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RESEARCH ARTICLE

Data-Driven LightGBM Controller for Robotic Manipulator

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ABSTRACT This paper introduces a data-driven approach employing the Light Gradient Boosting Machine (LightGBM) algorithm as a controller for robotic manipulators. By harnessing data-driven techniques and machine learning, the method captures the intricate dynamics, uncertainties, and nonlinearities inherent in robotic manipulators, including variations in inertia, Coriolis terms, and torque disturbances. This comprehensive approach leads to more precise and flexible control strategies. The LightGBM model is trained on representative datasets, enabling it to discern underlying patterns and correlations between control inputs and desired manipulator responses, even in the presence of uncertainties. The proposed controller is evaluated through extensive simulations and real-world experiments, revealing superior performance with evaluation metrics such as Root Mean Squared Error (RMSE) of 0.584, Mean Absolute Error (MAE) of 0.132, and R-squared of 0.999 (99.9%). Additionally, the controller demonstrates a settling time of 0.528 seconds and an overshoot of 4.132%. These show the exceptional performance of the data-driven LightGBM controller, demonstrating its high accuracy, adaptability, and robustness. This research advances the capabilities of robotic manipulators through the integration of data-driven methodologies and machine-learning techniques.

INDEX TERMS Robotic manipulators, data-driven control, machine learning, LightGBM, exact feedback linearization.

I. INTRODUCTION

Robotic manipulators have become increasingly prevalent in various industries, ranging from manufacturing to healthcare, due to their ability to perform complex tasks with precision and efficiency [1], [2], [3]. However, achieving better control of robotic manipulators remains a formidable challenge. Conventional control methods, such as sliding mode control [4], backstepping method [5], PID control [6], and fuzzy control [7], often grapple with capturing the intricate dynamics and uncertainties inherent in robotic manipulators, resulting in suboptimal performance. As a result, researchers are increasingly turning to innovative approaches, including data-driven techniques and machine learning, to enhance the control performance of robotic manipulators.

Uncertainties, stemming from variations in load conditions, environmental changes, and inaccuracies in model parameters, are inherent in robotic manipulators and pose significant challenges [8]. These uncertainties make it difficult to accurately predict and account for the system's behavior, leading to suboptimal control performance, reduced accuracy and compromised system stability [9]. Furthermore, the inherent nonlinearities arising from complex interactions between manipulator joints, actuators, and external forces further exacerbate the control complexities [10].

In response to these limitations, data-driven approaches leverage the power of large datasets and advanced machine-learning algorithms to extract valuable insights and patterns from the available data. By training models on representative datasets, these approaches adeptly capture the intricate dynamics, uncertainties, and nonlinearities intrinsic to robotic manipulators, thereby enabling the development of improved control strategies. Machine learning techniques, such as deep learning, reinforcement learning, and supervised learning, have shown promise in learning control policies,

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optimizing trajectories, and handling system uncertainties in a data-driven manner.

Data-driven control approaches have emerged as powerful tools for addressing the intricate challenges of control systems. These methods leverage extensive datasets to synthesize controllers that can effectively manage complex and nonlinear systems. One noteworthy example of this paradigm shift is exemplified by the novel data-driven synthesis method proposed in [11], where the Light Gradient Boosting Machine (LightGBM) controller was employed for spacecraft attitude control. This pioneering work showcased the potential of data-driven approaches to overcome nonlinearities in spacecraft dynamics using machine learning methodologies. Despite the inherent uncertainties and disturbances present in real-world scenarios, the LightGBM controller demonstrated commendable closed-loop performance. Building upon this foundation, our paper explores the application of the LightGBM controller to a different domain: the realm of robotic manipulators. This work aims to elucidate how the LightGBM controller, originally tailored for spacecraft, can be adapted and optimized to enhance the control and operation of robotic manipulators.

Researchers have extensively explored the use of machine learning algorithms to address a wide range of challenges in robotic manipulator control. In [12], a machine learning strategy based on the Support Vector Machine (SVM) method is proposed for optimal path planning of robotic manipulators in on-orbit servicing. In [13], an adaptive sliding mode control for a robot manipulator based on the Radial Basis Function (RBF) neural network is proposed. In [14], a neural network-based adaptive controller design is proposed for a robotic manipulator subject to varying loads and unknown dead zones. In [15], a robust finite-time tracking controller with adaptive neural networks is proposed for uncertain robotic manipulators without velocity measurements. Moreover, these pioneering studies underscore the continual evolution of machine learning applications in enhancing the capabilities of robotic manipulator control, showcasing a diversified range of strategies to address challenges ranging from path planning and adaptive control to addressing uncertainties in real-world manipulator dynamics.

Building on the extensive exploration of machine learning algorithms in robotic manipulator control, LightGBM has emerged as the preferred choice among researchers when seeking to enhance predictive accuracy and evaluate dimensionality reduction effects, surpassing Extreme Gradient Boosting (XGBoost) in these aspects [16]. Comparisons involving multiple machine learning models have further demonstrated that LightGBM outperforms neural networks in terms of prediction accuracy, along with easier hyper-parameter optimization and a simpler architecture [17]. Leveraging the higher accuracy of LightGBM, we anticipate improved performance in the closed-loop dynamics of our system.

