Curvature Tracking of a Double Section Soft Bending Actuator Using MPC Method

1st Sina Rabiee
Department of Electrical Engineering
AmirKabir university of Tech.
Tehran, Iran
sinarabiee@aut.ac.ir

2nd Sajad Sadeghi Nalkenani
Department of Mechanical Engineering
AmirKabir university of Tech.
Tehran, Iran
sajadsadeghi996@aut.ac.ir

3rd Iman Sharifi
Department of Electrical Engineering
AmirKabir university of Tech.
Tehran, Iran
imansharifi@aut.ac.ir

Abstract—The movement control of soft robot manipulators with pneumatic actuators is an emerging and interesting new topic in automatically controlled robots. In this paper, the Model Predictive Control (MPC) method, is proposed to solve the curvature tracking problem of a two link soft robot with bending pneumatic actuators and to further reduce the steady state error and oscillations. First, we calculate a proper mapping matrix between the soft robot and the rigid manipulator with equal dynamics characteristics. After that, the MPC method is used to realize the curvature tracking control of the robot in question. Stability of the proposed MPC method is proven using lyapunov theory of stability. To evaluate the performance of the MPC controller, simulations are performed and the results are compared to the ones obtained from a tuned PID controller. This verifies the effectiveness of the control approach mentioned above for the dynamic control of the soft robot manipulators.

Index Terms—Soft robot manipulators, Pneumatic actuators, Model Predictive Control (MPC), Curvature Control

I. Introduction

In the realm of robotics, living organisms have always been a source of innovation [1]. Compliance and secure interaction with the environment are among many interesting advantages of this commodities. Soft robots are build from highly flexible materials like fluids, gels or elastomers [2]. Because of their compliance with their surroundings, these robots can be used in fields that human contact or dealing with delicate items is necessary. For example these manipulators can be very useful in rehabilitation applications.

One of the major applications of soft robots is in the development of grippers [3] and prosthetic gloves [5], [6]. This application can be divided to static grasping and dynamics grasping or in-hand object manipulation (IOM). Capabilities of soft manipulators enables prosthetic hands to imitate the human hand more accurately.

Numerous studies has been done to calculate the dynamic model of soft actuators. Wang and Hirai [4] develop a serial rigid manipulator with point masses and viscoelastic revolute joints to model each soft finger Using the Lagrangian equation. Piecewise constant curvature (PCC) hypothesis is considered in the work of Falkenhahn et al. [7]. Modeling the viscoelasticity is done by the means of parallel dampers and springs for each section of the manipulator.

In controller design on a three-sectioned continuum robot, Falkenhahn et al. [8] designed a controller that was a combination of feedforward and feedback linearization controllers.

The conventional and simpler control methods, such as PID (Proportional Integral Derivative) [9] and LQR (Linear Quadratic Regulator) [10], can achieve a stable and effective control of soft manipulators. Their primary advantage is their simplicity. However, cumbersome gain tuning, difficulties in obtaining optimal parameters of classical PID controllers [11], Not being able to deal with changes in the system and adjustment requirements for implementation on a soft robots, are among many disadvantages of this methods. As a result, advanced control methods have been the center of attention in the past decade. The control techniques like Adaptive Control [12], Sliding Mode Control [13] and Robust Control [14] are highly promising for implementation on a rigid and soft manipulator. Alian et al. [21] designed an adaptive sliding mode controller for a 2-link soft bending pneumatically actuated robot. Despite their promising performance, this methods have some disadvantages. For instance having a regressor form is crucial for using adaptive control methods, or using sliding mode controllers may result in chattering effects. However, Model Predictive Control (MPC) or Receding Horizon Control (RHC) is not only robust enough to eliminate the impacts of nonlinear behaviour, coupling effects in dynamics, and model complexity, but also adheres to the state and input variable requirements and constraints [15].

MPC applications in robot manipulator control have grown in popularity in recent years. There are certain complications due to the manipulator's non-linearities. The linearization approach with inverse dynamics feedback is the most commonly used solution. The disadvantage of this method is that compensation measures after linearization are not considered [16], [17]. Another option is to integrate MPC with other advanced control techniques. In [18], Baek presents a hybrid form of MPC and H-infinity control. The result of this combination, however, could

979-8-3503-0810-5/23/$31.00

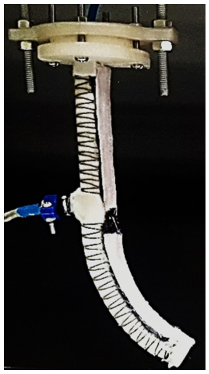

Fig. 1. Two link soft bending pneumatically actuated soft robot manipulator reinforced on one side with fiber and inputs connected to controlled pressure valves.

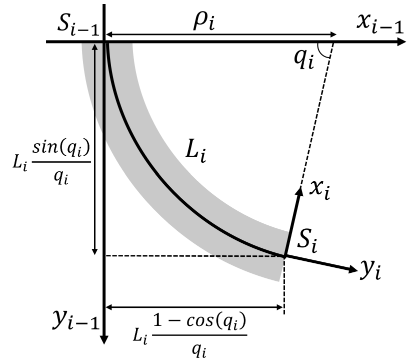

Fig. 2. Two dimensional constant curvature segment kinematic representation. The length of the segment is L_i, and q_i is the degree of curvature.

not combine the respective advantages of these schemes while trying to avoid their flaws.

