Robust Control Design for Accurate Trajectory Tracking of Multi-Degree-of-Freedom Robot Manipulator in Virtual Simulator

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This work was supported by the Nuclear Research and Development Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (MSIT), South Korea, under Grant NRF-2019M2C9A1057807.

ABSTRACT Robot manipulators have complex dynamics and are affected by significant uncertainties and external disturbances (perturbations). Consequently, determining the exact mathematical model of a robot manipulator is a tedious task. Accordingly, accurate trajectory tracking is a dominant feature in the design of position control for robot manipulators. The main objective of this research is to design a robust and accurate position control for a robot manipulator despite the absence of an exact model. For this purpose, an extended state observer (ESO)-based sliding mode control (SMC) is proposed. The main concept in the ESO is to define and estimate the assumed perturbation, which includes known and unknown system dynamics, uncertainties, and external disturbances. Additionally, the ESO estimates the system states. This estimated perturbation information, which is combined with the SMC input, is utilized as a feedback term to compensate for the effect of the actual perturbation. The perturbation compensation improves the controller performance, resulting in a slight position error, less sensitivity to perturbation, and a small switching gain required for the SMC. The advantage of the proposed algorithm is that it only requires partial state information and position feedback. Thus, identifying the system parameters for the nominal model before designing the controller is unnecessary. The proposed algorithm is implemented and compared with the conventional SMC and the SMC with a sliding perturbation observer (SMCSPO) in a virtual environment based on MATLAB SimMechanics. The comparison results validate the robustness of the proposed technique in the presence of perturbation and show that the technique has a significantly reduced trajectory tracking error than the conventional SMC and SMCSPO.

INDEX TERMS Robust control, sliding mode control, perturbation estimation, perturbation compensation, state observer, and extended state observer.

I. INTRODUCTION
The dismantling of nuclear power plants (NPPs) is a challenging problem in the 21st century. Currently, 450 NPPs are operating worldwide. In South Korea, the Kori power plant unit 1 was phased out in 2017, and the remaining three units are expected to be phased out in the upcoming years. The use of robots is feasible for dismantling NPPs, which have a dynamic environment (reactor vessel internals (RVIs)) [1]–[8]. However, trained manpower is required, and a virtual simulator is an acceptable platform for manpower training.

The purpose of this research is to develop a virtual simulator consisting of an XY crane, a telescope, a robot manipulator with five degrees of freedom (DOF), and an RVI. The simulator, developed using MATLAB/SimMechanics, is a slave system controlled by a master joystick. In this study, a robust controller was designed for the accurate trajectory tracking of a five-DOF robot manipulator.

Multi-DOF robot manipulators are nonlinear systems, and deriving accurate mathematical models for such systems is a tedious task. Researchers have proposed unique ideas to formulate mathematical models; model development includes derivation and system identification techniques [9]–[18]. Usually, these estimation techniques only identify the linear
parameters of the system. The nonlinear parameters, system kaolinites, and external disturbances are considered as perturbations.

Nonlinear control strategies, such as sliding mode control (SMC), have been implemented for the position control of the abovementioned system. The SMC is robust and exhibits satisfactory performance against perturbations. The SMC has many practical applications, including motor drivers, robot position control, and underwater vehicles [24]–[43]. In the SMC, the main idea is to design the sliding surface and move the system states to this surface [44]–[46]. The SMC has two stages: reaching and sliding phases (Fig. 1). It also has two types of regulators: switching and equivalent controls. The switching control forces the system states to move toward the sliding surface in the presence of perturbation (Fig. 2). During the reaching phase, the stability of the SMC is not ensured owing to the effect of the perturbation on the sliding surface dynamics [45]. For the system to remain stable, a considerable switching gain is necessary; however, this introduces chattering in the system. In a real system, chattering is not acceptable because it can affect the performance of actuators. To reduce chattering, researchers have proposed a smooth switching function [45]. However, the use of such a switching function increases the position error in the case of robot control.

To overcome the abovementioned drawbacks of SMCs, researchers have proposed a disturbance observer (DO)-based SMC (DOSMC) for an accurate position tracking control of robot manipulators [26], [33], [47]–[57]. In the DOSMC, the DO estimates the system perturbation (uncertainties and external disturbance) at a subsequent period. This estimated information has been used as feedback in the SMC to cancel the effect of actual perturbation. Owing to perturbation compensation, a small magnitude of switching gain is required to cancel the effect of perturbation estimation error. This phenomenon not only increases the stability of the system but also removes chattering. Most DOs estimate the system states along with perturbation (i.e., a sliding perturbation observer (SPO) and an extended state observer (ESO)). In the abovementioned DOs, perturbations are estimated using the measurable states and known dynamics of the system.

