INEGRATE PREDICTIVE REFERENCE GOVERNOR FOR CONSTRAINED 2 DOF's ROBOT OPERATES UNDER PD-CONTROLLERS

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الملخص

أخذت تطبيقات الضابط (الحاكم) التنبؤي الطبقي الامثل للعمليات انماط عديدة، أبسطها أن يتم من خلال طبقتي تحكم بحيث يشغل حاكم تنبؤي الطبقة العليا (الخارجية) والتي مهمتها توليد القيم المثالية لمسارات العمل وفي نفس الوقت تتولى مراعاة قيود التشغيل بينما يكون عمل الطبقة المباشرة (الداخلية) تتبع مسارات التشغيل المولدة من حسابات الطبقة العليا. هذه الطريقة تعني، لحد كبير أن طبقتي التحكم تعملان بشكل مستقل (منفصل). في هذه الورقة تم تنفيذ تكامل بين الطبقتين ففي كل لحظة (تعيين) من لحظات توليد اشارة التحكم (في العليا) يوخذ المخرج النهائي للعملية التي سبقتها كنقطة اتزان لعملية تحويل نموذج ديناميكية العملية (على اساسه يتم حساب اشارة التحكم المُثلى) من لا خطي الى خطي ويستخدمها المُحكم التنوبي في توليد القيمة المُثلى للمسار (حركة المفصل) كمُدخل للطبقة المباشرة. كما يتم تضمين قانون التحكم للطبقة الداخلية في عملية حساب قيم المسارات المثالية من طرف حاكم الطبقة العليا من خلال دمجه في نموذج ديناميكية العملية. العملية المستهدفة في هذه الورقة هي التحكم في حركة ريبوت بدرجتين حرية يعمل تحت نظام تحكم تقليدي (تناسبي + تفاضلي). حيث أُعتبر نظام التحكم التقليدي هو نظام الطبقة المباشرة بينما يشغل نظام التحكم التنبؤي الطبقة العليا. تم استعمال طريقة مسلسلات تايلر من الدرجة الاولى لتحويل النماذج اللاخطية الى خطية عند كل نقطة اتزان (موضع مفاصل ريبوت) وتم احتسابها في لحظة تعيين سابقة. الهدف من مخطط التحكم المنفذ هو تنفيذ اعلى درجة من التتبع لمسار التشغيل مع مراعاة (عدم انتهاك) قيود التشغيل الفنية. نتائج المحاكاة (برنامج ماثلاب) اظهر تحسن كبير في الأداء مقارنة بطريقة الحاكم الطبقي المستقل.

ABSTRACT

Application of the predictive optimizing reference governor to a process can be realized in different schemes. The easiest is to have two layers operate such that the higher (outer) layer generates the optimum reference trajectory and at the same time considers the constraints, while the inner (direct) layer fulfils the tracking problem, this means that the two layers operate almost independently. In this paper, an integration between the two layers is implemented. At each successive instant, the target output of the process is considered as the equilibrium point about which the process model is linearized and used in calculating the optimum trajectories. Moreover, the direct layer's control law is implicated in the process model. The process is a two degree of freedom robot that operates under low level PD-controllers. PD-controllers is considered as a direct (basic) control layer in the inner feedback loop of the hierarchical structure. The direct control receives its reference trajectories values from the nonlinear constrained governor (outer loop). Process dynamics are lineaized at each sampling time, from application of Taylor's series method, about the instantaneous calculated joint positions. The objective of the developed scheme is to fulfill high position tracking with no

violation of the technical constraints. The simulation results show good improvements in the performance of the proposed technique in compare with convention reference governor.

KEYWORDS: Compared Integrated Multi-layer; Reference Governor; Predictive Control; Industrial's Robot.

INTRODUCTION

Constraints violation is essential problem in control engineering, since constraints are inherently characterizing almost all practical control systems, appearing most commonly as actuator bounds. However, other constraints on inputs, outputs and/or states also exist and are important. Violation of such constraints may degrade the control scheme and in worst cases leads to instability [1-3]. A robot, Figure (1), has a build-in joint independent low-level PD-controllers, one controller for each joint (SISO strategies), which may be considered as Distributed Control System (DCS), will form the inner loop in the applied two-layer control scheme.