In this paper, we propose a novel approach utilizing the LightGBM algorithm as a data-driven controller for robotic manipulators. LightGBM has gained recognition and popularity in various domains due to its efficiency and ability to handle large-scale datasets. By harnessing the power of LightGBM, we aim to develop a data-driven controller that can effectively capture and exploit robotic manipulators' complex dynamics, uncertainties, and nonlinearities, leading to more accurate and adaptable control strategies.

The core idea behind the proposed data-driven approach lies in its capacity to learn from available data and make informed control decisions. By training the LightGBM model on a representative dataset consisting of control inputs and corresponding desired manipulator responses, we can establish a controller that can learn the underlying patterns, relationships, and mappings. This data-driven controller has the potential to adapt to changing system dynamics and uncertainties, thereby enhancing the overall performance and robustness of robotic manipulators.

This research paper aims to investigate the application of the proposed data-driven LightGBM controller for robotic manipulators. We will outline the methodology for training the data-driven controller and validate its performance through extensive simulations and real-world experiments. By comparing the proposed data-driven approach against traditional control methods, we aim to demonstrate its superiority in terms of accuracy, adaptability, and robustness. Furthermore, we will evaluate the computational efficiency and scalability of the data-driven LightGBM controller, ensuring its practical applicability in real-world scenarios. The main contributions of this paper can be summarized as follows:

1) We proposed a novel data-driven approach utilizing the LightGBM algorithm to design a controller for robotic manipulators. This controller effectively captured intricate dynamics, uncertainties, and nonlinearities, enhancing precision and adaptability.
2) Extensive simulations and real-world experiments verified the practical applicability of our proposed controller in various industrial applications, showcasing its effectiveness in real-world scenarios. This research significantly advanced the field of robotic control strategies, opening new possibilities for the development of intelligent and adaptive robotic systems.
3) By using the Lyapunov stability approach and adopting the concept of nominal motion, practical stability, and total stability, we show that the tracking error dynamics have some stability properties, namely practical stability and total stability.

To delve into the topics discussed in this paper, we begin by providing an overview of related work in Section II. Following this, Section III introduces the mathematical model of the robotic manipulator. Moving forward to Section IV, this Section furnishes intricate details of the controller synthesis process, encompassing the construction of both the Exact Feedback Linearization Controller and the LightGBM Controller, as well as the stability analysis of the closed-loop system. Section V is dedicated to simulation and discussion, initiating with the synthesis of the LightGBM controller through training and testing, presenting simulation results, and extending the analysis to scenarios involving uncertainty and disturbance. Finally, our paper concludes in Section VI, where we summarize key findings and suggest potential avenues for future research.

II. LITERATURE REVIEW

In recent years, a notable paradigm shift has occurred in the field of robotics, emphasizing the integration of data-driven methodologies. This shift is particularly evident in the pursuit of enhancing control strategies for robotic manipulators. The literature review explores fundamental aspects within this domain, tracing the evolution from traditional control methods to the rise of data-driven approaches. The structured exploration encompasses traditional control methods in robotic manipulators, the transformative influence of data-driven approaches in robotics, and the unique capabilities offered by Gradient Boosting Algorithms in control systems.

A. TRADITIONAL CONTROL METHODS

In the realm of robotic manipulators, the foundation of control strategies has long been anchored in traditional control methods. These established methodologies, characterized by their adherence to classical principles, have played a pivotal role in ensuring the precision, stability, and reliability of robotic manipulator operations. The cornerstone of these methods often lies in applying traditional feedback control mechanisms, prominently exemplified by the Proportional-Integral-Derivative (PID) controller [6]. In addition, other traditional approaches such as feedback linearization, robust control, adaptive control, optimal control, fuzzy control, and backstepping control have played crucial roles in regulating the behavior of robotic manipulators.

In terms of robust control and feedback linearization, a robust tracking control of aerial robots via a simple learning strategy-based feedback linearization is proposed to facilitate accurate tracking in unknown/uncertain environments [18]. Furthermore, in [5], an adaptive fuzzy state feedback control method is proposed for the single-link robotic manipulator system, by combining the command-filter technique with the backstepping design algorithm, a novel adaptive fuzzy tracking backstepping control method is developed. Additionally, in [19], an optimal control method involving covariant control equations as optimality conditions, to command the actuators of robot manipulators.

While these traditional methods have proven successful in many applications, their linear and deterministic nature may struggle to capture the complexities inherent in robotic manipulators' nonlinear and dynamic behaviors. As the demand for more sophisticated and adaptive control systems grows, there is a discernible shift towards integrating data-driven methodologies to augment or replace these traditional control strategies. This transition marks a pivotal juncture in the evolution of control systems for robotic manipulators, prompting a deeper exploration into the realm of data-driven approaches in the subsequent sections of this literature review.