There has been very few studies on implementing MPC on soft robots. In [19] data-driven approaches and the Koopman operator theory are used to derive a linear model for MPC which preforms better than the linear state space models for the same system. In this paper the dynamics equations for a soft bending pneumatic actuator is calculated with transformation of an equivalent rigid robot based on the works in [20]. The MPC proposed in [15] is recalculated with a new and more rational objective function based on error and input magnitudes for the soft robot while considering constant curvature constraints on actuator.

In this paper we derive the kinematics and dynamics equations for the robot manipulator shown in Fig. 1. After that we define an objective function based on the future values of the manipulators variables. Finding the MPC method gains consists of solving the optimization problem based on the objective function defined above. Finally, we demonstrate the efficacy of the proposed controller using simulation on an object grasping task and compare the results to those of the typical PID controller.

II. Preliminaries

In this section we introduce two types of modeling for soft robot manipulators. In different applications, soft manipulator can be estimated with an equivalent rigid manipulator if they have the same characteristics needed in the named application. Using a proper transformation matrix, any equation obtained for rigid bodies can be modified for the use in soft manipulators.

A. Kinematic Model

Each actuator has a curvature described by q_i. The transformation matrix T^i_{i-1} for each actuator gives the positioning of the actuators tip relative to its base frame. Fig. 2 shows the bending pneumatic actuator assuming the curvature along this link is constant (constant curvature assumption). The two frames can be converted together using (1). It is good to note that this actuators are planar, So there is no movement in Z-axis and the transformation matrices are 3×3.

$$T^i_{i-1}(q_i) = \begin{bmatrix} \cos(q_i) & -\sin(q_i) & L_i \frac{1-\cos(q_i)}{q_i} \\ \sin(q_i) & \cos(q_i) & L_i \frac{\sin(q_i)}{q_i} \\ 0 & 0 & 1 \end{bmatrix} \quad (1)$$

B. Dynamic Model

If two robot have the same inertia characteristics, they will have similar dynamic behavior. The 4-DOF RPPR rigid manipulator showcased in Fig. 3-B, is a good estimate for the soft bending actuators in 3-A with constant curvature. The dynamics equation of a robotic manipulator using Euler–Lagrange method (keeping stiffness and damping coefficients of the material in mind) is formulated in (2).

$$M(q)\ddot{q} + (C(q,\dot{q}) + D)\dot{q} + g(q) + Kq = \tau + J^T f_{ext} \quad (2)$$

where the $M(q)$ is the positive definite mass matrix, $C(q,\dot{q})$ is the coriolis matrix, D is a constant damping coefficient matrix, K is a constant stiffness coefficient matrix, $g(q)$ is a vector containing gravity effect on joints center of masses, τ is the vector of joint inputs (air pressure in the case of soft manipulator), J is the jacobian matrix of end-effector and $q = [q_1 q_2 \cdots q_n]^T$ is the vector of joint variables (actuator curvature in the case of soft manipulator). Reformulating (2) results in:

$$\begin{aligned} \ddot{q} =& M^{-1}(q) \\ & [-(C(q,\dot{q}) + D)\dot{q} - g(q) - Kq + \tau + J^T f_{ext}] \end{aligned} \quad (3)$$

C. Mapping Matrix

In order to take advantage of control strategies which are introduced in rigid robots, we approximate the soft robot behavior with an equivalent rigid body under the hypothesis of piecewise constant curvature. By the works in [20] an appropriate rigid robot model would be the 4-DOF RPPR manipulator. Denavit–Hartenberg

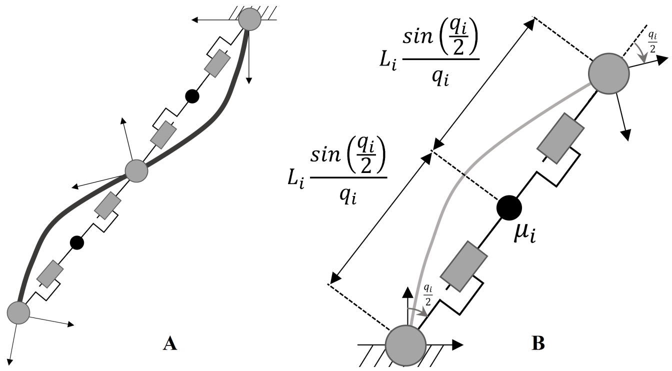

Fig. 3. Soft robot with 2 pneumatic actuators (A) and an equivalent 4-DOF RPPR rigid manipulator for each soft bending actuator (B).

parameters of the RPPR rigid robot are chosen so that it will mimic the dynamic characteristics of the soft bending actuator. This parameters are listed in Table I. The Mapping vector form the rigid robot to the soft robot is described in (4). The final transformation matrix for a soft manipulator with n actuators is formulated in (5). Using the calculated transformation matrix and its jacobian, one can easily derive the dynamics equation for soft robot manipulator [20].