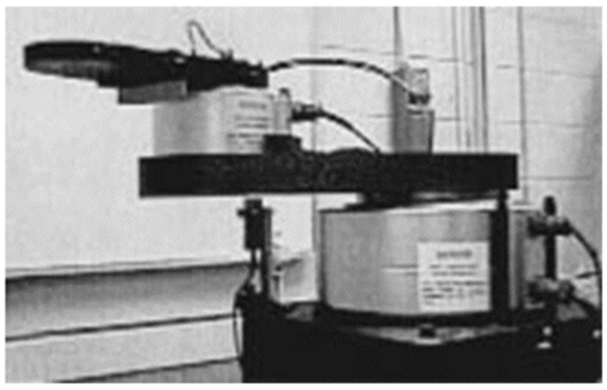

Figure 1: the underlying 2 DOF"s robot

The PD-controllers can perform high position tracking accuracy [4, 5]. However, their main drawback is their disability to handle different constraints in particular output constraints. Whereas in [6], a constrained (input and output constraints) predictive control algorithm (MPC) was successfully applied to a 2-DOF Direct Drive Actuator (DDA) robot. Stability is guaranteed under MPC provided that the prediction horizon is infinity and/or long compared to control horizon [7, 8]. Moreover, MPC considered very robust and uncompetitive technique regarding disturbance and noise rejection because a compensation for model uncertainty and disturbances is explicitly considered in the controller control law [8, 9]. The main problem of the MPC technique is its computation burden particularly in case of non-linear optimization problems (solve of non-Quadratic programming function, (non-QP)). However, this problem becomes not significant due to new computer capabilities [8]. A hybrid or multi-layer control system solves both the problem of tracking and problem of obeying the deferent technical constraints. Indeed, for example in [10, 11] the idea of multi-layer control (reference governor) strategy was discussed, where constraints, stability and tracking requirements are fulfilled by adding to a primal compensated nonlinear system a reference governor. Two different techniques were proposed. In [10] Co-operation of model predictive control algorithms with economic steady-state optimization is investigated. Two general approaches are investigated, namely approximate formulations of the target set-point optimization and integration of MPC with economic optimization, whereas in [11] as hybrid system, the problem of satisfying point-wise-in-time input and/or state hard constraints in nonlinear control systems. The approach is based on conceptual tools of predictive control and consists of adding to a primal compensated nonlinear system a reference governor. The resulting hybrid system proved fulfillment the constraints, stability and tracking requirements. Moreover, in [12] the multi-layer technique is applied in a form of computationally tractable fashion, where multiple inner loops are closed by separate MPC techniques. The only outer loop does handle the constraints and hence bears the problem of optimize the reference trajectories for the inner controllers. In [13] presents the advantages of applying the MPC reference governor to control multistage processing machines, with focus on a dual-stage dual-axis machine provided with a small-and-fast actuator and a large-and-slow actuator per processing axis. The reference governor exploited to obtain the fastest feasible reference trajectory with guaranteed future constraint satisfaction that does not cause machining error while modifying the infeasible parts of the trajectory. Then, use the reference and the maximum constraint admissible set of the reference governor in the MPC, thus obtaining recursively feasibility, and under mild assumptions, finite time processing of the machined path.

In this paper, an integrated predictive optimizing multi-layer (reference governor) control strategy is applied to a two degree of freedom robot. The two-degree robot has a build-in PD-controllers form the direct control layer, which operates under the supervision of a higher control layer, see Figure (2).

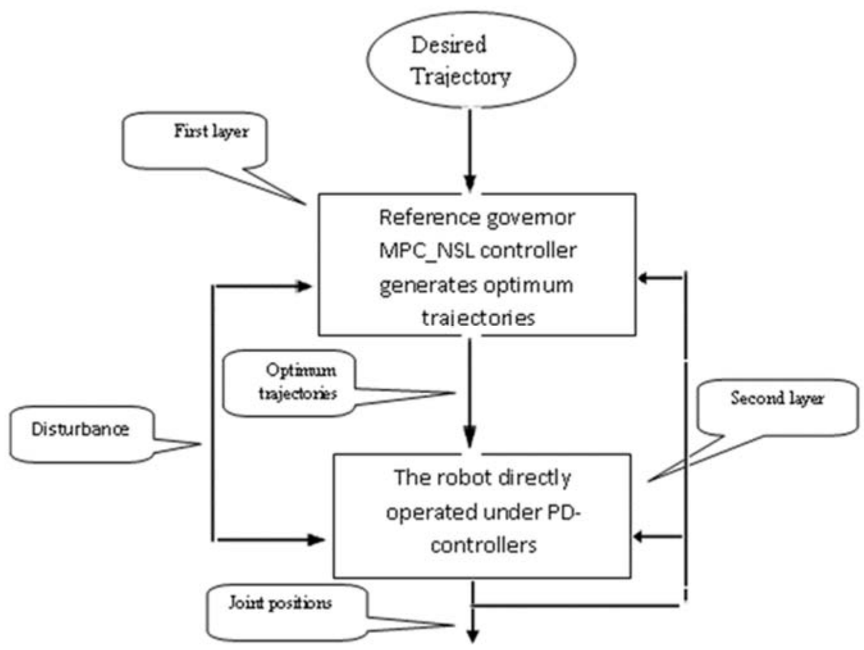

Figure 2: Integrated Multi-layer control structure

The supervisory layer, also called governor, is designed as a MPC-NSL (Model-based Predictive Control- Nonlinear with Successive Linearization) type controller [8]. The role of the higher control layer is to generate the desirable point-wise in time optimum values set-point trajectories for the direct controllers taking in consideration all the operation's constraints. The two layers are integrated in the sense that the output position is used as the equilibrium point for the objective model and at the same time considered as the state vector of the higher layer, in other words, the model of the process is amended such that it includes the direct controller laws, whereas the output of the higher layer is considered as reference points of the direct layer control algorithm. Although this approach is integrated, it decouples the problem of meeting constraints from obtaining a good local control design (PD-controllers in this case) such that the two layers may operate at different frequencies [8, 10].

It is assumed that; disturbances and the process have the same rate of dynamics and the optimizing governor and the direct controllers have the same sampling time.

The paper is organized as follows: Section 2 presents MPC-NSL algorithm and its optimization problem, in Section 3, description of the process model dynamics, the process constraints and the desired trajectories. In Section 4 the proposed control scheme structure and the related algorithm terms are presented. Section 5-presents the simulation results and the paper ends with the conclusion in Section 6.

