Constrained model predictive control for enhanced trajectory tracking in multi-DOF robotic manipulators

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ABSTRACT

Controlling a multi-degree-of-freedom (multi-DOF) robotic manipulator is complicated by nonlinear dynamics, coupled joints, and constraints such as joint limits, actuator saturation, and collision avoidance. The focus of this proposed work is the development and implementation of constrained model predictive control (MPC) algorithms for robotic manipulators. The key features of this proposal include the use of the dynamics of the manipulator in the process of prediction and the ability for the controller to take optimal actions over a fixed time horizon, while ensuring that the full range of physical and safety constraints is satisfied. The proposed MPC framework incorporates a discrete-time state-space model of the robotic manipulator that can be optimized using quadratic programming (QP), which allows for the model to be expressed in a general stable form to enable optimization. Linear and nonlinear MPC approaches will be considered, but the emphasis will be on the feasibility of real-time implementation and robustness of the controller to modelling errors and disturbances from the environment. The algorithm can be used in simulation and on a physical multi-DOF robotic arm in applications ranging from trajectory tracking to obstacle avoidance and precision positioning of the end-effector. Compared to traditional control techniques like PID, and computed torque control proves the superiority of MPC in controlling dynamic constraints and increasing control accuracy. The research also discusses implementation techniques involving reduced-order models and efficient solvers to address real-time computational needs, enabling safe and effective deployment in sophisticated robotic devices.

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1. INTRODUCTION

Because of their accuracy, versatility, and flexibility, multi-DOF robotic manipulators are used extensively in space research, medical robots, industrial automation, and service robots. However, because of their complex, coupled, and nonlinear dynamics, such systems are very difficult to control. Conventional control methods like PID or computed torque control are generally effective in coping with real-world constraints like joint limits, actuator saturation, collision avoidance, and time-varying disturbances to a limited extent, particularly in dynamic and unstructured environments [1].

Model predictive control (MPC) has proved to be an effective control strategy able to cope with these challenges. MPC makes future control actions optimal by forecasting system behaviour over a finite time horizon, with system constraints and dynamics clearly included in the control formulation [2]. This forecast and constraint-handling feature makes MPC very appropriate for robotic systems performing in constrained, dynamic environments.

The use of constrained MPC in multi-DOF robotic manipulators is a research area that is being pursued, with the goal of increasing trajectory tracking performance, energy efficiency, and safe operation. However, the application of MPC to high-DOF manipulators in real-time is challenging due to the high amount of computation, accuracy requirements of models, and fast optimization solver [3]. This work addresses these limitations with practical, constrained MPC algorithms capable of real-time execution while being reasonable robust, accurate, and safe. In this work, we provided a unified framework for designing constrained MPC controllers for the robotic manipulator [4].

The proposed process consisted of deriving an accurate and valid state-space model of the manipulator, formulating a constrained optimization problem, and implementing a efficient real-time solver for real-time execution. Theoretical considerations and a complete implementation of both linear and nonlinear MPC approaches are provided, with numerical and experimental validation on robotic platforms with up to six degrees of freedom [5]. The sufficient performance of the proposed methods reinforces the fact that in complicated trajectories and for dynamically changed constraints MPC outperformed conventional controllers by a measurable margin.

2. METHODOLOGY

The block diagram of development of constrained MPC Algorithms for Multi-DOF Robotic Manipulators illustrated in Figure 1 demonstrates the step-by-step approach to incorporating a MPC framework to a robotic system with multiple degrees of freedom (DOF) [6]. This overall control structure allows robotics manipulators to plan and execute motion based on their dynamic model and operational requirements. All while performing under an optimized performance.