In the last two decades, ESO-based SMC has been proposed and implemented [48]–[51]. In the ESO, the concept is to define and estimate the total perturbation and then compensate for this perturbation in the real system. System perturbation is defined as a new state of the system. Ren and Li used ESO-based SMC for the friction compensation of a three-wheeled omnidirectional mobile robot [50]. The accurate friction modeling of an omnidirectional mobile robot is difficult; however, the friction compensation is important for an accurate trajectory tracking. In their research, they considered a friction model as unknown and defined it as a perturbation. Using the known dynamic model of a mobile robot, they designed a reduced-order ESO for perturbation compensation. Li and Li proposed an ESO-based SMC to reduce the chattering in the system [54]. They proposed a nonlinear ESO based on a hyperbolic tangent function to estimate the matched and mismatched disturbances. A disturbance compensation reduced the chattering in the system.

Long and Peng proposed an ESO-based terminal SMC with perturbation compensation for lower extremity exoskeletons [55]. By utilizing the ESO, they estimated the uncertainties and external disturbances (perturbations). Subsequently, this estimated information was used to compensate for the actual perturbation. Qu and Wei proposed an ESO-based sliding mode speed control to improve the tracking performance of permanent-magnet synchronous motors [56]. The ESO is designed to estimate the perturbation and subsequently compensate for it in a real system. Although the above researchers utilized the ESO for estimating system uncertainties and external disturbances, they considered the known system dynamics (system nominal model) in the design procedure. However, obtaining the nominal model of a multi-DOF robot is difficult.

In this research, an ESO-based SMC was proposed for the position control of a five-DOF robot manipulator. Each joint of the manipulator is considered as a second-order system consisting of control input, system dynamics, uncertainties, and external disturbances. All the elements (other than the control input), which include system dynamics, kaolinites, and external disturbances, have been defined as perturbations. A nonlinear ESO based on the saturation function was used to accelerate the convergence of the estimation error to zero. The implementation of the proposed ESO requires minimal system information. It only utilizes the position feedback.
of a joint to estimate the system states and perturbations. Subsequently, this estimated perturbation information was used along with the SMC input to cancel the effect of the actual perturbation. A controller was designed for each joint of the robot manipulator. The main contributions of this study are as follows.

1) The sliding surface dynamics are affected by the perturbation estimation error owing to perturbation compensation. This phenomenon completely validates system stability (Fig. 3).

2) A small switching gain is required to tackle the estimation error of perturbation; this can reduce the chattering in the system (Fig. 4).

3) The implementation of the proposed logic requires minimal system information (position feedback).

The proposed and existing schemes were both implemented in MATLAB/Simulink, and experiments were performed on a virtual simulator designed in SimMechanics. In the experiments, the trajectory was obtained through the master joystick. The results show that the trajectory tracking of the ESO-based SMC is superior to that of the conventional SMC and SMCSPO.

This manuscript is organized as follows. Section 2 presents the system information. Section 3 explains the proposed control methods for target-position tracking. Section 4 provides the simulation details, discussion, and experimental results. Finally, Section 5 concludes the paper.
The system has three states: \( x_1, x_2, \) and \( x_3 \); the observer has to estimate these states. The ESO structure is similar to that of the Luenberger observer. The mathematical structure of the nonlinear ESO is expressed as

\[
\begin{align*}
\dot{x}_1 &= \dot{x}_2 + l_1 \text{sat}(\tilde{x}_1), \\
\dot{x}_2 &= u + \dot{x}_3 + l_2 \text{sat}(\tilde{x}_1), \\
\dot{x}_3 &= l_3 \text{sat}(\tilde{x}_1),
\end{align*}
\]