MPC-NSL CONTROL ALGORITHM

The principal of the MPC control law is summarized in the following:

At each consecutive sampling instant k= 0, 1, 2, (time kT_s where T_s is the controller sampling period), having:

- A dynamic process model plus an assumed disturbances model and models of constraints;
- Current and past process outputs measurements together with past values of control inputs;
- Known references trajectories for assumed prediction horizon N_p ;

The control inputs $u(k)= u(k/k), u(k+1/k), u(k+2/k)\ldots u(k+N_u-1/k)$ are calculated, assuming $u(k+i/k) = u(k+N_u -1/k)$ $for\, i \geq N_u$, where N_u is the control horizon, from minimization of objective function, also called cost and/or performance function. Consequently, if the process model is non-linear a non-quadratic optimization function (***fmincon***) is applied otherwise if the model is linear the optimization function is quadratic (***quadprog***).

For linear processes subjected to constraints, the optimal control sequence can be found relatively fast as a solution to the quadratic optimization problem. However, for nonlinear processes model the problem is no longer convex, may has many minima, some cases no global minimum, hence the computation of the function over the prediction horizon becomes computationally intensive and sometimes very hard to solve.

The underlying process (built-in PD-controller robot) has a nonlinear dynamics model. The dynamical model is locally linearized at each sampling instant about an equilibrium point using a well-known Taylor's series Expansion method, i.e. the nonlinear function $f(x)$ may be replaced by:

$$f(x) \cong f(a) + \frac{\partial f(x)}{\partial x} \downarrow_{x=a} (x-a) \tag{1}$$

where $f(x)$ has the point a as an equilibrium point.

The process outputs calculated in the previous instant are considered as equilibrium points for the current instant. Consequently, the used Nonlinear MPC (NMPC) algorithm is named Model-Based Predictive Control-Nonlinear with Successive Linearization algorithm, MPC-NSL [8].

At each consecutive sampling instant k a set of future optimal control increments $\Delta U(k)$, over a control horizon N_u, is computed:

$$\Delta u(k) = [\Delta u_1(k), \Delta u_2(k)],$$

$$\Delta U(k) = [\Delta u(k/k)^T, \Delta u(k+1/k)^T ....\Delta u(k+Nu-1/k)^T]^T \tag{2}$$

Leads to calculate:

$$u(k/k) = u(k-1/k) + \Delta u(k/k)],\ u(k+1/k) = u(k-1/k) + \Delta u(k/k) + \Delta u(k+1/k)],...$$

$$U(k) = [u(k/k)^T, u(k/k+1)^T,..., u(k/k+N_u-1)^T]^T$$

This optimal increment vector is a result of minimization of dynamic objective function containing in its first term the squares of the errors (deviation of the predicted outputs (q^{prd}) from the corresponding set-point trajectory points (q^d)) vector:

$$e(k+p/k) = q^d(k+p/k) - q^{prd}(k+p/k) \quad \forall p = 1,2,........, N_p \tag{3}$$

and in its second term the squares of the future control increments vector $\Delta U(k)$, subjected to the plant constraints,

$$\left.\begin{aligned} x(k) &= A.x(k-1) + B.u(k-1) + v(k-1) \\ q^{opt}(k) &= C.x(k) \end{aligned}\right\} \tag{4}$$

$$\left.\begin{aligned} &\min_{\Delta U(k)} \left\{ \left\| q^d(k) - q(k) \right\|_{\Psi}^2 + \left\| \Delta U(k) \right\|_{\lambda}^2 \right\} \\ &subject\ to \begin{cases} -\Delta U_{\max} \le \Delta U(k) \le \Delta U_{\max} \\ U_{\min} - U(k-1) \le J.\Delta U(k) \le U_{\max} - U(k-1) \\ q_{\min} - q^O(k) \le \Delta q(k) \le q_{\max} - q^O(k) \end{cases} \end{aligned}\right\} \tag{5}$$

Where equation (4), represents the discrete state-space linearized model, in which x is the state vector, A system matrix, B input matrix and C is the output matrix and $v(k) \in R^{n_u}$ represents the integrated white noise state and disturbance and modeling errors [8]. Whereas equation (5), is the cost function, $\Delta U_x, U_x \in \Re^{n.N_u}$ where ΔU_x and U_x are the maximum /minimum optimized input and increment vectors respectively, N_u is the control interval and J is a diagonal matrix of dimension $n.N_p$ its elements are identity matrices $n\ x\ n$. $q^d \Re^{output\ vector\ length}$ are the desired joint angle, $q_x \in \Re^{output\ vector\ length}$ maximum / minimum admissible predicted joint angles specified by the manufacturer (output constraints), $q^o \in \Re^{output\ vector\ length}$ free output joint angle and $\Delta q \in \Re^{output\ vector\ length}$ the forced output joint angle increments calculated over the prediction horizon N_p. In

MPC strategies only the first set of increments, $\Delta u(k|k)$, corresponding to sampling instant k, is applied to the process:

$$\left.\begin{aligned} u(k) &= [u_1(k), u_2(k)], \\ u_i(k) &= [u_i(k-1) + \Delta u_i(k \mid k)] \ \ \forall i = 1,\ 2 \end{aligned}\right\} \tag{6}$$

$\psi \geq 0$, and $\lambda \succ 0$ are diagonal weight matrices of dimensionality $n_u.N_p \times n_u.N_p$ and $n_y.N_u \times n_y.N_u$ respectively.