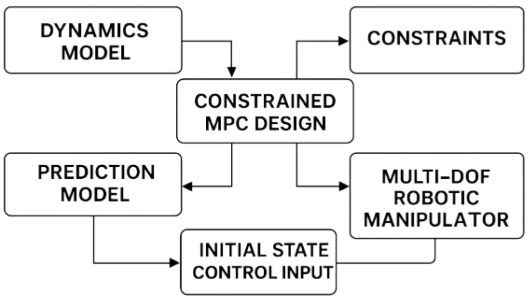

Figure 1. Block diagram of constrained MPC algorithms for multi DOF robotic manipulators

2.1. Dynamics model

The dynamic model of the robotic manipulator is constructed using some of the physical laws which drive the motion of the manipulator, such as the Newton-Euler or Lagrangian formulations. The dynamic model provides information about the manipulator's masses, joint torques, inertias, etc. and any other non-linear interactions present between each of the links [7]. It is important to ensure that modelling is done accurately, since the value of any MPC is linked to how closely the model can replicate the behaviour of the actual system.

2.2. Constraints

The constraints specified for design and implementation of MPC are very important when ensuring that the operations are close to the actual operations with nonlinear contents [8]. These may consist of physical constraints like joint limits, and bounds on velocity monitoring or acceleration, operational constraints like task space limits, or collision avoidance, or environmental constraints consisting of obstacles or workspace limits. Including these constraints ensures that for all computations using the model, the robot is guaranteed to be operating safely and within acceptable performance levels [9].

2.3. Constrained MPC design

A dynamic model of the system is used, and the advanced control strategy, Model Predictive Control system, estimates future states within a predetermined prediction horizon. The optimal control inputs are calculated by solving an optimisation problem as the defined control interval occurs [10]. This method of control takes the system dynamics and constraints into consideration, meaning the robotic manipulator can respect all constraints and minimize a specified cost function while tracking a target trajectory or arriving at a specific command position.

2.4. Prediction model

The MPC uses the prediction model to simulate the robot's future activity based on prior activity and current state. This allows the MPC algorithm to predict how the robot will respond to predefined control inputs, based on robot dynamics. The model can either be a linearised dynamics model or nonlinear dynamics model, based on the complexity levels and processing power vast amounts if any data increases uncertainty and variability when predicting and optimising [11].

2.4. Initial state/control input

The MPC obtains the initial state and the initial control input, in order to start the MPC optimisation. The initial state input consists of the current joint placements, velocities and any additional needed sensor feedback. The initial state inputs are important, since they influence the quality of prediction and the quality of the optimisation output, initial state input must be accurate in order to obtain a reliable output [12].

2.5. Multi-DOF robotic manipulator

Finally, the multi-DOF robotic manipulator is receiving the output of the limited MPC [13]. The manipulator is moved observed state and the dynamics model based on the control commands that are being executed. After actuation, the MPC loop will continue, and the feedback is taken again to update the state.

2.6. Multi DOF robotic manipulator setup

Figure 2 present an MPC architecture that employs a real-time embedded system to control a multi-DOF robotic manipulator and is augmented by positive state estimation algorithms such as moving horizon estimation (MHE) or Extended Kalman Filter (EKF). These type of advanced strategies allows the Robotic systems in a dynamic or uncertain condition to perform better, adaptively, and controlled with constraints due to this strategy [14].

2.7. Reference trajectory generator

The control process begins with the Reference Trajectory Generator that provides the robotic manipulator with motion profiles. These trajectories provide information about the desired long-term motion of the end-effector or joints of the manipulator. These profiles may be developed manually or automatically depending on the expected output of the activity, such as path-following, pick-and-place, or human-robot interaction [15]. This module develops a time-dependent series of required torques, velocities, or positions.