B. DATA-DRIVEN APPROACHES IN ROBOTICS

Researchers increasingly turn to data-driven machine learning-based algorithms to extract control strategies directly from operational data. A seminal study in [20] exemplifies this shift, investigating an improved neural network algorithm to track various trajectories of robot manipulator arms efficiently. Furthermore, in [21], a novel proportional-derivative iterative second-order neural-network learning control (PDISN) method is proposed for motion-tracking control problems of robotic manipulators.

Moreover, in [22], a RISE-based adaptive neural network prescribed performance control is presented for the robotic manipulator with unknown disturbance. The unknown dynamics of the robotic manipulator are approximated by using the radial basis function neural network which requires fewer adaptive parameters.

Expanding the exploration of data-driven control, [23] contributes to the field by introducing deep reinforcement learning algorithms to the manipulation of robotic arms. The study referred to the challenges faced by the application of deep reinforcement learning and its application in the field of industrial robotic arms and then made a detailed analysis and explanation.

Complementing these efforts, recent work in [12] proposes a machine learning strategy based on the Support Vector Machine (SVM) method for optimal path planning of robotic manipulators in on-orbit servicing, demonstrating enhanced optimization convergence rates through precise joint angle estimates derived from Cartesian positions.

Collectively, these studies underscore the transformative impact of incorporating data-driven elements into control strategies within the broader field of robotics. The findings not only highlight the adaptability of such approaches in dynamic environments but also open avenues for further exploration and optimization of ensemble learning methodologies across various robotic applications. The reviewed literature establishes a robust foundation, demonstrating the potential and versatility of the data-driven approach in advancing control strategies for robotic systems.

C. GRADIENT BOOSTING ALGORITHMS IN CONTROL SYSTEMS

The utilization of machine learning techniques, particularly gradient-boosting algorithms, has gained significant attention in the field of control systems. This shift towards data-driven methodologies represents a departure from traditional model-based approaches, offering the potential for adaptive, robust, and efficient control strategies. In this context, the exploration of gradient-boosting algorithms, such as LightGBM and XGBoost, has emerged as a promising avenue for enhancing control system performance.

A key study in [11], delves into the application of LightGBM, a gradient-boosting framework, for spacecraft attitude control. The study presents a novel data-driven synthesis method, demonstrating that, under realistic conditions, the LightGBM controller provides practical stability, establishing a smaller bounded error ball. Furthermore, simulation results reveal an intriguing phenomenon where the LightGBM controller maintains robust closed-loop performance despite uncertainties in satellite parameters and disturbances.

Expanding on the use of gradient boosting in control systems, in [24], a new approach combining standard statistical and machine learning models, named hybrid gradient boosting, is proposed to predict failures in industrial robots. Results show that the hybrid gradient boosting achieves significant improvement as compared to statistical and machine learning methods.

In summary, the exploration of gradient boosting algorithms, including influential frameworks such as LightGBM and XGBoost, within the domain of control systems underscores their potential to revolutionize traditional control methodologies. With their adaptability, efficiency, and real-time learning capabilities, these algorithms serve as valuable tools for addressing challenges in dynamic and uncertain control environments. This literature review lays the groundwork for understanding the applications and benefits of gradient boosting algorithms in control systems, and it anticipates the forthcoming integration of LightGBM in this study, specifically applied to enhance control strategies for robotic manipulators. This promising direction offers a distinctive avenue for advancing control methodologies within the evolving landscape of robotic manipulation.

III. MATHEMATICAL MODEL OF ROBOTIC MANIPULATOR

The manipulator robot's dynamics system is characterized by strong nonlinearity, time-varying behavior, and numerous coupled components. Moreover, the system model introduces uncertainties, including external noise, parameter variations, and sensor errors. Over the past few decades, various control system designs, such as robust control, adaptive control, neural networks, and feedback linearization, have been extensively researched and applied to address these challenges.

Following the formulation by Slotine [25], the dynamic system of the robot manipulator can be expressed as follows:

$$H(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = \tau, \tag{1}$$

where $H(q) \in \mathbb{R}^{n\times n}$ is the inertial matrix of a number of n-dimension robot arms where each element is a nonlinear function of the angular position $q(t) \in \mathbb{R}^{n\times 1}$, C denotes the centripetal and Coriolis forces caused by the movement of the robot arm, t denotes time, g denotes the gravitational torque vector, and τ is the torque input that we give to the system.

The manipulator robot's design exhibits significant diversity. As an example, we can consider a specific case with two degrees of freedom (2DOF), as illustrated in Figure 1.

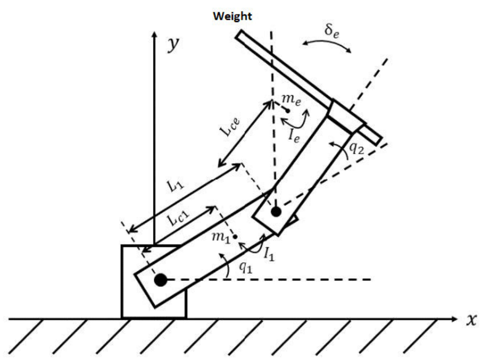

FIGURE 1. Robotic manipulator with 2DOF.