$$m_i\left(q_i\right) = \begin{bmatrix} \frac{q_i}{2} & L_i\frac{\sin(\frac{q_i}{2})}{q_i} & L_i\frac{\sin(\frac{q_i}{2})}{q_i} & -\frac{q_i}{2} \end{bmatrix} \tag{4}$$

$$m_(q) = \begin{bmatrix} m_1^T(q_1) & m_2^T(q_2) & \cdots & m_n^T(q_n) \end{bmatrix}^T \tag{5}$$

TABLE I
Denavit–Hartenberg Parameters of the RPPR Rigid Robot Equivalent to a Single Constant Curvature Soft Bending Actuator

Link	θ	d	α	a
1	$\frac{q_i}{2}$	$\frac{q_i}{2}$	0	$\frac{\pi}{2}$
2	0	$L_i\frac{\sin(\frac{q_i}{2})}{q_i}$	0	0
3	0	$L_i\frac{\sin(\frac{q_i}{2})}{q_i}$	0	$\frac{\pi}{2}$
4	$\frac{q_i}{2}$	0	0	0

III. Curvature Control of The Soft Bending Actuator

There are numerous methods of control for robotic manipulators. The control method is chosen according to the limitations in equipment and the application in question. MPC consists of solving an optimization equation (analytically or numerically in each step) to find the desired control gain. The control law is used to produce the required levels of air pressure inputs with the help of pressure valves and sensors.

A. MPC for Soft Bending Actuators

Calculating the MPC gain can be obtained by solving the optimization problem below:

$$T(k)^* = \text{argmin}_{T(k)} J(q(k), \dot{q}(k), T(k), m, p) \tag{6}$$

where $T(k)$ is the vector of $\{\tau(k+i|k),\ i = 0, \cdots, m-1\}$. Using the Taylor series, one can define the predicted curvature values as [22]:

$$Q(k+1|k) = \mathbf{I}_a q(k) + \mathbf{I}_b \dot{q}(k) + \mathbf{A}\ddot{Q}(k) \tag{7}$$

where

$$Q(k+1 \mid k) = \left[q(k+1 \mid k)^T,\ \cdots,\ q(k+p \mid k)^T\right] \tag{8}$$

$$\ddot{Q}(k) = [\ddot{q}^T(k),\ \ddot{q}^T(k+1),\ \cdots,\ \ddot{q}^T(k+m-1)]^T \tag{9}$$

$$I_a = [I,\ I,\ \cdots,\ I]^T_{pn\times n} \tag{10}$$

$$I_b = [I,\ 2I,\ \cdots,\ pI]^T_{pn\times n}\,\Delta t \tag{11}$$

$$A = \begin{bmatrix} \frac{1}{2}I & 0 & 0 & \cdots & 0 \\ \frac{3}{2}I & \frac{1}{2}I & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{2m-1}{2}I & \frac{2m-3}{2}I & \frac{2m-5}{2}I & \cdots & \frac{1}{2}I \\ \frac{2m+1}{2}I & \frac{2m-1}{2}I & \frac{2m-3}{2}I & \cdots & \frac{3}{2}I \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{2p-1}{2}I & \frac{2p-3}{2}I & \frac{2p-5}{2}I & \cdots & \frac{2p-2m+1}{2}I \end{bmatrix} \Delta t^2 \tag{12}$$

where Δt is the sampling period, p is prediction horizon and m is the control horizon. Using (3) and considering no external forces on the manipulator:

$$\ddot{Q}(k) = \mathbf{M}(T - H) \tag{13}$$

where

$$\mathbf{M} = \text{diag}(M^{-1}(q(k+1)) \quad M^{-1}(q(k+2)) \quad \cdots \quad M^{-1}(q(k+m))) \tag{14}$$

$$H = [h^T(q(k+1), \dot{q}(k+1)) \quad h^T(q(k+2), \dot{q}(k+2)) \quad \cdots \quad h^T(q(k+m), \dot{q}(k+m))] \tag{15}$$

Objective function is defined as:

$$J(q, \dot{q}, T(k), m, p) = [\Psi_q(Q(k+1|k) - Q_d(k+1|k))]^T [\Psi_\theta(Q(k+1|k) - Q_d(k+1|k))] + [\Psi_\tau T(k)]^T [\Psi_\tau T(k)] \tag{16}$$

where the design parameters matrices and the desired curvature joint vectors are:

$$\Psi_q = \text{diag}(\Psi_{q,1}, \Psi_{q,2}, \cdots, \Psi_{q,p}) \tag{17}$$

$$\mathbf{\Psi}_\tau = \text{diag}(\Psi_{\tau,1}, \Psi_{\tau,2}, \cdots, \Psi_{\tau,m}) \tag{18}$$

$$Q_d = \left[q_d(k)^T q_d(k+1)^T \cdots q_d(k+p)^T\right]^T \tag{19}$$

Plugging (13) in (16), the objective function is simplified as:

$$J = T^T(k)PT(k) - Z(k+1|k)^T T(k) + L(k+1|k) \tag{20}$$

where

$$P = [\Psi_q A\mathbf{M}]^T [\Psi_q A\mathbf{M}] + \Psi_\tau^T \Psi_\tau \tag{21}$$

$$Z(k+1|k) = [\Psi_q A\mathbf{M}]^T \Psi_q E(k+1|k) + [\Psi_q E(k+1|k)]^T \Psi_q A\mathbf{M} E(k+1|k)^T \tag{22}$$

$$L(k+1|k) = E(k+1|k)^T \Psi_q^T \Psi_q E(k+1|k) \tag{23}$$

$$E(k+1|k) = A\mathbf{M}H + Q_d(k+1|k) - I_a q - I_b \dot{q} \tag{24}$$

Solving the optimization problem yields the following:

$$\begin{aligned}&\frac{\partial J}{\partial T(k)} = 0\\ &\rightarrow 2PT(k)^* - F = 0\\ &\rightarrow T(k)^* = \frac{1}{2}P^{-1}F = K_{mpc}E(k+1|k)\end{aligned} \tag{25}$$

where

$$K_{mpc} = P^{-1}[A\mathbf{M}]^T\Psi_q^T\Psi_q \tag{26}$$

$T(k)^*$ has the future inputs which are not applicable. Using the receding horizon method, we extract the input calculated for the kth step and discard the rest:

$$\tau(k)^* = k_{mpc}E(k+1|k) \tag{27}$$

where

$$k_{mpc} = I_eP^{-1}[A\mathbf{M}]^T\Psi_q^T\Psi_q \tag{28}$$

where

$$I_e = [I \quad 0 \quad \cdots \quad 0]_{n\times nm} \tag{29}$$

Applying the input calculated by the MPC method to the system without external forces:

$$\begin{aligned}M(q(k))\ddot{q}(k) + (C(q(k),\dot{q}(k)) + D)\dot{q}(k) + g(q(k))\\ + Kq(k) = \tau(k)^*\end{aligned} \tag{30}$$

B. Stability Analysis

Stability of the suggested predictive controller is demonstrated in this section using lyapunov's stability theorem and the works done in [22].
We need to define the system in state space form. Considering (7) and (13), we can write the desired future curvature vector as:

$$\begin{aligned}Q_d(k+1|k) =& I_aq_d(k) + I_b\dot{q}_d(k) + A\mathbf{M}(q_d(k))\\ &(T_d - H(q_d(k),\dot{q}_d(k)))\end{aligned} \tag{31}$$

The acceleration of each joint with the input calculated by the MPC method is:

$$\ddot{q}(k) = M^{-1}(q(k))\left[\tau^*(k) - h(q(k),\dot{q}(k))\right] \tag{32}$$

for simplicity, from this point on $\mathbf{M}(q(k)) = \mathbf{M}$, $h(q(k),\dot{q}(k)) = h$ and $H(q(k),\dot{q}(k)) = H$. Taking (27) into consideration:

$$\begin{aligned}&\ddot{q}(k) = M^{-1}[k_{mpc}\\ &[Q_d(k+1|k) + A\mathbf{M}H - I_a(q(k)) - I_b\dot{q}(k)] - h]\end{aligned} \tag{33}$$

replacing $Q_d(k+1|k)$ from (31) and taking $\mathbf{M}(q_d(k)) = \mathbf{M}_d$ and $H(q_d(k),\dot{q}_d(k)) = H_d$:

$$\begin{aligned}\ddot{q}(k) = M^{-1}[k_{mpc}[(I_aq_d(k) + I_b\dot{q}_d(k) + A\mathbf{M}_d(T_d - H_d))\\ + A\mathbf{M}H - I_aq(k) - I_b\dot{q}(k)] - h]\end{aligned} \tag{34}$$

Defining the error variable q_e and its derivatives as:

$$q_e(k) = q_d(k) - q(k) \tag{35}$$

$$\dot{q}_e(k) = \dot{q}_d(k) - \dot{q}(k) \tag{36}$$

$$\ddot{q}_e(k) = \ddot{q}_d(k) - \ddot{q}(k) \tag{37}$$

replacing (34) in (37):

$$\ddot{q}_e = \ddot{q}_d(k) - M^{-1}k_{mpc}(I_aq_e(k) + I_b\dot{q}_e(k)) - X(k) \tag{38}$$

where

$$X(k) = M^{-1}(k_{mpc}A[\mathbf{M}_d(T_d - H_d) + \mathbf{M}H] - h) \tag{39}$$

Rewriting this equation with the state vector $x(k) = [x_1(k)x_2(k)]^T$ where $x_1(k) = q_e(k)$ and $x_2(k) = \dot{q}_e(k)$:

$$\begin{cases}\dot{x}_1(k) = x_2(k)\\ \dot{x}_2(k) = \ddot{q}_d(k) - M^{-1}k_{mpc}(I_ax_1 + I_bx_2) - X(k)\end{cases} \tag{40}$$

the state space form of (40):

$$\begin{aligned}\dot{x}(k) = &\begin{bmatrix}0 & I\\ -M^{-1}k_{mpc}I_a & -M^{-1}k_{mpc}I_b\end{bmatrix}x(k)\\ &+ C(q(k),\dot{q}(k),q_d(k),\dot{q}_d(k))\end{aligned} \tag{41}$$

where

$$C(q(k),\dot{q}(k),q_d(k),\dot{q}_d(k)) = \begin{bmatrix}0\\ -X(k)\end{bmatrix} \tag{42}$$

