the unique ability of MPC to accommodate deck clearance constraints directly in the control design.

It is also observed from the position error plot that a variation in position error for the constrained case is much larger than the unconstrained case. This is a fundamental trade-off, due to the activation of the deck clearance constraint on θ_{GTR}.

3) Comparison of linear MPC design for various constraint bounds: In this section we compare the results of the constrained system by varying the constraint bounds. Results are shown in Figure 8. We use Weight 2 from Table III for linear MPC design. We show the comparison for $|\theta_{GTR}| \leq 5^\circ, 10^\circ, 15^\circ$ and unconstrained case. It is observed from θ_{GTR} that MPC respects constraints for all cases.

To properly understand the simulation results of Figure 8, a few comments are in order. Namely, for the gun to be stabilized over rough terrain, it needs to be moving relative to the moving vehicle. Recall θ_{GTR} measures this vehicle-relative position while the position error measures the inertial position of the gun relative to space. As we impose constraints on the movement of the gun, the inherent ability of the system to stabilize the weapon becomes compromised. Therefore tighter constraints on θ_{GTR} will necessarily degrade performance due to the physical reality of the situation.

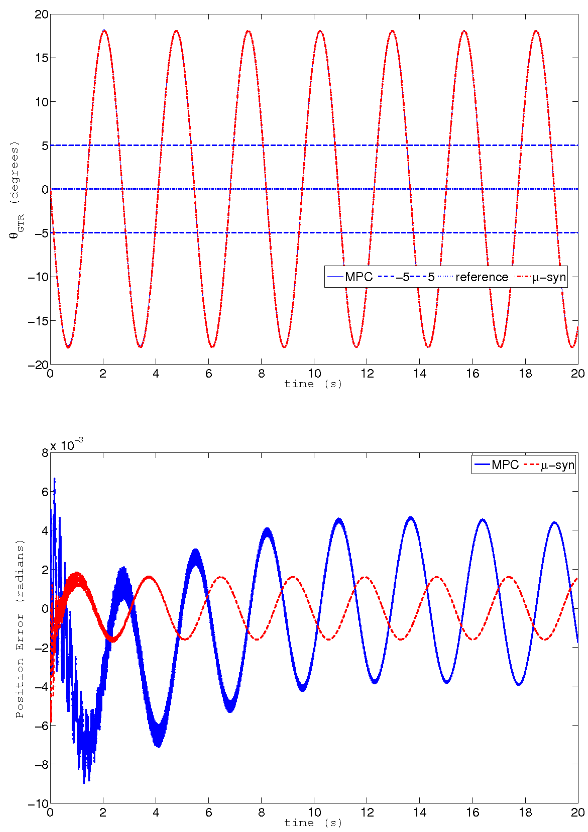

Fig. 6. Comparison of MPC with μ-synthesis design for unconstrained linear case

Imposing tighter constraints on θ_{GTR} will lead to a larger position error. This is shown in position error plot. As we tighten the constraint bound on θ_{GTR} (from unconstrained to $|\theta_{GTR}| \leq 5^\circ$), the position error increases. This validates the physics of the gun-turret assembly motion.

4) Comparison of linear unconstrained MPC and μ-synthesis designs, tested on the non-linear model: In previous sections, we studied the linear case of the system where we neglected the non-linear friction block. We discussed various scenarios of constrained and unconstrained cases. In this section, we compare the non-linear case where we include Coulomb friction block into the plant model dynamics. We assume this non-linear friction block as an unmeasured output and use linear MPC for the unconstrained system. We compare the results with the MPC algorithm and the μ-synthesis design.

The results for this scenario are shown in Figure 9. We use Weight 1 from Table III for linear MPC design. It is observed from Figure 9 that μ-synthesis (position error plot) performs superior than MPC for the unconstrained non-linear deck clearance problem.

VI. Future Direction: Addressing Coulomb Friction

It is seen from the results that the comparative performance of the unconstrained MPC degrades considerably