This image represents two controllable elements, namely the positions or angles of the two arms, referred to as q_1 and q_2.

In case of two degrees of freedom, manipulator $H(q)$, $C(q,\dot{q})$, and $g(q)$ can be written as follows:

$$H(q) = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}, \tag{2}$$

$$C(q,\dot{q}) = \begin{bmatrix} -h\dot{q}_2 & -h(\dot{q}_1+\dot{q}_2) \\ h\dot{q}_1 & 0 \end{bmatrix}, \tag{3}$$

$$g(q) = \begin{bmatrix} g_1 \\ g_2 \end{bmatrix}, \tag{4}$$

with

$$\begin{aligned} H_{11} &= a_1 + 2a_3\cos q_2(t) + 2a_4\sin q_2(t) \\ H_{12} &= H_{21} = a_2 + a_3\cos q_2(t) + a_4\cos q_2(t) \\ H_{22} &= a_2 \\ h &= a_3\sin q_2(t) - a_4\cos q_2(t), \end{aligned} \tag{5}$$

and

$$\begin{aligned} a_1 &= I_1 + m_1 l_{c1}^2 + I_e + m_e l_{ce}^2 + m_e l_1^2 \\ a_2 &= I_e + m_e l_{ce}^2 \\ a_3 &= m_e l_1 l_{ce}\cos\delta_e \\ a_4 &= m_e l_1 l_{ce}\sin\delta_e \end{aligned} \tag{6}$$

also

$$\begin{aligned} g_1 &= m_e l_{ce} g\cos[q_1(t)+q_e(t)] + (m_1+m_e)l_1 g\cos q_1(t) \\ g_2 &= m_e l_{ce} g\cos[q_1(t)+q_e(t)] \end{aligned} \tag{7}$$

IV. CONTROLLER SYNTHESIS

A. CONSTRUCTION OF EXACT FEEDBACK LINEARIZATION CONTROLLER

Consider the model of the robotic manipulator (1), and as options for the state variables in the feedback linearization, the vector component q and $\dot{q}$ are selected.

Given the simple structure of Equation (1), the derivation of a feedback linearizing transformation is straightforward. Taking τ of the form

$$\tau = H(q)v + C(q,\dot{q})\dot{q} + g(q). \tag{8}$$

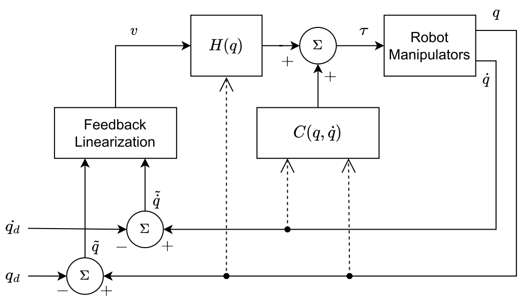

FIGURE 2. Exact feedback linearization controller block diagram.

where $v : \mathbb{R}^+ \to \mathbb{R}^n$ is the new control input, which leads to

$$\ddot{q} = v \tag{9}$$

Here, we will express the tracking problem of the robotic manipulators. Let $q_d(t)$ denote the desired angular position. Note that $q_d(t)$ may vary with time.

The expression (8) is known as the "computed torque" in the robotics literature. Let us define $\tilde{q}(t) = q(t) - q_d(t)$ as the tracking error. Letting:

$$v = \ddot{q}_d - 2\zeta\lambda\dot{\tilde{q}} - \lambda^2\tilde{q} \tag{10}$$

It can be shown easily that the closed-loop dynamics from (8) and (10)

$$\ddot{\tilde{q}} + 2\zeta\lambda\dot{\tilde{q}} + \lambda^2\tilde{q} = 0 \tag{11}$$

We also assume that $q_d(t)$ can be differentiated at least two times at $t \in (0, \infty)$.

Therefore, by choosing the appropriate value of ζ and λ, we can have exponentially stable tracking error dynamics.

B. CONSTRUCTION OF LIGHTGBM CONTROLLER

LightGBM, when applied as a data-driven controller for robotic manipulators, provides a sophisticated solution based on gradient boosting tree (GBT) regression. By utilizing extensive datasets, LightGBM empowers the creation of accurate control strategies. One of its standout characteristics is its exceptional scalability, allowing it to effectively manage extensive datasets. This attribute proves particularly valuable in the realm of robotic manipulators, where real-time data analysis is essential for making optimal decisions and improving system performance. Hence, the incorporation of LightGBM as a data-driven controller presents significant promise for advancing the control and functionality of robotic manipulators.

The LightGBM regressor is trained and evaluated using a dataset derived from the dynamic behavior of a robotic manipulator system under the influence of an exact feedback linearization control law. This dataset encompasses diverse initial conditions and specific target tracking scenarios, ensuring the generation of a robust training dataset for the LightGBM regressor. Notably, this identical dataset serves the dual purpose of assessing the regressor's performance. To elucidate, the LightGBM regressor undergoes training through a simulation involving the exact feedback linearization control law, subsequently subjecting it to testing within the same simulation framework. This comparative approach allows for an appraisal of the LightGBM regressor's efficacy in mitigating the uncertainties and disturbances inherent in real-world robotic manipulator systems.