DESCRIPTION OF THE PROCESS MODEL

Process model dynamics

The Euler-Lagrange equation of robot dynamics takes the following general form [5]:

$$\tau(k) = M(q(k))\ddot{q} + N(q(k), \dot{q}(k)) + G(q(k)) + F(q(k), \dot{q}(k)) \tag{7}$$

where; $M(q)$ is a nxn symmetric positive definite manipulator's inertia matrix, $N(q, \dot{q})$ is the nx1 vector of centrifugal and Coriolis terms, $F(q, \dot{q})$ is nx1 vector representing viscous and Coulomb friction, $G(q)$ is the gravity vector, $\dot{q}$ *and* $\ddot{q}$ are the angular velocity and acceleration, and n is the number of joints (=DOFs). For the underlying robot, values of the elements of these matrices and vector are given by the compact form [14]:

$$\left.\begin{aligned} &The\,inertia\,matrix; M(q) = \begin{bmatrix} p_1 + 2p_3\cos(q_2) & p_2 + p_3\cos(q_2) \\ p_2 + p_3\cos(q_2) & p_2 \end{bmatrix} \\ &The\,cent.\,and\,coril\,term; N(q, \dot{q}) = \begin{bmatrix} -p_3\sin(q_2)\dot{q}_2 & -p_3\sin(q_2)(\dot{q}_1 + \dot{q}_2 \\ p_3\sin(q_2)\dot{q}_1 & 0 \end{bmatrix}\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} \\ &The\,friction\,term; F(q, \dot{q}) = \begin{bmatrix} f_{d1} & 0 \\ 0 & f_{d2} \end{bmatrix}\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} + \begin{bmatrix} f_{s1} & 0 \\ 0 & f_{s2} \end{bmatrix}\begin{bmatrix} \mathrm{sgn}(\dot{q}_1) \\ sign(\dot{q}_2) \end{bmatrix} \end{aligned}\right\} \tag{8}$$

The nominal values of the manipulator parameters are (the inertial parameters have been regrouped into parameters p_1, p_2 *and* p_3, the mass distribution is not given): $p_1 = 3.473\ kgm^2$; $p_2 = 0.193\ kgm^2$ and $p_3 = 0.242\ kgm^2$ whereas the friction constants as: $f_{d1} = 1.3\ \tilde{I}$, $f_{d2} = 0.88\ N$; $f_{s1} = 1.519\ Nm/s$, and $f_{s2} = 0.932\ Nm/s$.
The gravity vector $G(q)$ equals to zero, because the robot has only horizontal motion.

Constraints

The joint limit input torque values (input constraints) are [14]:

$$\tau_{jo\,\mathrm{int(max/min)}} = \pm[225.2,\ 36.4]\ Nm \tag{9}$$

The output constraints are listed in Table (1) below, where subsequent columns contain: joints number, links length, twists angle, off-set and last column shows the maximum angles swept by joints movements. L_i and d_i are the length and off-set of link i.

Table 1: Links parameters of the 2-DOF's Robot using modified D-H convention

i	a_{i-1}	α_{i-1}	d_i	ϑ_i	ϑ_i limits Degrees
1	0	0	0	ϑ_1	$-25 < \vartheta_1 < 60$
2	L_1	0	d_2	ϑ_2	$-170 \prec \vartheta_2 \prec 170$

Desired trajectories

Trajectories are defined in joint space coordinates. For simulation, either a smooth trajectories of the 5th order or higher polynomial, with respect to time, describing paths from initial q_{int} position to the goal position q_g in time t_f with assumption of zero velocity and acceleration at start and end of the trajectory, Peter Corke jtraj toolbox may be used [15]. Alternatively, abrupt motion trajectories (step trajectories) are used. In this paper the later alternative is applied, because in this study high input changes are required, therefore the desired trajectories are given by:

$$q_i^d(t) = \begin{cases} 1 \ \forall t > 0, i = 1,\ 2 \\ 0 \ \forall t < 0, i = 1,\ 2 \end{cases} \tag{10}$$

where q_i^d is the desired trajectory for joint i.

APPLIED CONTROL SCHEME AND ALGORITHMS

The reference governor control scheme consists of two layers, the direct (basic) layer and the supervisory or governor (also called constraint control and optimizer) layer as shown in Figure (3). The supervisory control layer has joints pre-determined desired trajectories equation (10), whereas the direct control layer receives the optimal joint set-point trajectories from the supervisory (governor) layer, as following:

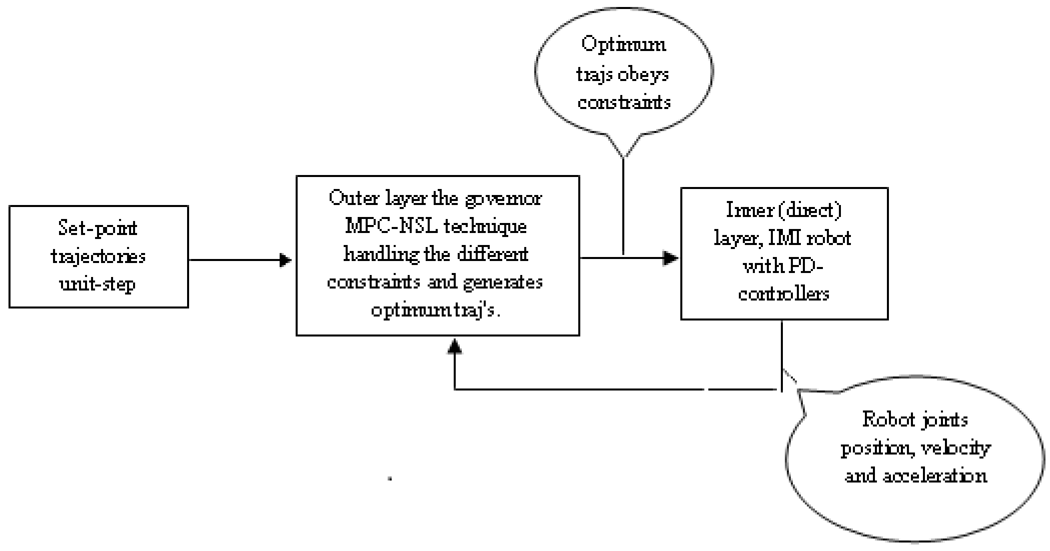

Figure 3: the applied control system structure

Direct (Basic) controller

The robot build-in PD-controllers will be considered as the direct controllers. Their roles are to generate the necessary manipulated variables (input to the robot's joints). The robot actuators input torque vector at sampling instant k, $\tau_d(k)$ is calculated according to the formula, dropping k for space whenever clear, [4, 5]:

$$\tau_d(k) = M(\ddot{q}^{opt} + K_p e(k) + K_v \dot{e}(k)) + N(q,\dot{q}) + F(\dot{q}) \quad (11)$$

For position control purpose, it is commonly working on forward dynamics:

$$\ddot{q}(k) = M^{-1}(q(k))[\tau_d(k) - N(q(k),\dot{q}(k)) - F(q(k),\dot{q}(k))] \quad (12)$$

From equation (11 and 12) we may compute the joints position, velocity and acceleration as:

$$\left.\begin{aligned} &\ddot{q} = M^{-1}(q^{opt})[\tau_d - N(q^{opt},\dot{q}^{opt}) - F(q^{opt},\dot{q}^{opt})] \\ &\quad = M^{-1}(q^{opt})[M(\ddot{q}^{opt} + K_p e(k) + K_v \dot{e}(k)) + V(q,\dot{q}) + F(\dot{q}) + \\ &\quad - N(q^{opt},\dot{q}^{opt}) - F(q^{opt},\dot{q}^{opt})] \\ &\dot{q}(k) = \Delta T\, \ddot{q}(k) + \dot{q}(k-1) \\ &q(k) = \Delta T\hat{}2\, \ddot{q}(k) + \Delta T\, \dot{q}(k-1) + q(k-1) \end{aligned}\right\} \quad (13)$$

where $K_p \in \Re^{n\times n}$ is the proportional gain diagonal matrix, $K_d \in \Re^{n\times n}$ is a diagonal matrix of derivative constants, $n = 2$. $e_d \in \Re^{n_y}$ is the angular position error vector ($e_d(k)$ = joints optimum reference position $q^{opt}(k)$ - joints current position $q(k)$ calculated from equation (13), $\dot{e} \in \Re^{n_y}$ is the joint velocity error vector ($\dot{e}(k)$ =joints optimum reference velocity $\dot{q}^{opt}(k)$ - joints current velocity $\dot{q}(k)$ calculated from equation (12), $n_y = 2$ is the number of outputs. The quantities $q^{opt}(k)$, $\dot{q}^{opt}(k)$ and $\ddot{q}^{opt}(k)$ are the joint position, the joint velocity and the second derivative of the optimal trajectory vector at instant *k* generated in the first layer, equation (4).

The Governor

It is a nonlinear device (computer program) occupying the higher layer in the hierarchical structure (see Figure 2 &3). The governor's applied control law is the MPC-NSL algorithm. The most important and distinctive role of this layer is to modify the reference (desired) trajectories supplied to the closed-loop system (direct control and plant) to enforce fulfillment of constraints and position tracking performance at the same time receives the updated joint position, velocity and acceleration, equation 13, which are used as a new process equilibrium points.

At the end of each optimization operation, optimal values of the predicted joint positions, velocities and accelerations denoted by $q^{opt}, \dot{q}^{opt}, \ddot{q}^{opt}$, equation 3, are sent to the basic PD controllers as the desired trajectories. Whereas the actual joint quantities $q(k), \dot{q}(k), \ddot{q}(k)$ generated in the direct layer, are send back to the governor for calculating the optimum $q^{opt}, \dot{q}^{opt}, \ddot{q}^{opt}$ values at instant k as clarified above.

Equation 13 reveals that, the forward dynamics explicitly include dynamics of the manipulator and the direct controller.

SIMULATION RESULTS

Simulation under bared unconstrained PD-controllers

In this part, the 2-DOF robot is simulated under PD-controllers alone. The system is tuned for best results of tracing, minimum overshoot and settling time. The applied control parameters are:

K_p= [450 0;0 60], K_d= [10 0;0 0.7], T_s= 0.05s.

The result (see Figure 4) shows quite high inputs are required with overshoots and long settling time.