(5), (6), (7)

where \( \dot{x}_1, \dot{x}_2, \) and \( \dot{x}_3 \) are the estimated states of the system; \( l_1, l_2, \) and \( l_3 \) are the observer gains selected through pole placement; and \( \tilde{x}_1 \) is the estimation error of state \( (\tilde{x}_1 = e = x_1 - \hat{x}_1) \). Moreover, sat is a saturation function defined as

\[
\text{sat}(\tilde{x}_1) = \begin{cases} 
\tilde{x}_1/\delta, & \text{if } |\tilde{x}_1| > \delta \\
\tilde{x}_1/\delta, & \text{if } |\tilde{x}_1| \leq \delta,
\end{cases}
\]

(8)

where \( \delta \) is a constant (boundary layer for the estimation error). The estimation errors of states \( \dot{x}_1, \dot{x}_2, \) and \( \dot{x}_3 \) can be calculated as (9)–(11), respectively:

\[
\begin{align*}
\dot{x}_1 &= \ddot{x}_2 - l_1 \text{sat}(\hat{x}_1), \\
\dot{x}_2 &= \ddot{x}_3 - l_2 \text{sat}(\hat{x}_1), \\
\dot{x}_3 &= G - l_3 \text{sat}(\hat{x}_1).
\end{align*}
\]

(9), (10), (11)

To calculate the value of gains \( (l_1, l_2, \) and \( l_3) \), the estimation error is assumed to be within the boundary layer \( (|\tilde{x}_1| \leq \delta) \). Therefore, the saturation function can be written as

\[
\text{sat}(\tilde{x}_1) = \tilde{x}_1/\delta. \quad (12)
\]

Further, (9)–(11) can be rewritten as

\[
\begin{align*}
\dot{x}_1 &= \ddot{x}_2 - l_1/\delta \dddot{x}_1, \\
\dot{x}_2 &= \ddot{x}_3 - l_2/\delta \dddot{x}_1, \\
\dot{x}_3 &= G - l_3/\delta \dddot{x}_1.
\end{align*}
\]

(13), (14), (15)

In state-space error dynamics, the foregoing can be written as

\[
\dot{x} = Ax + E \dddot{x},
\]

(16)

where

\[
A = \begin{bmatrix} -l_1/\delta & 1 & 0 \\ -l_2/\delta & 0 & 1 \\ -l_3/\delta & 0 & 0 \end{bmatrix}, \quad E = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}. \quad (17)
\]

The characteristic equation of state matrix \( A \) can be easily derived as follows:

\[
|\lambda I - A| = \begin{vmatrix} \lambda + l_1/\delta & 1 & 0 \\ l_2/\delta & \lambda - 1 & 1 \\ l_3/\delta & 0 & \lambda \end{vmatrix} = \lambda^3 + (l_1/\delta)\lambda^2 + (l_2/\delta)\lambda + l_3/\delta. \quad (18)
\]

The error dynamics are stable if \( l_1, l_2, \) and \( l_3 \) are positive constants. The values of these gains are calculated by the pole placement method as follows:

\[
(s + \lambda)^3 = s^3 + 3s^2\lambda + 3s\lambda^2 + \lambda^3. \quad (19)
\]
By comparing the coefficients of (18) and (19), the following relationship is derived:

\[ l_1 = 3.\lambda_1 \delta, \quad l_2 = 3.\lambda_2 \delta, \quad l_3 = \lambda^3 \delta. \quad (20) \]

**B. SMC**

The SMC is a robust control that exhibits superior performance against perturbation. It has a number of practical applications to the position control of robot manipulators. The main concept is to design a sliding surface, such that the initial state of the system moves toward this surface:

\[ s = \dot{e} + c \cdot e, \quad (21) \]

where \( e = \bar{x} - x \) is the error and \( c \) is a positive constant. The SMC has two stages: the reaching and sliding phases (Fig. 1). Similarly, it has two controls: switching and equivalent controls, which add up to the control input \((u)\) as follows:

\[ u = u_{sw} + u_{eq}. \quad (22) \]

During the reaching phase, the switching control forces the system states to move toward the designed sliding surface to converge and satisfy the Lyapunov stability criteria [45]:

\[ s \cdot \dot{s} \leq 0. \quad (23) \]