Algorithm 1 LightGBM Algorithm

1: Define the parameters used for simulation.
2: Construct the exact feedback linearization controller.

$$\tau = H(q)v + C(q, \dot{q})\dot{q} + g(q)$$

where v is defined as follows:

$$v = \ddot{q}_d - 2\zeta\lambda\dot{\tilde{q}} - \lambda^2\tilde{q}$$

3: Prepare dataset generated by the robotic manipulator's dynamic of a system which is controlled by using exact feedback linearization control law
4: Split data into training and testing sets (80 : 20).
5: Initialize the LightGBM Regressor model.
6: Perform model training using training data.
7: Evaluate the model's performance by employing R-squared (R^2) and Root Mean Square Error (RMSE) as the evaluation metrics.
8: Utilize the trained model to acquire torque values based on pre-defined input data.

$$\tau_M = \tau_M(q, \dot{q})$$

9: Return τ_M.

In LightGBM, the input features are represented by a vector of input variables denoted as q and $\dot{q}$, and the output variable is labeled as τ, which is the torque in this case, that is based on the exact controller. This notation is exactly the same as defined before. The relationship between the input and output variables is modeled using some probabilistic distribution. The goal is to find a function $\tau_M(q, \dot{q})$ that maps the input features to the output variable with minimal error. This is formalized by introducing some loss function $L(\tau, f(q, \dot{q}))$ and minimizing it in expectation:

$$\tau_M = \arg\min_f \mathbb{E}_{(q,\dot{q}),\tau}[L(\tau, f(q, \dot{q}))] \tag{12}$$

The model is designed to manage data of substantial dimensionality while offering capabilities for feature selection and dimensionality reduction. Its operation entails partitioning the data into compact subsets and subsequently constructing a tree-based model for each subset. These individual models' outcomes are amalgamated to yield the ultimate prediction. The algorithm incorporates histogram-based gradient boosting, a methodology that effectively curtails computational expenses and memory requirements.

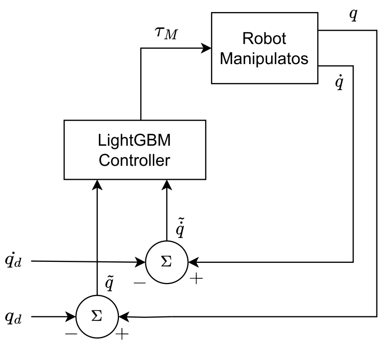

FIGURE 3. LightGBM controller block diagram.

C. STABILITY ANALYSIS OF THE CLOSED LOOP SYSTEM

Even though the LightGBM controller is a statistical machine-learning algorithm, more detailed analysis shows that the statistical learning process is only conducted in the training step. After the training, when we use the result of the training for controlling the robot manipulator, it does not have any statistical property anymore.

Here, we will discuss the stability analysis of the closed-loop system of the robot manipulator under the LightGBM controller. Let the LightGBM controller have the following form:

$$\tau_M = \tau_M(q, \dot{q}) \tag{13}$$

and let

$$e \overset{\text{def}}{=} \tau_M(q, \dot{q}) - \tau(q, \dot{q}) \tag{14}$$

denotes the LightGBM controller error.

The closed-loop system dynamics of the robot manipulator under the LightGBM controller is

$$\begin{aligned} H(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) &= \tau + e \\ H(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) &= H(q)(\ddot{q}_d - 2\zeta\lambda\dot{\tilde{q}} - \lambda^2\tilde{q}) \\ &\quad + C(q, \dot{q})\dot{q} + g(q) + e(q, \dot{q}) \\ H(q)(\ddot{\tilde{q}} + 2\zeta\lambda\dot{\tilde{q}} + \lambda^2\tilde{q}) &= e \end{aligned} \tag{15}$$

Since we are analyzing the tracking problem, therefore we want to know the stability property of error dynamics, $\tilde{q}(t) = q(t) - q_d(t)$. Here, we adopt the concept of nominal motion [see Slotine [25], page 45-47].

Therefore, instead of examining the deviation of $(q(t), \dot{q}(t))$ from $(q_d(t), \dot{q}_d(t))$ for the original system, we may simply examine the stability of the tracking error $(\tilde{q}(t), \dot{\tilde{q}}(t))$ dynamics.

Thus, we can rewrite

$$\begin{aligned} e(q, \dot{q}) &= e(\tilde{q}(t) + q_d(t),\ \dot{\tilde{q}}(t) + q_d(t)) \\ &= e(\tilde{q}(t), \dot{\tilde{q}}(t), t) \end{aligned} \tag{16}$$

which shows us that e is a function of $\tilde{q}$, $\dot{\tilde{q}}$, and also t.