Take the lyapunov candidate function as:

$$V = \frac{1}{2}x_1^TM^{-1}k_{mpc}I_ax_1 + \frac{1}{2}x_2^Tx_2 \tag{43}$$

where $M^{-1}k_{mpc}I_a$ is a positive definite matrix, so V is a positive scalar. Taking the derivative of (43):

$$\dot{V} = x_1^TM^{-1}k_{mpc}I_a\dot{x}_1 + x_2^T\dot{x}_2 \tag{44}$$

Replacing $\dot{x}_1$ and $\dot{x}_2$ from (40):

$$\begin{aligned}\dot{V} =& x_1^TM^{-1}k_{mpc}I_ax_2 + x_2^T[\ddot{q}_d(k) - M^{-1}k_{mpc}\\ &(I_ax_1 + I_bx_2) - X(k)]\end{aligned} \tag{45}$$

Simplifying the resultant derivative:

$$\dot{V} = -x_2^TM^{-1}k_{mpc}I_bx_2 - x_2^TX(k) \tag{46}$$

Taking the norm of the calculated derivative:

$$\dot{V} \le -\|x_2\|^2\lambda_{\min}(M^{-1}k_{mpc}I_b) - \|x_2\|\|X(k)\| \tag{47}$$

so the derivative is negative if:

$$\lambda_{\min}(M^{-1}k_{mpc}I_b) > 0 \tag{48}$$

$$\|x_2\| > -\frac{\|X(k)\|}{\lambda_{\min}(M^{-1}k_{mpc}I_b)} \tag{49}$$

Since $\lambda_{\min}(M^{-1}k_{mpc}I_b)$ is positive, both conditions are satisfied and the errors are ultimately bounded.

IV. Simulation

In this section the curvature tracking of a 2-link soft bending actuator robot manipulator using the formulated model predictive method is simulated in Simulink. For better clarification of the proposed method effectiveness, a PID controller is tuned to track the same input on the same soft robot. The desired trajectory of the end effector is designed such that it mimics a grasping situation, so the small steady state error and minimal oscillation in transient state is required. The desired curvature trajectories are taken as saturation-like functions with the upper bound set such that the end effector position reaches the desired coordinates of (x,y) = (2.087, 141.397) mm. Keep in mind that solving the inverse kinematics equation results in number of final values for link curvatures that realize the coordinate mentioned above.

$$\begin{cases} q_1 = 0.1 & t \leq 0.5 \\ q_2 = 0.1 & \\ q_1 = 0.25(t-0.5)+0.1 & 0.5 < t \leq 1.5 \\ q_2 = 0.35(t-0.5)+0.1 & \\ q_1 = 0.35 & t > 1.5 \\ q_2 = 0.45 & \end{cases} \tag{50}$$

Control horizon and prediction horizon are taken equal and small to reduce the calculations needed in each step ($m = p = 2$). Sampling time is 1 ms with the fixed time Dormand-Prince solver. The physical specification of the manipulator in question is listed in table III. The positive definite controller parameters used in MPC method are chosen as (51). Because the error and the input of the present time is of high importance, the weights related to this properties in the gain matrices are significantly larger than the weights acting on next step errors and inputs.

$$\begin{aligned} \Psi_q &= \mathrm{diag}\{800I_2, 100I_2\} \\ \Psi_\tau &= \mathrm{diag}\{5I_2, 0.1I_2\} \end{aligned} \tag{51}$$

PID controller is a simple yet effective and useful tool for controlling different systems. For the sake of comparison, a PID controller is tuned to track the same inputs for each link. The controller gains are listed in table (II).

TABLE II
Tuned PID Controller Gains

Controller Gains	Magnitude
K_p	4
K_I	1
K_d	0

Fig. 4 and Fig. 5 show the curvature of the first and second link controlled with the MPC method in comparison with the PID controller and the desired value, respectively. For better understanding the superiority of the model predictive controller,' Fig. 6 shows the comparison of the error from the actual value for the first and second actuators. The control effort that caused the outputs mentioned before is depicted and Fig. 7. Fig. 8 showcases the changes of the objective function (16) with respect to time. The end effector coordinate in X-Y plane for both controllers is shown in Fig. 9. As it can be seen in this figure, the steady state error for MPC in X-axis direction is 0.071 mm and in Y-axis direction is 0.038 mm. This errors are considerably lower than the errors obtained from the PID controller which are 0.272 mm and 0.556 mm in X-axis and Y-axis, respectively.