The control input can be calculated as follows:

\[ \dot{s} = -K \text{sat}(s), \quad (24) \]

where \( K \) is the switching gain and sat is the saturation function defined as

\[ \text{sat}(s) = \begin{cases} \frac{s}{|s|}, \text{ if } |s| > e_c \\ \frac{s}{e_c}, \text{ if } |s| \leq e_c \end{cases} \quad (25) \]

where \( e_c \) is the boundary layer thickness. The use of (24) yields the following:

\[ \ddot{e} + c \cdot \dot{e} = -K \text{sat}(s), \quad (26) \]

\[ \ddot{x} - \ddot{x}_d + c \dot{e} = -K \text{sat}(s), \quad (27) \]

\[ u - \ddot{x}_d + c \dot{e} = -K \text{sat}(s), \quad (28) \]

\[ u = -K \text{sat}(s) + \ddot{x}_d - c \dot{e}. \quad (29) \]

In (29), \( K \text{sat}(s) \) is the switching control that forces the system state to move toward the desired sliding surface, and the remaining terms are considered as equivalent controls. The sliding surface dynamics can be calculated as follows:

\[ \dot{s} = \ddot{e} + c \cdot \dot{e}, \quad (30) \]

\[ \dot{s} = \ddot{x} - \ddot{x}_d + c \dot{e}, \quad (31) \]

\[ \dot{s} = u + \Psi (x, \dot{x}, t) - \ddot{x}_d + c \dot{e}, \quad (32) \]

\[ \dot{s} = -K \text{sat}(s) + \ddot{x}_d - c \dot{e} + \Psi (x, \dot{x}, t) - \ddot{x}_d + c \dot{e}, \quad (33) \]

\[ \dot{s} = -K \text{sat}(s) + \Psi (x, \dot{x}, t). \quad (34) \]

As shown above, the sliding surface dynamics are affected by the perturbation. For the system to remain stable, the magnitude of the switching gain \((K)\) must exceed that of the perturbation. The system stability can be calculated as

\[ s \cdot \dot{s} \leq 0, \quad (35) \]

\[ s \cdot \dot{s} \leq |s| \cdot (\ddot{e} + c \cdot \dot{e}) \leq 0. \quad (36) \]

\[ s \cdot \dot{s} \leq |s| \cdot (\ddot{x} - \ddot{x}_d + c \dot{e}) \leq 0. \quad (37) \]

\[ s \cdot \dot{s} \leq |s| \cdot (u + \Psi (x, \dot{x}, t) - \ddot{x}_d + c \cdot \dot{e}) \leq 0. \quad (38) \]

\[ s \cdot \dot{s} \leq |s| \cdot (-K \text{sat}(s) + \ddot{x}_d - c \dot{e} + \Psi (x, \dot{x}, t) - \ddot{x}_d + c \cdot \dot{e}) \leq 0. \quad (39) \]

\[ s \cdot \dot{s} \leq |s| \cdot (-K \text{sat}(s) + \Psi (x, \dot{x}, t)) \leq 0. \quad (40) \]

To maintain system stability,

\[ K > |\Psi (x, \dot{x}, t)|. \quad (41) \]

The system dynamics can be written as

\[ \ddot{x} = u_{sw} + u_{eq} + \Psi (x, \dot{x}, t). \quad (42) \]

The switching controller compensates for the perturbation and forces the system state to move toward the desired state in the presence of perturbation. When the system reaches the sliding surface, the equivalent control keeps the system on the designed sliding surface. The following are the problems with the conventional SMC.

1) **STABILITY NOT ENSURED**

During the reaching phase, the stability of SMC is not ensured. As expressed in (40), the magnitude of the switching gain \((K)\) must exceed that of the perturbation (41) for the system to remain stable. Information regarding the upper bound of perturbation must be known to the designer; however, obtaining this information is a tedious task. Therefore, reducing the effect of perturbation on sliding surface dynamics is necessary.

2) **CHATTERING IN CONTROL INPUT**

The large switching gain value degrades the controller output and increases the magnitude of the control input; a large gain is not feasible for a real system.

To reduce the foregoing problems in the conventional SMC, a nonlinear ESO is integrated into the SMC for enhanced system performance.