Furthermore,

$$H(\tilde{q} + q_d(t)) \cdot (\ddot{\tilde{q}} + 2\lambda\zeta\dot{\tilde{q}} + \lambda^2 q^2) = e(\tilde{q}(t), \dot{\tilde{q}}(t), t) \tag{17}$$

By observing that the inertia matrix H is always nonsingular and by choosing a new state variable:

$$x = \begin{pmatrix} \tilde{q} \\ \dot{\tilde{q}}, \end{pmatrix} \tag{18}$$

then we can write the closed-loop error dynamics as a non-autonomous system as follows:

$$\dot{x} = A_{CL}x + \delta(x, t) \tag{19}$$

where

$$A_{CL} = \left[\begin{array}{c|c} 0_{(n\times n)} & I_{(n\times n)} \\ \hline -\lambda^2 I_{(n\times n)} & -2\lambda\zeta I_{(n\times n)} \end{array}\right] \tag{20}$$

$$\delta(x, t) = \left[\begin{array}{c} 0_{(n\times 1)} \\ \hline H^{-1}(x, t) \cdot e(x, t) \end{array}\right] \tag{21}$$

Here, it is obvious that A_{CL} is a strictly stable matrix.

In reality, the LightGBM controller can be chosen very close to the exact controller.

Assumption 1: Let a positive constant M exist such that $\|\delta(x, t)\| \leq M$. We can choose the parameter design of the LightGBM such that M is small enough.

Now, we are positioned to state an important proposition that guarantees a kind of stability property of error dynamics of a closed-loop system under the LightGBM controller.

Proposition 1: Let $r > 0$, where r any small positive number, and $B_r \overset{def}{=} \{x \in \mathbb{R}^{2n}, \|x\| \leq r\}$.

Let P be the symmetric definite positive solution of:

$$A_{CL}^{\mathsf{T}}P + PA_{CL} = -\mathbf{I} \tag{22}$$

If:

$$M = \frac{r}{4\lambda_{max}(P)}, \tag{23}$$

where $\lambda_{max}(P)$ is the maximum eigenvalue of P, then there exist a finite time t_r, such that the closed-loop tracking error dynamics $x(t)$ enter B_r, for $t \geq t_r$.

Proof: We will use the Lyapunov stability analysis to prove this proposition.

Since A_{CL} is strictly stable, then there exists P a symmetric definite positive solution of the Algebraic Lyapunov Equation.

$$A_{CL}^{\mathsf{T}}P + PA_{CL} = -\mathbf{I} \tag{24}$$

where $\mathbf{I}$ is the identity matrix.

Let us choose:

$$V(x(t)) \overset{\text{def}}{=} x^{\mathsf{T}}(t)Px(t) \tag{25}$$

It is obvious that V is a positive definite function of x. Further, we can derive as follows:

$$\begin{aligned} \dot{V} &= x^{\mathsf{T}}P(A_{CL}x + \delta(x, t)) + (x^{\mathsf{T}}A_{CL} + \delta^{\mathsf{T}}(x, t))Px \\ \dot{V} &= x^{\mathsf{T}}(PA_{CL} + A_{CL}^{\mathsf{T}}P)x + 2\delta^{\mathsf{T}}(x, t)Px \\ \dot{V} &= -x^{\mathsf{T}}\mathbf{I}x + 2\delta^{\mathsf{T}}(x, t)Px \\ \dot{V} &= -\|x\|^2 + 2\delta^{\mathsf{T}}(x, t)Px \end{aligned} \tag{26}$$

Observe that:

$$\|\delta(x,t)\| \le M$$
$$\|P\| \le \lambda_{max}(P) \tag{27}$$

Therefore:

$$\dot{V} \le -\|x\|^2 + 2M\lambda_{max}(P)\|x\|$$
$$\dot{V} \le -\|x\|^2\left(1 - \frac{2M\lambda_{max}(P)}{\|x\|}\right) \tag{28}$$

If we choose $M = \frac{r}{4\lambda_{max}(P)}$,

$$1 - \frac{2M\lambda_{max}(P)}{\|x\|} = 1 - \frac{r}{2\|x\|} \tag{29}$$

For $\|x\| \ge r$, $0 \le \frac{r}{\|x\|} \le 1$, then

$$\frac{1}{2} \le 1 - \frac{r}{2\|x\|} \le 1$$

Therefore, the minimum value of $\left(1 - 2M\frac{\lambda_{max}(P)}{\|x\|}\right)$ for $\|x\| \ge r$ is $\frac{1}{2}$. This implies:

$$\dot{V} \le -\frac{1}{2}\|x\|^2 \tag{30}$$

Further, we can write:

$$V(t) = x^{\intercal}(t)Px(t) \le \lambda_{max}(P)\|x\|^2 \tag{31}$$

and

$$\dot{V}(t) \le -\frac{1}{2}\|x\|^2 \tag{32}$$

Let us rearrange as follows:

$$\|x(t)\|^2 \ge \frac{V(t)}{\lambda_{max}(P)}$$
$$\|x(t)\|^2 \le -2\dot{V}(t) \tag{33}$$