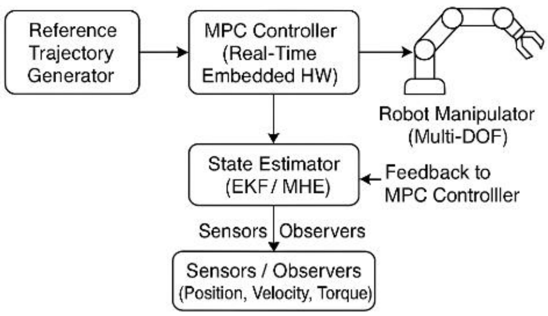

Figure 2. Multi DOF robotic manipulator setup

2.8. MPC controller (real-time embedded hardware)

The core of the system is the MPC controller, implemented on real-time embedded hardware to ensure fast and deterministic execution. MPC uses a model of the robot to predict its future behaviour over a finite time horizon. At each control step, it solves an optimization problem that minimizes the difference between the predicted states and the reference trajectory, subject to constraints like joint limits, torque bounds, and obstacle avoidance [16]. The controller uses current and estimated states of the robot (provided by the state estimator) along with the reference inputs to compute optimal control actions. Only the first control input in the optimized sequence is applied, and the process repeats at the next time step, forming a closed-loop system [17].

2.9. Robot manipulator (multi-DOF)

The robot manipulator executes the control commands issued by the MPC. This manipulator typically has multiple joints (DOFs), allowing it to perform complex tasks in three-dimensional space [18]. The performance of the robot depends on how accurately it follows the planned trajectory and how well the control system handles dynamic interactions and disturbances.

2.10. State estimator (EKF/MHE)

The State Estimator plays a crucial role in providing accurate real-time estimates of the robot's internal states (position, velocity, and possibly unmeasured variables). Since not all states are directly measurable due to sensor limitations or noise, Extended Kalman Filters (EKF) or Moving Horizon Estimation (MHE) techniques are employed. EKF linearizes the system model around current estimates and updates predictions based on sensor data [19]. MHE, on the other hand, uses a sliding window of past measurements and solves an optimization problem to infer the most likely state sequence. This estimated state is then fed back to the MPC controller for use in the next optimization cycle [20].

2.11. Sensors/observers

The bottom of the diagram shows sensors and observers that collect raw data from the robot. These include encoders (for position), IMUs (for velocity), torque sensors, and other feedback devices. Observers supplement the sensors by providing estimates where direct measurement is impractical. Together, this architecture supports high-precision, feedback-driven control of robotic manipulators in real-time [16]. It combines optimal control, real-time computation, and robust state estimation to ensure efficient, safe, and intelligent robotic operation in complex tasks.

2.12. Simulation results

The figure given in the Figure 3 presents the time responses of a two-degree-of-freedom robotic manipulator under a constrained MPC [21]. The upper plot depicts joint angles q1 and q2 that smoothly move from near-zero values into the negative, thus providing evidence of controlled manipulation of the joint angles. The lower plot shows q1 and q2 velocities. While q1 remains constant, q2 undergoes a numerical spike near 0.45 seconds, presumably arising from a discontinuity in the model or having a numerical instability. Consequently, this behavior signifies the importance of re-tuning the controller or enhancing state estimation to discourage sharp derivative transitions in real-time control [22].