**C. ESO-BASED SMC**

To improve system performance, stability, sliding surface sensitivity to perturbation, and controller output, a nonlinear ESO is integrated with the SMC. The ESO estimates the system states and perturbation, and this estimated information can be used to cancel the effect of the actual perturbation (complete disturbance rejection). The control input can be written as

\[ u = \ddot{u} - \dot{\hat{\Psi}}, \quad (43) \]

where \( \ddot{u} \) is the controller output similar to (22), \( \dot{\hat{\Psi}} \) is the estimated perturbation, and \( u \) is the new input to the system. The system dynamics can be rewritten as follows:

\[ \ddot{x} = \ddot{u} - \dot{\hat{\Psi}} (x, \dot{x}, t) + \Psi (x, \dot{x}, t), \quad (44) \]

\[ \dot{\hat{\Psi}} (x, \dot{x}, t) = \Psi (x, \dot{x}, t) - \dot{\hat{\Psi}} (x, \dot{x}, t), \quad (45) \]
\( \ddot{x} = \ddot{u} + \ddot{\Psi}(x, \dot{x}, t), \quad (46) \)
\[ \ddot{x} = u_{sv} + \dot{u}_{eq} + \ddot{\Psi}(x, \dot{x}, t). \quad (47) \]

As can be observed in (47), the switching gain has to compensate for the estimation error of perturbation (\( \ddot{\Psi} \)), whereas in the conventional SMC, the gain has to compensate for the actual perturbation. The estimation error of the perturbation is considerably smaller than that of the actual perturbation. This phenomenon (disturbance rejection) improves system performance. The control input in (43) can be rewritten as
\[ u = -K' \text{sat}(s) + \ddot{x}_d - c\dot{e} - \dot{\Psi}. \quad (48) \]

The sliding surface dynamics can be calculated using (48), as follows:
\[ \dot{s} = \ddot{x} - \ddot{x}_d + c \cdot \dot{e}, \quad (49) \]
\[ \dot{s} = u + \Psi(x, \dot{x}, t) - \ddot{x}_d + c \cdot \dot{e}, \quad (50) \]
\[ \dot{s} = -K' \text{sat}(s) + \ddot{x}_d - c \cdot \dot{e} - \dot{\Psi} \]
\[ + \Psi(x, \dot{x}, t) - \ddot{x}_d + c \cdot \dot{e}, \quad (51) \]
\[ \dot{s} = -K' \text{sat}(s) - \dot{\Psi} + \Psi(x, \dot{x}, t), \quad (52) \]
\[ \dot{s} = -K' \text{sat} + \dot{\Psi}(x, \dot{x}, t). \quad (53) \]

From (53), it can be understood that the sliding surface is affected by the estimation error of perturbation. In the SMC, the sliding surface dynamics are affected by the actual perturbation. This improves the system performance compared with the performance of the existing SMC. The stability of the ESO-based SMC can be calculated as
\[ s \cdot \dot{s} \leq 0, \quad (54) \]
\[ s \cdot \ddot{s} \leq |s| \cdot (\ddot{\Psi} + c \cdot \dot{e}) \leq 0, \quad (55) \]
\[ s \cdot \ddot{s} \leq |s| \cdot (\ddot{x} - \ddot{x}_d + \ddot{e}) \leq 0, \quad (56) \]
\[ s \cdot \ddot{s} \leq |s| \cdot (\dot{u} - \ddot{\Psi}(x, \dot{x}, t) + \dot{\Psi}(x, \dot{x}, t) - \ddot{x}_d + c \cdot \dot{e}) \leq 0, \quad (57) \]
\[ s \cdot \ddot{s} \leq |s| \cdot (-K' \text{sat}(s) + \ddot{x}_d - c \cdot \dot{e} - \dot{\Psi}(x, \dot{x}, t) \]
\[ \Psi(x, \dot{x}, t) - \ddot{x}_d + c \cdot \dot{e}) \leq 0, \quad (58) \]
\[ s \cdot \ddot{s} \leq |s| \cdot (-K' \text{sat}(s) + \dot{\Psi}(x, \dot{x}, t) \]
\[ - \ddot{\Psi}(x, \dot{x}, t) \leq 0, \quad (59) \]
\[ s \cdot \ddot{s} \leq |s| \cdot (-K' \text{sat}(s) + \dot{\Psi}(x, \dot{x}, t)) \leq 0. \quad (60) \]

For the system to remain stable,
\[ K' > |\dot{\Psi}(x, \dot{x}, t)|. \quad (61) \]

The following are the main features of the proposed scheme.

1) MORE STABLE than CONVENTIONAL SMC

As shown in (40), the conventional sliding surface dynamics are affected by perturbation. In contrast, the sliding surface of the proposed algorithm is affected by the estimation error of the perturbation shown in (60). Moreover, the following is known:
\[ |\dot{\Psi}(x, \dot{x}, t)| < |\dot{\Psi}(x, \dot{x}, t)|. \quad (62) \]

Therefore, the ESO-based SMC is more stable than the existing controller.