TABLE III
Soft Robot Manipulator Physical Parameters

	L(mm)	m(g)	K (Nm/rad)	D (Nms/rad)
Link 1	67	20	0.068	0.0029
Link 2	77	25.1	0.07	0.0029

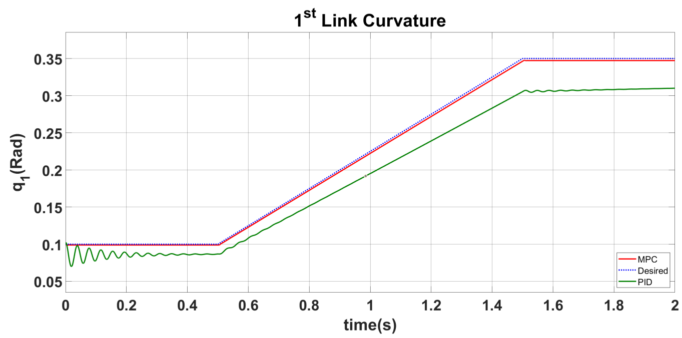

Fig. 4. Performance of the MPC method and Tuned PID controller for the first soft actuator. PID controller has some oscillations at the beginning and in places where there is a change in the desired trajectory.

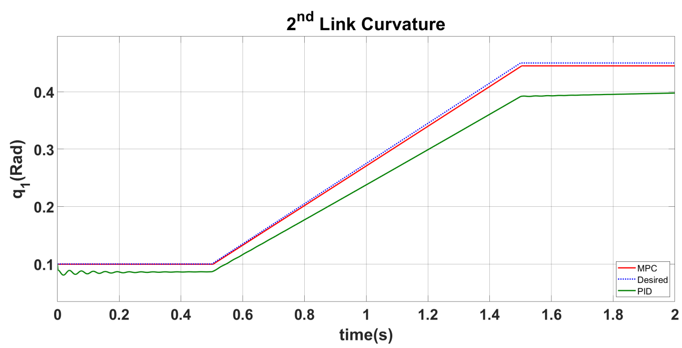

Fig. 5. Performance of the MPC method and Tuned PID controller for the second soft actuator. Oscillations caused by the PID controller are smaller for this link because there is no wight acting on the end of it.

Another intuitive simulation scenario can be the sine wave tracking of each pneumatic actuator. It is shown that the highest working frequency (without loss of movement range) for a human finger is lower than 2Hz [23]. Given that the mentioned manipulator will be used to mimic the

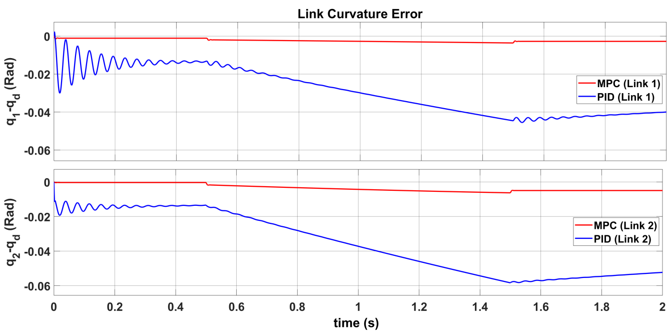

Fig. 6. Curvature error for the first (top) and second (bottom) link in MPC and PID. Lower error levels can be seen for the MPC method. There is no wight connected to the end of the second link, So smaller oscillations can be seen from the PID controller.

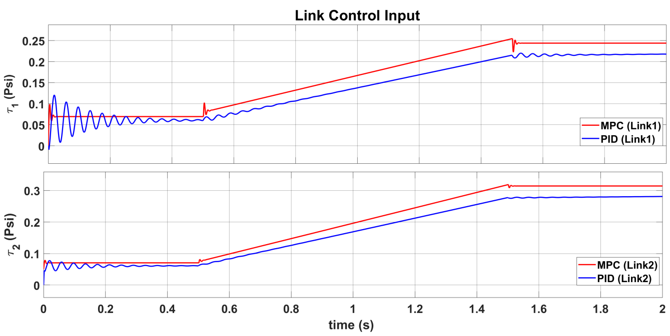

Fig. 7. Control input signal generated for the first (top) and second (bottom) link by model predictive controller in comparison with PID controller. There are high oscillations in PID input which cause oscillations of the same nature in output.

behavior of a genuine human finger, the desired trajectory is selected as shown in (52).

$$q_1 = q_2 = [30 + 10sin(4\pi t)] \times \frac{\pi}{180} \tag{52}$$

Fig. 10 and Fig. 11 depict the curvature of the first and second links controlled by the MPC approach in comparison to the PID controller and the desired sine wave mentioned above. As it is apparent, the link curvature

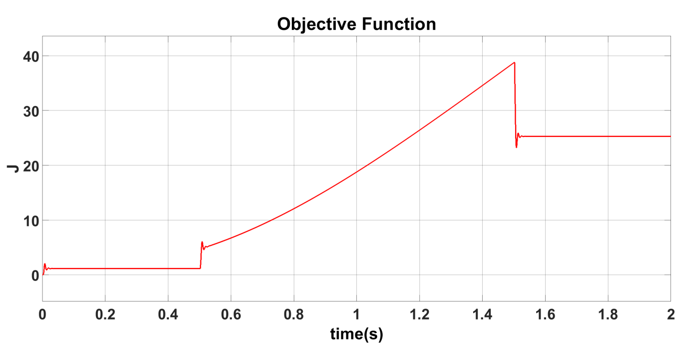

Fig. 8. Changes of the objective function versus time. As the desired value starts increasing, control input increases to match the output with the desired value. This causes the Objective function norm to rise.