Therefore:

$$\frac{V(t)}{\lambda_{max}(P)} \le -2\dot{V}(t) \tag{34}$$

or

$$V(t) + 2\lambda_{max}(P)V(t) \le 0 \tag{35}$$

By using the simple convergence Lemma (Slotine [25], page 91), we can conclude that for all $\|x(0)\| > r$, then:

$$V(t) \le V(0)e^{-2\lambda_{max}(P)t} \tag{36}$$

Further:

$$\lambda_{min}(P)\|x(t)\|^2 \le V(t) \le V(0)e^{-2\lambda_{max}(P)t}$$
$$\le \lambda_{max}(P)\|x(0)\|^2 e^{-2\lambda_{max}(P)t} \tag{37}$$

So that:

$$\|x(t)\|^2 \le \frac{\lambda_{max}(P)}{\lambda_{min}(P)}\|x(0)\|^2 e^{-2\lambda_{max}(P)t}$$
$$\|x(t)\| \le \sqrt{\frac{\lambda_{max}(P)}{\lambda_{min}(P)}}\|x(0)\|e^{-\lambda_{max}(P)t}. \tag{38}$$

It is obvious that $\|x(t)\|$ will be monotonically decreasing with respect to time as long as $\|x(t)\| > r$.

Therefore, there should be a finite time t_r such that the tracking error trajectory enters B_r.

We can calculate t_r as follows:

$$\sqrt{\frac{\lambda_{max}(P)}{\lambda_{min}(P)}}\|x(0)\|e^{-\lambda_{max}(P)t_r} = r$$
$$e^{-\lambda_{max}(P)t_r} = \frac{r}{\|x(0)\|}\sqrt{\frac{\lambda_{min}(P)}{\lambda_{max}(P)}}$$
$$-\lambda_{max}(P)t_r = \ln\left(\frac{r}{\|x(0)\|}\sqrt{\frac{\lambda_{min}(P)}{\lambda_{max}(P)}}\right)$$
$$t_r = -\frac{1}{\lambda_{max}(P)}\ln\left(\frac{r}{\|x(0)\|}\sqrt{\frac{\lambda_{min}(P)}{\lambda_{max}(P)}}\right) \tag{39}$$

□

Proposition 1 can be used to calculate the design parameter of the LightGBM controller if we want to have a smaller ball around the desired target trajectory. Hence, Proposition 1 guarantees a kind of practical stability of the equilibrium of the tracking error closed-loop dynamics.

In the next part, we will analyze the effect of uncertainty and disturbances. Let us assume that there are uncertainties in robotic manipulator of the form

$$H^* = H + \Delta H \tag{40}$$
$$C^* = C + \Delta C \tag{41}$$

where ΔH and ΔC are respectively uncertainties in inertia and Coriolis terms. Further, let us assume there is also a disturbance in the torque of the form:

$$\tau^* = \tau + \tau_d(t) \tag{42}$$

where $\tau_d(t)$ is the disturbance.

We use (1),(8),(10) as the control law. Then, the error dynamics of the closed-loop system will have the form:

$$\dot{x} = A_{CL}x + \Delta h(x,t) \tag{43}$$

where

$$A_{CL} = \left[\begin{array}{c:c} 0_{(n\times n)} & I_{(n\times n)} \\ \hdashline -\lambda^2 I_{(n\times n)} & -2\lambda\zeta I_{(n\times n)} \end{array}\right]$$

and $\Delta h : \mathbb{R}^{2n} \times \mathbb{R}^{+} \to \mathbb{R}^{2n}$ denotes the effect of LightGBM controller error, robotic manipulator uncertainties, and torque disturbance. It should be noted that here A_{CL} is strictly-stable.

Following [11] and [25], we are in the position of restating the theorem about total stability.

Definition 1: The equilibrium point $x = 0$ for the unperturbed closed-loop tracking error dynamics system (43) is said to be totally stable if, for every $\varepsilon \ge 0$, two numbers β_1 and β_2 exist such that $\|x(t_0)\| < \beta_1$ and $\|\Delta h(x,t)\| < \beta_2$ imply that every solution $x(t)$ of the perturbed system (43) satisfies the condition $\|x(t)\| < \varepsilon$.

Theorem 1: The closed-loop tracking error dynamics origin point $x = 0$ of (43) is totally stable

Proof: Note that, the origin point $x = 0$ of (43) is the equilibrium point of the unperturbed system

$$\dot{x} = A_{CL}\, x \tag{44}$$

The unperturbed system (44) is a time-invariant system or an autonomous system. Therefore, since A_{CL} is a strictly stable matrix, the equilibrium point $x = 0$ of (44) will be asymptotically stable. Further, because (44) is time-invariant or autonomous, asymptotic stability will be identical with uniform asymptotic stability. Further, the total stability property of the origin point $x = 0$ of (43) follows directly as a direct implication of Theorem 4.14 from Slotine [25]. □

Under theorem 1, the closed-loop tracking error dynamic system of the robotic manipulator under the LightGBM controller is totally stable, even in the presence of uncertainties in inertia, Coriolis terms, and torque disturbance.