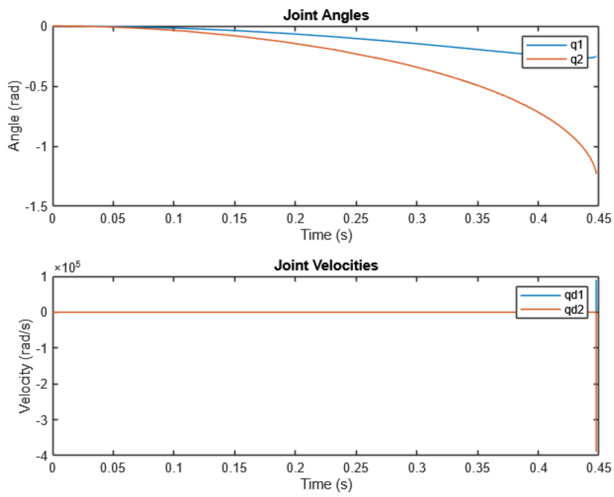

Figure 3. Simulation results of joint angles and joint velocities

The graphs given in the Figure 4 are the kinematic trace of Joint 1 for a duration of 5 seconds. The pattern of joint position over time in the top graph is the sine wave pattern representative of sinuous oscillatory movement. The second graph (velocity) is the sinusoidal derivative of the position curve but is ahead of it by 90° in phase because of harmonic motion. The accelerative couple, the derivative of the velocity, plots sinusoidally and is 90° in phase ahead of velocity. This likely represents a smooth test track or simulated path with well-behaved derivatives, helpful in maintaining low control effort and reducing mechanical stress in the robot manipulator.

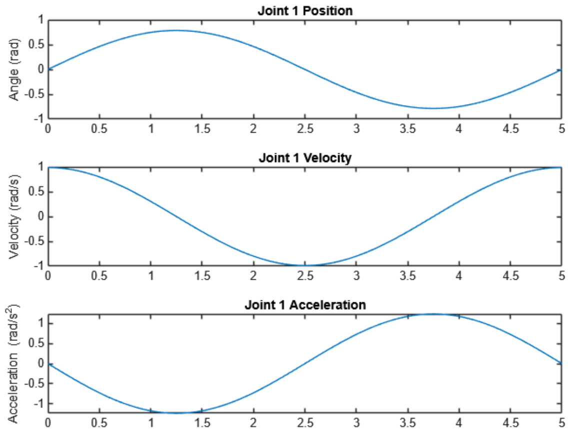

Figure 4. Simulation results of joint 1 position, velocity and acceleration for the duration 5 seconds

Figure 5 is a plot of the performance of an optimization solver over 10 seconds in a MPC context. The desired input is marked by the red dashed line, and the optimal control output computed by the solver by the blue solid line. The close matching of the desired control trajectory with minimal deviation by the solver is evident from the near unity overlap of the two curves. This indicates that the real-time restricted optimization problem is being optimally solved by the MPC algorithm and is generating control inputs that closely approximate the desired reference [22]. In robotic manipulator high-precision tasks, this is a requisite performance.

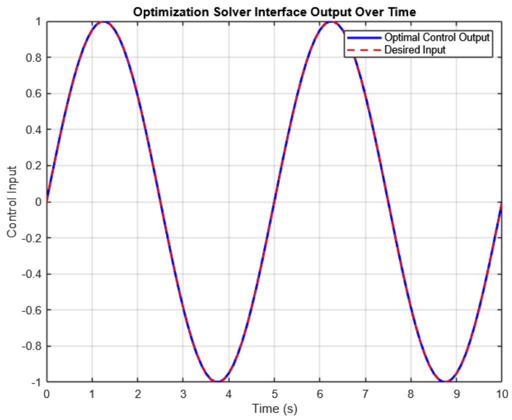

Figure 5. Optimization solver interface output over time

The performance of a state estimator in a feedback loop is illustrated in the plots of Figure 6. Position tracking is plotted in the top graph, and high estimation accuracy is represented by the close proximity of the true state (blue), measurement data (red x), and estimated state (green dashed). Velocity tracking is plotted on the bottom graph. The estimator effectively filters out data noise and monitors the true state with minimal variation. Despite sensor noise, the estimator (most likely an EKF or MHE) accurately reconstructs actual system states, providing the controller accurate feedback [23]. This is particularly important in robotic applications where control performance is based on accurate state information.