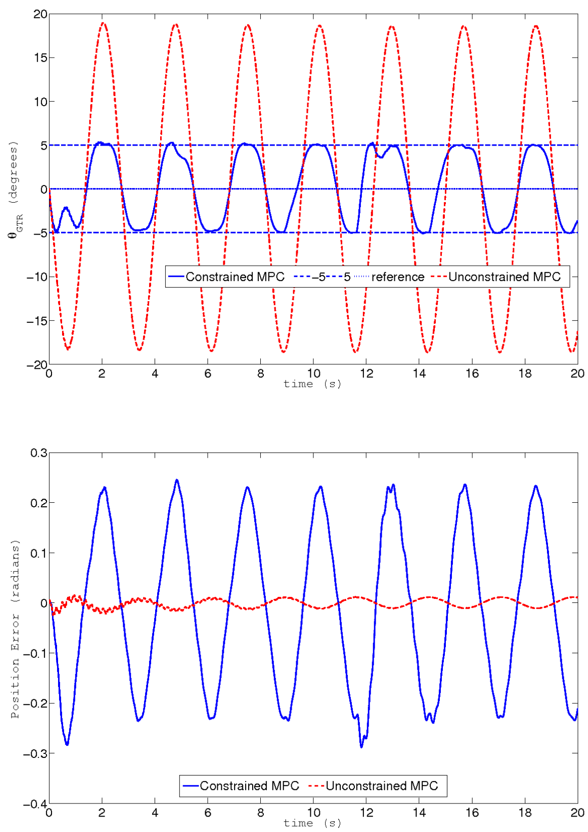

Fig. 7. Comparison of MPC results for constrained and unconstrained linear case

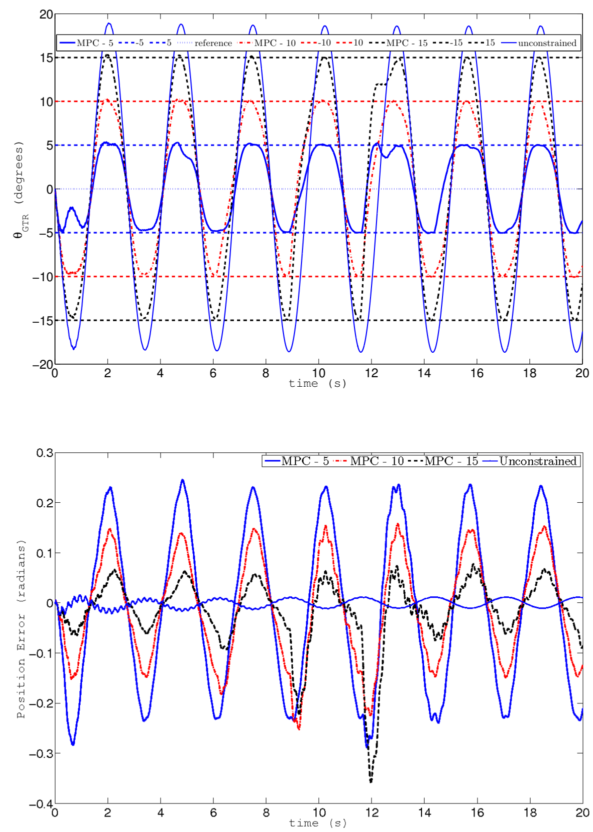

Fig. 8. Comparison of MPC results for various constraint bounds

for the non-linear plant deck clearance problem. Figure 9 shows that as the non-linearity is introduced, position error grows significantly. Although the performance of μ-synthesis approach is superior for unconstrained non-linear case, its inability to handle constraints limits its application to the deck clearance problem. While MPC can handle the constraints, in presence of the frictional non-linearity its performance may not be acceptable.

It is essential that we investigate further the deck clearance problem in order to understand the possible cause of MPC performance degradation. As seen in previous sections, performance of linear MPC for unconstrained and constrained case is acceptable as long as the original non-linearity present in the plant is not introduced. This leads to the conclusion that the plant model mismatch introduced by the presence of the non-linear friction block contributes significantly towards this degradation. It may be necessary to model the coulomb friction block and incorporate it along with the plant model for the purpose of controller design. The non-linear nature of friction requires use of non-linear modeling/control approach e.g. Non-linear MPC (NLMPC), Piece-wise Affine formulation and similar techniques.

Figure 10 shows the coulomb friction block which consists of two diagonally arranged saturation functions. The piece-wise nature of saturation function makes PWA formulation an excellent choice for modeling the friction. This is a topic currently under investigation.

VII. Conclusion

We have studied the deck clearance for weapon stabilization using *Matlab*® based MPC toolbox. We have designed an MPC controller to fulfill the objectives of weapon stabilization while operating within the physical constraints of the weapon installation and have compared our results with the frequency based μ-synthesis approach. We have shown firstly that the MPC design approach appears to be a viable alternative for the nominal unconstrained weapon stabilization problem. We have further shown how MPC can integrate deck clearance constraints directly into the design, whereas a purely linear technique such as μ-synthesis requires the augmentation of an entirely separate deck clearance controller mode in order to respect constraints. We have also illustrated how MPC exhibits a graceful degradation with respect to the severity of the deck clearance constraint. Namely tighter constraints result in increased performance degradation, which is physically unavoidable, whereas less severe constraints will result in less degradation. Finally, we have shown that the linear MPC formulation breaks down when Coulomb friction is included. However, we have further discussed that this issue can be addressed via a PWA formulation, which is the subject of our ongoing work.