2) BETTER CONTROL INPUT

The output of the controller is smoother than that of the conventional SMC because a small switching gain value is required to compensate for the perturbation estimation error, i.e.,
\[ K' < K. \quad (63) \]

The detailed block diagram of the ESO-based SMC is shown in Fig. 9. The figure indicates that the ESO estimates the perturbation at a subsequent period to cancel the actual perturbation of the system.

IV. SIMULATIONS, EXPERIMENTS, AND DISCUSSIONS

This section presents the simulations, experiments, and discussions. The simulations were initially performed on a second-order system in MATLAB/Simulink. In the subsection discussing the second-order system simulation, three different cases are considered to improve understanding. The next subsection presents the simulation of the five-DOF robot manipulator in MATLAB/SimMechanics. In the last subsection, the implementation of the proposed scheme on a virtual simulator developed in MATLAB/SimMechanics is discussed.

A. SIMULATION AND DISCUSSION

The simulations have been initially performed on a second-order system (64):
\[ \ddot{x} = u - 5 \cdot \ddot{x} + d, \quad (64) \]
where \( 5\ddot{x} \) denotes the known system dynamics, \( d \) is an external disturbance, \( u \) is the control input, and \( x \) is the system state. In this scenario, the known dynamics of the system and external disturbances are considered as perturbations:
\[ \Psi = -5\ddot{x} + d, \quad (65) \]
\[ \ddot{x} = u + \Psi. \quad (66) \]

The upper bound of the perturbation is known. Three different cases (based on disturbance) are discussed with respect to the simulation to better understand the system. Similarly, three different logics were implemented. The results of PID controller, SMC, and ESO-based SMC were compared. The block diagram of the simulation is shown in Fig. 10. The controller parameters are listed in Tables 1–3. For the PID controller, the parameters were selected using the MATLAB toolbox (auto-tuner). In the SMC, the switching gain (\( K \)) must be greater than the upper bound of the perturbation. In the simulation, the upper bound of perturbation is considered as 20 N-m; note that the introduced perturbation must not exceed 20 N-m. However, the value of \( c \) determines the error convergence to zero. In the ESO-based SMC, the switching gain (\( K \)) must exceed the estimation error of the perturbation, which is low in magnitude (depending on estimation accuracy). Therefore, a small gain (\( K' \)) is required for better performance.
In the first case, no disturbance \( d = 0 \) was introduced in the simulation. Constant (1) was given as the reference input. The trajectory tracking results are presented in Fig. 11, and the output of the controller is shown in Fig. 12. The output error of the PID controller has an overshoot and...
slowly converges to zero. The convergence to zero can be enhanced by tuning the control gains; however, this increases the overshoot.

2) CASE 2
In the second case, a perturbation was introduced from the start of the simulations (Fig. 13). The tracking performance of the controllers is illustrated in Fig. 14. Owing to the perturbation, the PID controller (pale yellow) performance is inadequate, and the convergence of SMC (dotted red) to zero is unsatisfactory. However, the ESO-based SMC converges to zero (solid blue line). The SMC output error (red dotted line) is greater than that of the ESO-based SMC (solid blue line). The control input is illustrated in Fig. 15. Similarly, the SMC sliding surface did not converge to zero, compared with that of the ESO-based SMC (Fig. 16).

3) CASE 3
In the third case, the impulse response was introduced in the previous perturbation (Fig. 17). In this scenario, the ESO-based SMC demonstrates satisfactory performance compared with the conventional SMC and PID controller, as shown in Fig. 18–20. Owing to complete disturbance
rejection, the performance of the proposed scheme is satisfactory compared with that of the conventional SMC.

The disturbance estimation of the ESO is shown in Fig. 21, (a) case 2 and (b) case 3.