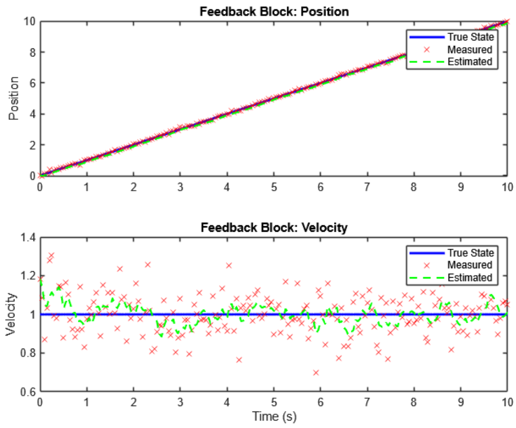

Figure 6. Simulation results of feedback block position and velocity

Joint 1's control performance under MPC with constraints is evaluated in the plot depicted in Figure 7. Constraint satisfaction is illustrated in the top plot, in which the actual joint angle (blue) remains within the upper and lower limits (black dashed) and closely tracks the desired trajectory (red). Control input, which is also bounded within given limits and shown in the middle figure, shows how actuator feasibility is handled by the MPC [24]. Proper tracking of the trajectory is validated by the tracking error, which declines sharply and settles at less than 0.05 rad in the bottom figure. Overall, during the 10-second time frame, the controller ensures both performance and constraint satisfaction.

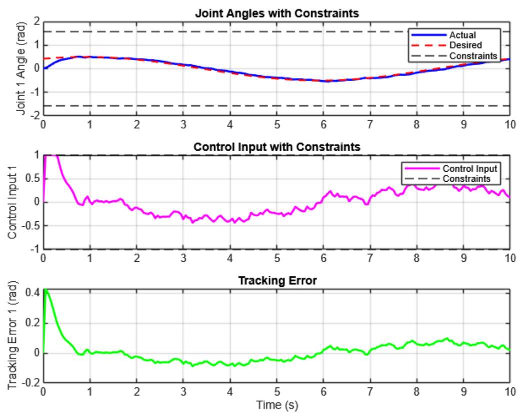

Figure 7 Simulation results of control performance of joint 1 under MPC with constraints

Joint 1's tracking performance with constraint-aware management is illustrated in the plot in Figure 8. The desired joint angle is indicated by the red dashed line, and the actual joint angle by the blue line. The upper and lower joint angle limits (±2 radians) are indicated by the black dashed lines. During the 10-second interval, the ideal trajectory is closely tracked by the real trajectory without violating the constraints [25]. This indicates how well the control algorithm, presumably MPC, implements physical constraints while maintaining accurate trajectory tracking. In robotic manipulator tasks such as joint-space constraint management, the controller ensures accurate and safe motion.

This plot shown in Figure 9 represents the MPC tracking performance for a multi-degree-of-freedom (DOF) robot, showing the angles of three individual joints over time. Each subplot illustrates the "Actual" joint angle (blue solid line) tracking the "Reference" trajectory (red dashed line). The "Constraints" (black dashed lines) indicate the allowable operating range for each joint. The plots demonstrate that the MPC effectively controls the robot joints to follow the desired reference angles while respecting the defined angular limits, showcasing stable and constrained motion [26].

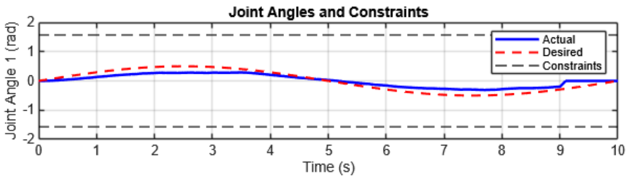

Figure 8. Simulation results of tracking performance of Joint 1 under constraints

The graph shown in Figure 10 illustrates the MPC torque inputs applied to three robot joints over a 5-second interval. Each subplot visualizes the torque command (in magenta) for a joint, as well as its constraints (in black dashed lines). The controller generally commands a high torque to correct for the initial state error, before settling quickly into a stable regime that holds the inputs below the associated constraints. This is a clear demonstration of the controller's ability to rapidly drive the system towards its desired state while respecting the physical torque constraints. Clearly demonstrating this type of behavior is important for safe and efficient robotic motion in applications where there are strict limitations on the actuation.