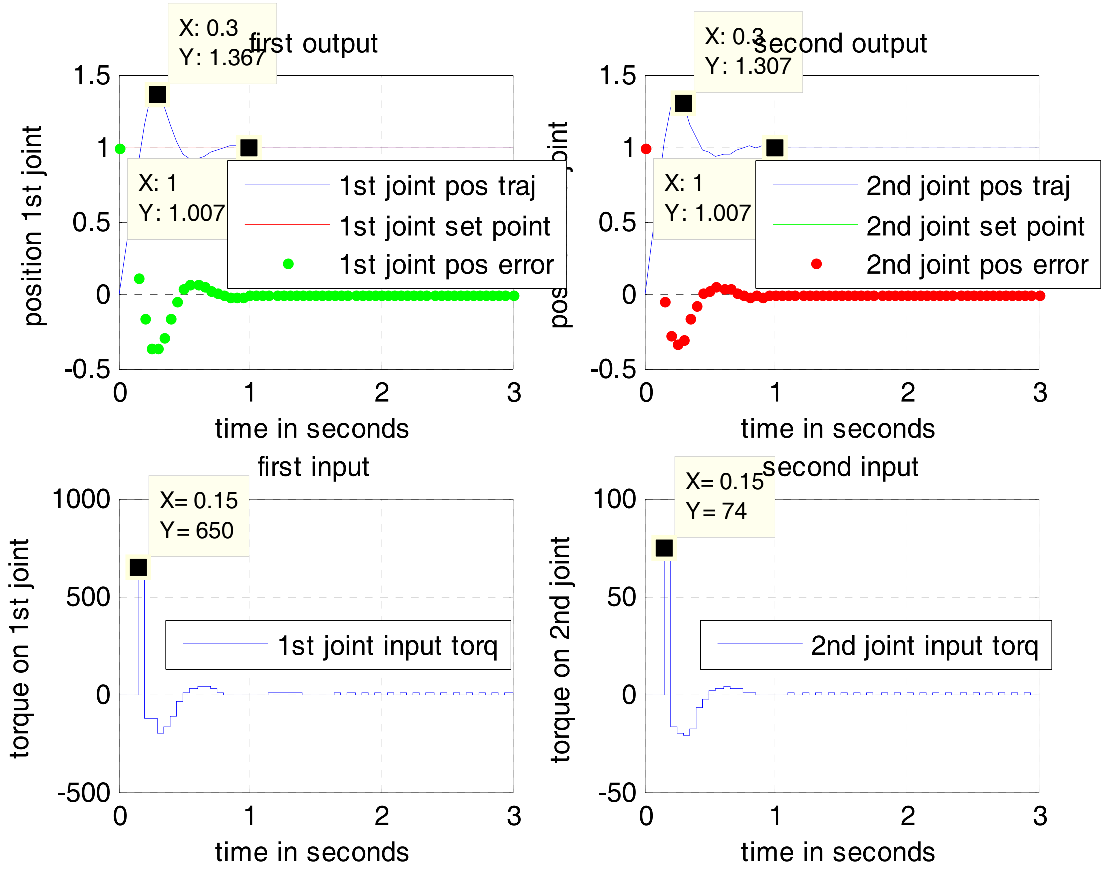

Figure 4: Simulation results under Un-constrained direct layer control only shows joint pos, joint pos error and the corresponding required input torque

Simulation under bared constrained PD-controllers

Appling the constraints to the bared PD-controllers certainly limit the required inputs, however the overshoot and settling time are not significantly affected, see Figure (5). The joint position errors are also shown in the figure. The applied controller parameters are:

K_p= [450 0;0 60], K_d= [10 0;0 0.7], T_s= 0.05s.