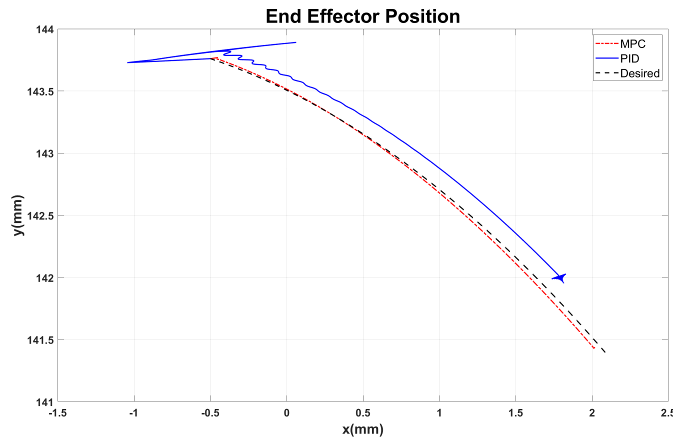

Fig. 9. End effector position in X-Y plane. MPC method has less oscillations and steady state error. It also offers better transient behavior than PID.

achieved by the MPC method contains less oscillations at the start of simulation and converges to the desired curvature more quickly. Less tracking error is also provided in the subsequent stages of simulation by the MPC.

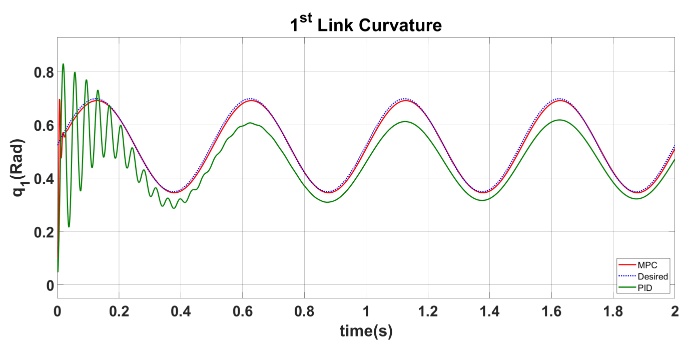

Fig. 10. Performance of the MPC method in comparison with the desired value and PID controller for the first soft actuator. Using MPC results in lower tracking error, faster convergence to the desired trajectory and less oscillations.

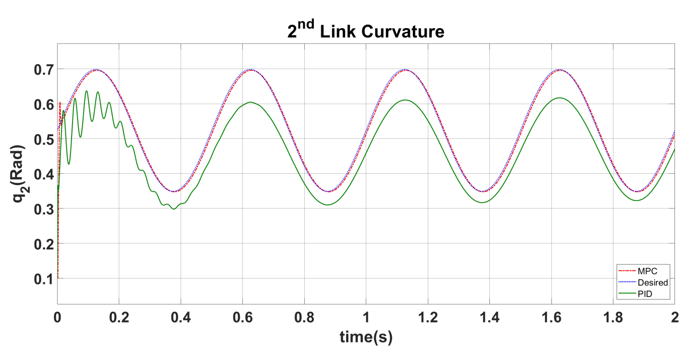

Fig. 11. Performance of the MPC method in comparison with the desired value and PID controller for the second soft actuator. Oscillations caused by the PID controller and MPC are smaller for this link because there is no wight acting on the end of it.

V. Conclusion

This article introduces a model predictive approach for soft robot manipulators. An optimization problem based on future values of joint variables and inputs was solved to derive the MPC gains. Simulations were conducted to show the superiority of MPC method over the conventional methods of control such as PID controller. The MPC method offers smaller steady state errors and fewer oscillations for the same desired curvature trajectory in comparison to the PID controller. Furthermore, cumbersome gain tuning in the beginning stages of controller design and in the case of a change in system characteristics is not needed when using the model predictive control algorithms.

In future works, a hybrid type of controller consisting of an Integrator added to the demonstrated MPC method can be studied to reduce the steady state error. Different type of restrictions, such as pressure constraints, can be considered to stimulate a more real and practical application. Adding the external forces term and treating it as a disturbance or uncertainty can be explored in the future as well.

References

[1] D. Rus and M. T. Tolley, “Design, fabrication and control of soft robots,” Nature, vol. 521, no. 7553, pp. 467–475, 2015.

[2] C.Majidi, “Soft robotics: A perspective—Current trends and prospects for the future,” Soft Robot., vol. 1, no. 1, pp. 5–11, 2014.