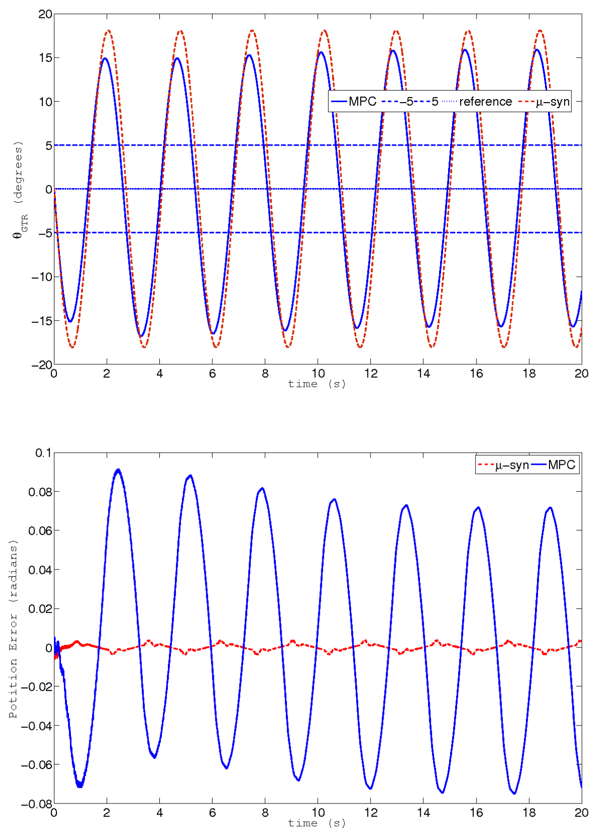

Fig. 9. Comparison of MPC design with μ-synthesis for unconstrained non-linear system

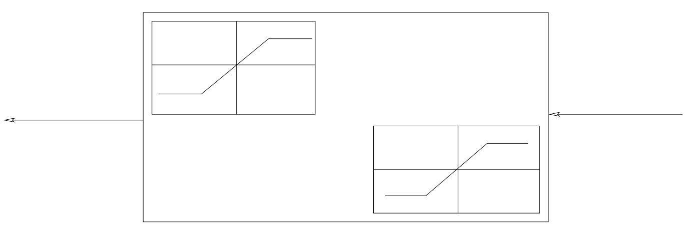

Fig. 10. Friction

REFERENCES

[1] L. Feng, X.-J. Ma, Z.-F. Yan, and H. Li, “Method of adaptive fuzzy sliding mode control of gun control system of tank,” *Dianji yu Kongzhi Xuebao/Electric Machines and Control*, vol. 11, no. 1, pp. 65–69, 2007.

[2] F. L. Lewis, D. M. Dawson, J. Lin, and K. Liu, “Tank gun-pointing control with barrel flexibility effects,” in *Winter Annual Meeting of the American Society of Mechanical Engineers, ASME Dynamic System and Control division*, Atlanta, GA, 1991, pp. 65–69.

[3] S. G. Kapoor, C. Kunpanitchakit, S. M. Wu, and N. Coleman, “Modeling and forecasting of maneuvering tank position for gun fire control,” in *Modeling and Simulation, Proceedings of the Annual Pittsburgh Conference*, 1979, p. 197.

[4] E. F. Camacho and C. Bordons, *Model Predictive Control*. New York: Springer, 1999.

[5] K. R. Muske and J. B. Rawlings, “Linear model predictive control of unstable processes,” *J. Proc. Cont.*, vol. 3, no. 3, pp. 85–96, 1993.

[6] C. V. Rao and J. B. Rawlings, “Steady states and constraints in model predictive control,” *AICHE Journal*, vol. 45, no. 6, pp. 1266–1278, 1999.

[7] K. R. Muske and J. B. Rawlings, “Model predictive control with linear models,” *AICHE Journal*, vol. 39, no. 2, pp. 262–287, 1993.

[8] P. J. Goulart and E. C. Kerrigan, “Output feedback receding horizon control of constrained systems,” *International Journal of Control*, vol. 80, no. 1, pp. 8–20, 2007.

[9] A. Zheng and M. Morari, “Control of linear unstable systems with constraints,” in *American Control Conference*, Seattle, Washington, 1995, pp. 3704–3708.

[10] G. Pannocchia, “Robust disturbance modeling for model predictive control with application to multivariable ill-conditioned processes,” *Journal of Process Control*, vol. 13, pp. 693–701, 2003.

[11] L. Shead and J. Rossiter, “Feasibility of non-square linear mpc,” in *American Control Conference*, New York City, 2007, pp. 4464–4469.

[12] K. R. Muske and T. A. Badgwell, “Disturbance modeling for offset-free linear model predictive control,” *J. Proc. Cont.*, vol. 12, pp. 617–632, 2002.

[13] G. Pannocchia and A. Bemporad, “Combined design of disturbance model and observer for offset-free model predictive control,” *IEEE Transactions on Automatic Control*, vol. 52, no. 6, pp. 1048–1053, 2007.

[14] G. Pannocchia and J. B. Rawlings, “Disturbances models for offset-free model predictive control,” *AICHE Journal*, vol. 49, no. 2, pp. 426–437, 2003.

[15] A. Bemporad, M. Morari, and N. L. Ricker, *Model Predictive Control Toolbox™ 2, User's Guide*, version 2.3.1 ed., 2008.

[16] M. Kvasnica, P. Grieder, and M. Baoti, *Multi-Parametric Toolbox*, version 2.6.2 ed., 2006. [Online]. Available: http://control.ee.ethz.ch/ mpt/