B. SIMULATION ON FIVE-DOF ROBOT MANIPULATOR

This section presents the simulations performed on the five-DOF robot manipulator in MATLAB/SimMechanics (Fig. 22). To further validate the proposed controller, another SMC with an SPO (i.e., DOSMC) was implemented along with the SMC and ESO-based SMC. The SMCSPO is a combination of SMC and an SPO. The SPO is a nonlinear
observer that utilizes partial-state feedback (position) to estimate system perturbation. However, the SPO implementation requires information regarding the nominal model of the system. In previous research, the nominal model of each joint of a five-DOF robot manipulator was estimated using the signal compression method [43]. The control parameters of the SMCSPO were selected based on the lambda ($\lambda$) value [46]. The results of the three foregoing controllers are presented and discussed in this section. A predefined trajectory was assigned to each joint of the robot manipulator (Fig. 23). Four different views of the robot manipulator after the desired trajectory tracking are shown in Fig. 24, along with (a) initial

TABLE 4. SMC parameters for five-DOF robot manipulator.

| Joint | PARAMETERS |
|-------|------------|
| 1     | $K = 30, c = 10, \varepsilon = 1$ |
| 2     | $K = 35, c = 10, \varepsilon = 1$ |
| 3     | $K = 85, c = 10, \varepsilon = 1$ |
| 4     | $K = 25, c = 10, \varepsilon = 1$ |
| 5     | $K = 15, c = 10, \varepsilon = 1$ |

TABLE 5. SMCSPO parameters for five-DOF robot manipulator.

| Joint | PARAMETERS |
|-------|------------|
| 1     | $\lambda = 21$ |
| 2     | $\lambda = 19$ |
| 3     | $\lambda = 20$ |
| 4     | $\lambda = 20$ |
| 5     | $\lambda = 5$ |

TABLE 6. ESO-based SMC parameters for five-DOF robot manipulator.

| Joint | PARAMETERS |
|-------|------------|
| 1     | $K' = 14, c = 10, \varepsilon = 1, \delta = 0.5$ |
| 2     | $K' = 15, c = 10, \varepsilon = 1, \delta = 0.5$ |
| 3     | $K' = 30, c = 10, \varepsilon = 1, \delta = 0.5$ |
| 4     | $K' = 10, c = 10, \varepsilon = 1, \delta = 0.5$ |
| 5     | $K' = 5, c = 10, \varepsilon = 1, \delta = 0.5$ |
The robot dynamics can be presented as
\[ \tau = M(q) \ddot{q} + V(q, \dot{q}) \dot{q} + G(q) + D, \] (67)
where \( M(q) \) denotes inertia; \( V(q, \dot{q}) \dot{q} \) is the centrifugal force; Coriolis, \( G(q) \), is the gravity term; and \( D \) is the external disturbance. In the current simulation scenario, an external disturbance is introduced to the 4th joint of the robot manipulator, as shown in Fig. 25. In this case, the velocity of each joint is low because the centrifugal and Coriolis forces are negligible.

The controller parameters of each joint are listed in Tables 4–6. These parameters were selected based on the upper bound of the perturbation. The tracking error of each joint is given by an observer, as shown in Fig. 26. An average error comparison of the five joints is shown in Fig. 27. The error of the ESO-based SMC is observed to be lesser than
those of the other two logics. The estimated perturbation of the joints by the observers is shown in Fig. 28.

C. EXPERIMENT ON VIRTUAL SIMULATOR

In the experiment conducted on the virtual simulator (Fig. 5), a slave system was interfaced with the master system joystick. The desired trajectory for each joint was calculated using inverse kinematics [58]. Both conventional SMC and ESO-based SMC were implemented for the reference trajectory tracking; the PXN 2119 gaming joystick was used for this purpose. In this section, the results of the 3rd and 4th sections are discussed. The estimation of perturbation at the joints is shown in Fig. 29. The tracking error of the proposed scheme (Fig. 30(b)) was considerably lesser than that of the conventional SMC (Fig. 30(a)).

A block diagram of the experimental setup, the setup of the virtual simulator, and the average error of the joints are shown in Fig. 31–33, respectively.

V. CONCLUSION

The ESO-based SMC has been used for the position control of five-DOF robot manipulators. The SMC is robust and exhibits superior performance against perturbations. However, during the reaching phase, the stability of SMC is not ensured because of the effect of perturbation on the sliding surface. To maintain system stability, the magnitude of the switching gain must exceed that of the perturbation, thereby enhancing the quality of the control input. Accordingly, a nonlinear ESO was integrated to the conventional SMC. The proposed logic reduces the effect of perturbation on the sliding surface because it is more stable, and a small magnitude of switching gain is required to achieve the desired trajectory. The results show that the performance of the ESO-based SMC is better in the position control of robot manipulators. In future research, an intelligent control algorithm will be implemented to tune the switching gain (K'). This strategy is anticipated to improve the performance of the system.

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