[3] J. Zhou, S. Chen, and Z. Wang, “A soft-robotic gripper with enhanced object adaptation and grasping reliability,” IEEE Robot. Autom. Lett., vol. 2, no. 4, pp. 2287–2293, Oct. 2017.

[4] Z.Wang and S. Hirai, “Soft gripper dynamics using a line-segment model with an optimization-based parameter identificationmethod,” IEEE Robot. Autom. Lett., vol. 2, no. 2, pp. 624–631, Apr. 2017.

[5] K. H. Heung, R. K. Tong, A. T. Lau, and Z. Li, “Robotic glove with soft-elastic composite actuators for assisting activities of daily living,” Soft Robot., vol. 6, no. 2, pp. 289–304, 2019.

[6] Ahmadjou, Ahmadreza, et al. ”A compact valveless pressure control source for soft rehabilitation glove,” The International Journal of Medical Robotics and Computer Assisted Surgery 17.5 (2021): e2298.

[7] V. Falkenhahn, A. Hildebrandt, R. Neumann, and O. Sawodny, “Dynamic control of the bionic handling assistant,” IEEE/ASME Trans. Mechatronics, vol. 22, no. 1, pp. 6–17, Feb. 2017.

[8] V. Falkenhahn, A. Hildebrandt, R. Neumann, and O. Sawodny, “Modelbased feedforward position control of constant curvature continuum robots using feedback linearization,” Proc. IEEE Int. Conf. Robot. Autom., 2015, pp. 762–767.

[9] F. Alambeigi, M. Bakhtiarinejad, S. Sefati, R. Hegeman, I. Iordachita, H. Khanuja, and M. Armand, “On the use of a continuum manipulator and a bendable medical screw for minimally invasive interventions in orthopedic surgery,” IEEE Trans. Med. Robot. Bionics, vol. 1, no. 1, pp. 14-21, Feb. 2019.

[10] J. Vertut, Teleoperation and Robotics: Applications and Technology. New York, NY, USA: Springer, 2013.

[11] M. B. Hong, S. J. Kim, Y. S. Ihn, G.-C. Jeong, and K. Kim, “KULEXhand: An underactuated wearable hand for grasping power assistance,” IEEE Trans. Robot., vol. 35, no. 2, pp. 420-432, Apr. 2019.

[12] F. Aghili, “Robust impedance-matching of manipulators interacting with uncertain environments: Application to task verification of the space station’s dexterous manipulator,” IEEE/ASME Trans. Mechatronics, vol. 24, no. 4, pp. 1565-1576, Aug. 2019.

[13] E. Simetti and G. Casalino, “Manipulation and transportation with cooperative underwater vehicle manipulator systems,” IEEE J. Ocean. Eng., vol. 42, no. 4, pp. 782-799, Oct. 2017.

[14] T. Shibata and T. Murakami, “Null space motion control by PID control considering passivity in redundant manipulator,” IEEE Trans. Ind. Informat., vol. 4, no. 4, pp. 261-270, Nov. 2008.

[15] Chen, Y., Luo, X., Han, B., Luo, Q., and Qiao, L. (2020). Model predictive control with integral compensation for motion control of robot manipulator in joint and task spaces. IEEE Access, 8, 107063-107075.

[16] M. I. Ullah, S. A. Ajwad, M. Irfan, and J. Iqbal, “Nonlinear control law for articulated serial manipulators: Simulation augmented with hardware implementation,” Elektronika Ir Elektrotechnika, vol. 22, no. 1, pp. 3-7, Feb. 2016.

[17] J. Baek, S. Cho, and S. Han, “Practical time-delay control with adaptive gains for trajectory tracking of robot manipulators,” IEEE Trans. Ind. Electron., vol. 65, no. 7, pp. 5682-5692, Jul. 2018.

[18] J. Baek, M. Jin, and S. Han, “A new adaptive sliding-mode control scheme for application to robot manipulators,” IEEE Trans. Ind. Electron., vol. 63, no. 6, pp. 3628-3637, Jun. 2016.

[19] Bruder, D., Gillespie, B., Remy, C. D., and Vasudevan, R. (2019). “Modeling and control of soft robots using the koopman operator and model predictive control,” arXiv preprint arXiv:1902.02827.

[20] Katzschmann, Robert. (2018). Building and controlling fluidically actuated soft robots : from open loop to model-based control.

[21] Alian, A., Zareinejad, M., and Talebi, H. A. (2022). Curvature tracking of a two-segmented soft finger using an adaptive sliding-mode controller. IEEE/ASME Transactions on Mechatronics, 28(1), 50-59.

[22] R. Hedjar, R. Toumi, P. Boucher and D. Dumur, ”Feedback nonlinear predictive control of rigid link robot manipulators,” Proceedings of the 2002 American Control Conference (IEEE Cat. No.CH37301), Anchorage, AK, USA, 2002, pp. 3594-3599 vol.5.

[23] Freund, H.J., 1986. ”Time control of hand movements,” Progress in brain research, 64, pp.287-294.