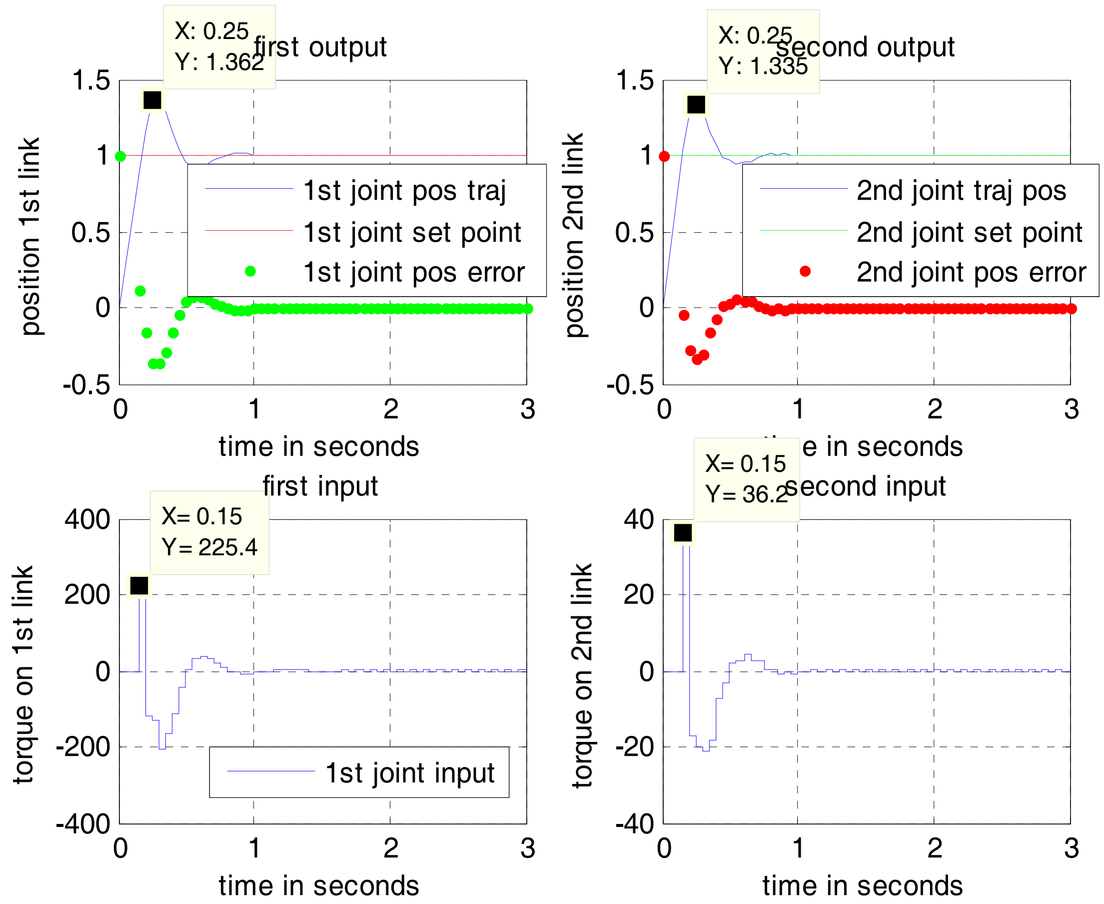

Figure 5: Results under constrained direct layer control only, joint position, joint position error and the corresponding input control signal

Simulation under Un-constrained governor

The main purpose of this simulation is to see the effect of adding the reference governor to the control system under the same applied conditions in the case of bared un-constrained PD-controllers. The controllers' parameters maintained:

K_p= [450 0;0 60], K_d= [10 0;0 0.7], T_s= 0.05s.

The governor's generated optimized set-point trajectories are shown in Figure (6). These optimum trajectories become the desired trajectories to the Un-constrained PD-controllers. Simulation of the governor shows tracking accuracy and relatively big reduction in input torques, see Figure (7). The governor control parameters are:

λ= [0.003 0;0 0.01], ψ= [18 0;0 3], T_s= 0.05s, N_p= 60, Nu= 4.

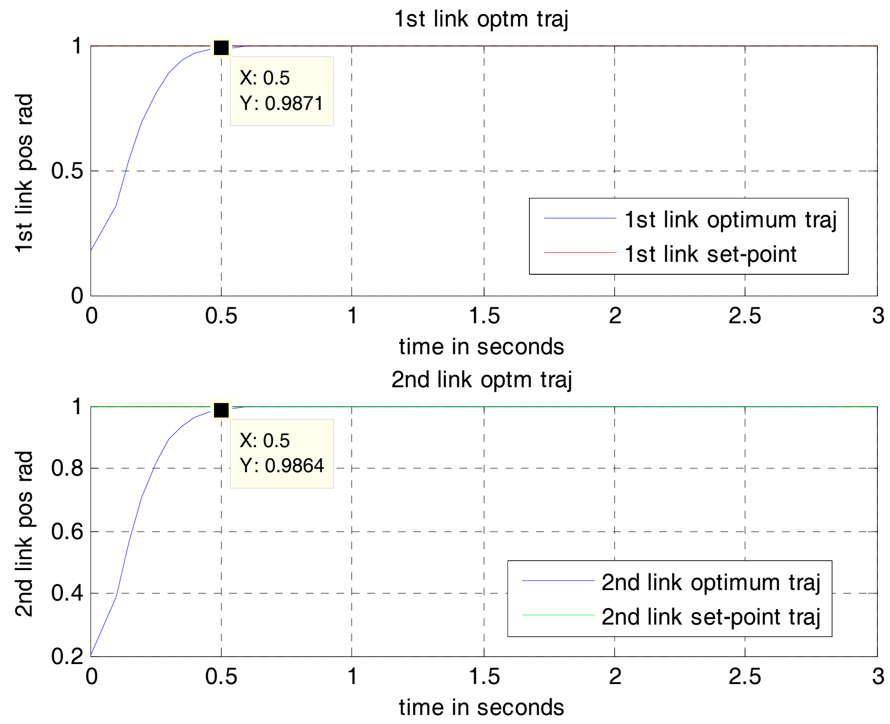

Figure 6: Results of simulation under Un-constrained integrated governor shows the generated optimum trajectories