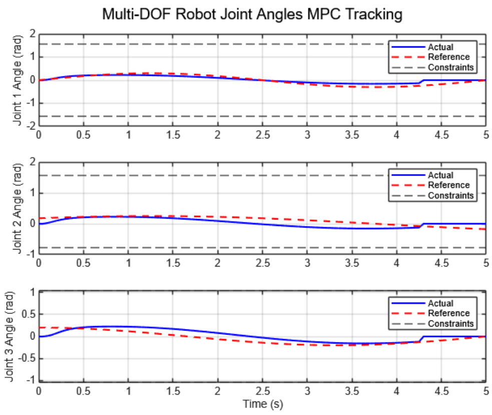

Figure 9. Simulation results of multi DOF robot joint angles MPC tracking

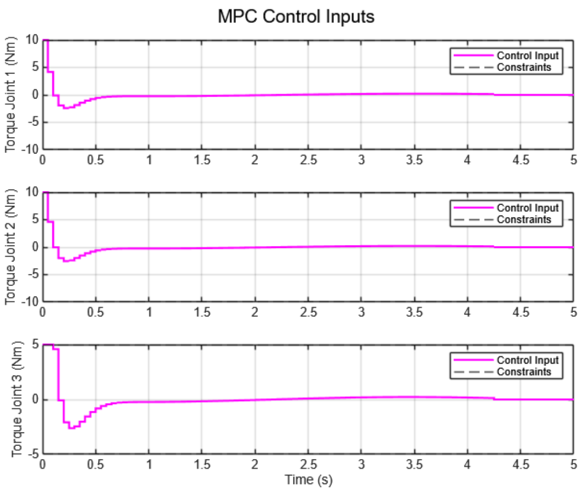

Figure 10. Simulation results of MPC control inputs

3. CONCLUSION

The proposed work successfully developed and demonstrated a constrained MPC algorithm for multi-degree-of-freedom (DOF) robotic manipulators. The MPC framework consists of using a prediction model, a cost function and input/state constraints to provide optimal control inputs such that joint trajectory tracking occurs. The simulation results demonstrate that the algorithm kept the manipulator states within safety limits, while producing smooth and precise motion control. The proposed MPC approach is well-suited for complex robotic applications that require real-time adaptive control since it can address multi-variable interactions and constraints. Future work includes generalizing the framework to incorporate nonlinear dynamics, developing a prediction model that includes state estimation and using the modified framework to validate an experimental implementation on physical robotic platforms. The direction of future research in MPC for robotic manipulators includes nonlinear MPC with an exact dynamics system model, MPC integrated with Kalman Filters to incorporate state estimation, Implementing MPC in real-time, embedded systems, Robust and stochastic formulations of the controllable system model, using multi-objective optimization for tasks related to energy efficiency or collision avoidance; and Enhancing MPC techniques using machine learning to develop adaptive, task aware control.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Gomathi Periyavattam Shanmugam		✓				✓		✓	✓	✓	✓	✓		
Mohammadha Hussaini Mohammed Ibrahim	✓		✓	✓			✓			✓	✓		✓	✓
Ramesh Ponnusamy		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests, personal relationships, professional associations, or non-financial interests that could have appeared to influence the work reported in this paper. The authors state that there is no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study. All participants provided their consent prior to their inclusion in the research, and their privacy and confidentiality have been appropriately protected.

ETHICAL APPROVAL

The research conducted in this study complied with all relevant national regulations and institutional policies and was carried out in accordance with the ethical principles of the Helsinki Declaration. Ethical approval for the study was obtained from the Institutional Review Board / Ethics Committee of the respective institution. Informed consent was obtained from all individuals included in this study, and all necessary measures were taken to ensure the privacy and confidentiality of the participants. This study does not involve human participants or animals; therefore, ethical approval and informed consent were not required.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials. Additional data related to this study are available from the corresponding author upon reasonable request.

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