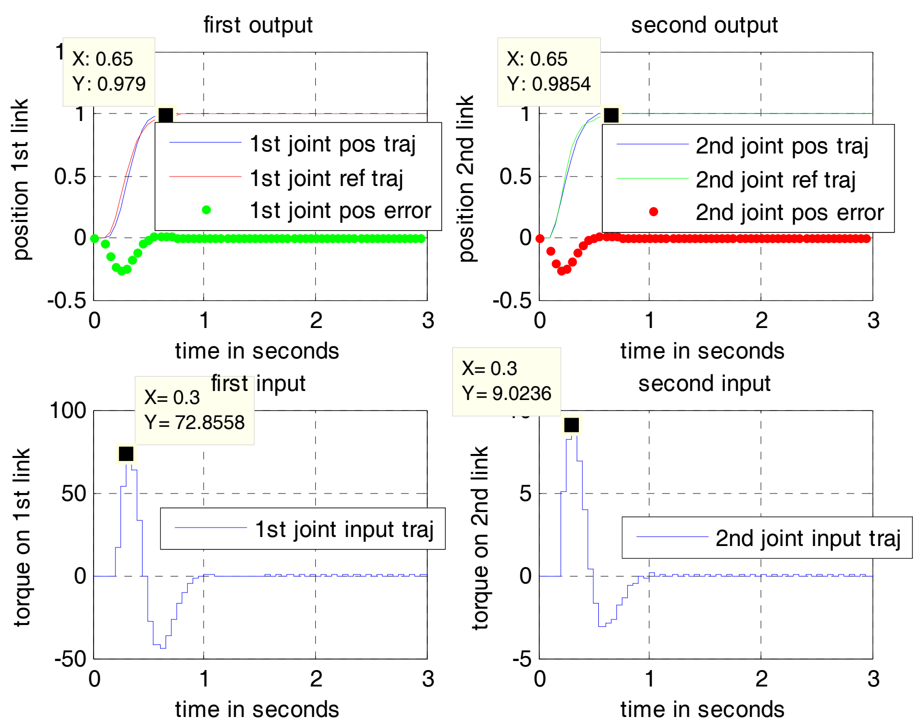

Figure 7: Results of simulation under Un-constrained integrated governor shows the joint positions and the corresponding required input torques and joint pos. errors

Simulation under constrained governor

In this part of simulation, the constraints are applied keeping the control parameters unchanged as in the case of 5.3. The results of simulation are shown in Figures (8 and 9). Figure (8) illustrates the generated optimized and constrained trajectories which fed to the direct layer to follow. Figure (9) shows the corresponding joint positions and required input torques. It is evident the achievement of both the accurate tracking and obeying the required constraints. The PD controllers' parameters are: K_p= *[450 0;0 60]*, K_d= *[10 0;0 0.7]* and for the governor: λ= *[0.003 0;0 0.01]*, ψ= *[18 0;0 3]*, T_s= *0.05s*, N_p= *60*, *Nu= 4*.

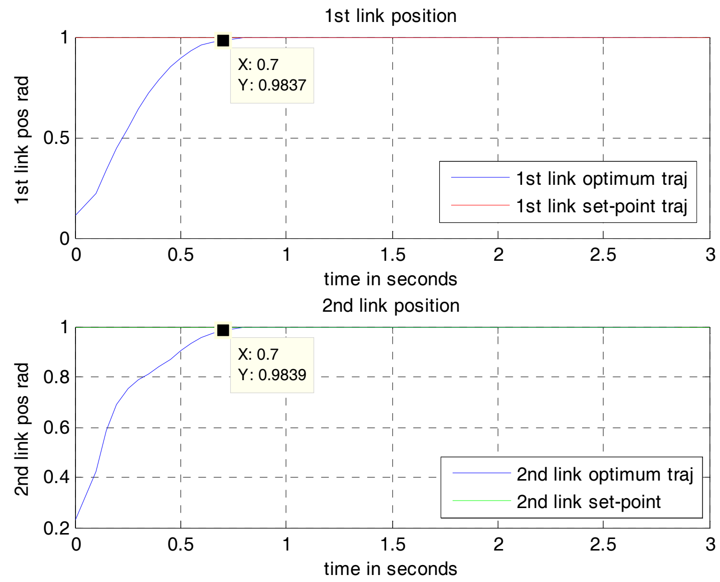

Figure 8: Simulation result shows the generated optimum trajectories under constrained integrated governor

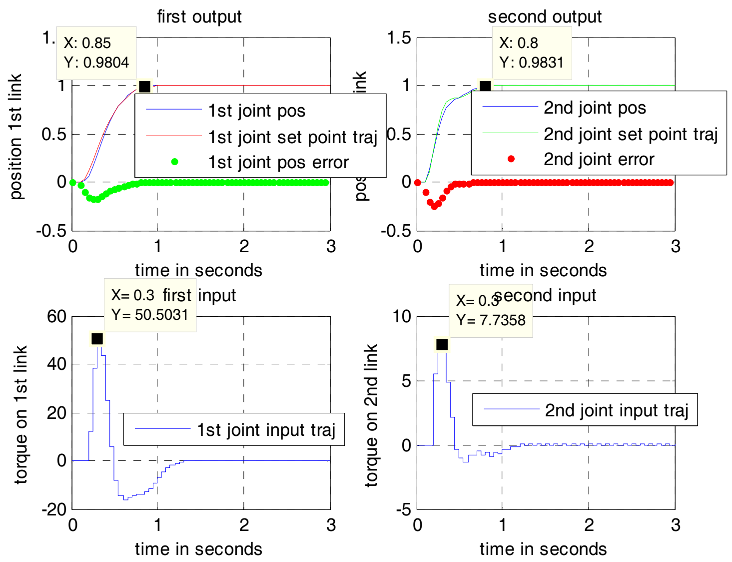

Figure 9: Results of simulation under constrained integrated governor show the joints positions, joint position errors and the corresponding required input torques

CONCLUSION

In this paper a 2-DOF's robot controlled with build-in PD-controllers is operating under supervision of MPC-NSL algorithm (governor) is investigated. The main purpose of the governor is to handle the manufacturer operation constraints. The governor uses the process output values as equilibrium points in its algorithm calculation in a sense the process and the governor algorithm form an integrated control system. The process is simulated in absence of the governor with and without applying the inputs constraints. For comparison, the same process is simulated involving the unconstrained and constrained governor. The results of simulation prove the promised advantage of using the integrated governor. The advantages appear mainly in the high reduction of the required input torques and shorter settling time with no overshoots. Moreover, the structure of the proposed scheme is easy and can be realized at a very low effort because the MPC-NSL is simply a computer program. Further studies should be devoted to full nonlinear control algorithms.

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