Further, let $r_1 > 0$, where r_1 is a positive number, and $B_{r_1} \overset{\text{def}}{=} x \in \mathbb{R}^{2n}, \|x\| \le r_1$. And, let $\|\Delta h(x,t)\| \le M_1$

Proposition 2: Let P be the symmetric definite positive solution of:

$$A_{CL}^{\mathsf{T}} P + P A_{CL} = -\mathbf{I} \tag{45}$$

If:

$$M_1 = \frac{r_1}{4\lambda_{max}(P)}, \tag{46}$$

where $\lambda_{max}(P)$ is the maximum eigenvalue of P, then there exist a finite time t_{r_1}, such that the closed-loop tracking error dynamics $x(t)$ enter B_{r_1}.

Proof: The way we prove this proposition is quite similar to how Proposition 1 was proven. We used a similar logical structure and mathematical principles to prove this proposition. □

Proposition 2 is slightly different from Proposition 1. Proposition 2 is applicable for the closed-loop system of tracking error dynamics of robotic manipulators under uncertainties in inertia, Coriolis terms, and some torque disturbances. Proposition 2 shows that the origin point of the closed-loop system of tracking error dynamics of robotic manipulators under LighGBM controller, in the presence of uncertainties in inertia, Coriolis terms, and some torque disturbances is ultimately bounded to some ball B_{r_1} around the origin $\tilde{x} = 0$ if a sufficient condition is fulfilled, namely $M_1 = \frac{r_1}{4\lambda_{max}(P)}$.

V. SIMULATION AND DISCUSSION

In this section, we'd like to present an in-depth exploration of our simulation procedures and subsequent discussions. We conducted the simulations using the Python programming (version 3.11) language to create a versatile and efficient framework for our analyses. The simulations involve a comparative study of two control methods: feedback linearization and the LightGBM controller. To facilitate our analyses, we initialized the simulations with crucial parameters, such as the dynamic properties of the robotic manipulator, environmental conditions, and target tracking specifications. These parameters play a critical role in evaluating the performance and adaptability of the control system. We examine various hyperparameters associated with the LightGBM controller to optimize its model performance. The primary objective is to assess the effectiveness of the LightGBM controller and its potential to outperform the feedback linearization method. Through rigorous simulations and extensive discussions, we delve into the controller's capacity to optimize model performance within the realm of robotic manipulators.

The parameter values used for the simulation of the robotic manipulator are:

$$\begin{aligned}
&m_1 = 1.5\text{ kg},\ m_e = 2.5\text{ kg},\\
&l_1 = 1\text{ m},\ l_{c1} = 0.5\text{ m},\ l_{ce} = 0.7\text{ m},\\
&I_1 = 0.2\text{ kg.m}^2,\ I_e = 0.35\text{ kg.m}^2,\\
&\delta_e = 45^\circ
\end{aligned}$$

The constant desired joint positions were set to:

$$q_{d1} = 0\ rad; \quad q_{d2} = 0\ rad$$

The initial conditions during the experimental test were:

$$\begin{aligned}
q_1 = \pi/10\ rad; &\quad q_2 = -\pi/10\ rad\\
\dot{q_1} = 0\ rad/s; &\quad \dot{q_2} = 0\ rad/s
\end{aligned}$$

A. SYNTHESIZING LIGHTGBM CONTROLLER: TRAINING AND TESTING

The synthesis of the LightGBM controller is presented in this section. The LightGBM training and testing dataset is generated from a closed-loop system without disturbance controlled by an exact feedback linearization controller. The controller's performance was evaluated based on the prediction accuracy of the robotic manipulator system, with evaluation metrics such as R-squared, RMSE, and MAE. The trained model was then used to predict the attitude response of the robot under various operating conditions. The simulation results showed that the LightGBM controller provided accurate predictions with high precision. all of the model training, testing, and simulations were carried out using Python v3.11 and Python package *LightGBM* v3.2.1

LightGBM training and simulations were carried out with various data sizes to show the importance of data size in LightGBM training, ranging from 2,525 to 1,080,900 in data size. The smaller datasets were generated with fewer combinations of initial conditions, as well as timesteps. We utilized *Optuna* for hyperparameter tuning, a versatile and efficient optimization framework [26]. The refined hyperparameter values resulting from this optimization process were as follows: (*'learning rate': 0.06140943968291145, 'num iterations': 347, 'lambda l1': 4.001711155980835, 'lambda l2': 0.17256176847566432, 'max bin': 1439, 'num leaves': 1915*). These values were obtained through an iterative optimization process, fine-tuning the hyperparameters for improved model performance. It is crucial to note that

TABLE 1. Evaluation metric for various data size.

Data Size	R^2	RMSE	MAE	Training Time
2 525	0.917	6.761	1.785	1.351
9 849	0.964	4.849	1.148	3.660
50 100	0.976	3.888	0.766	4.055
100 944	0.979	3.337	0.653	4.356
242 121	0.998	1.083	0.243	5.966
1 080 900	0.999	0.584	0.132	45.148

while these hyperparameters were optimized, other relevant hyperparameters were maintained at their default values.

In evaluating the performance of the LightGBM controller, various evaluation metrics such as R-squared, root mean squared error (RMSE), and mean absolute error (MAE) were utilized. These metrics were used to measure the accuracy of the predicted values compared to the actual values. R-squared is a statistical measure that indicates how well the predicted values match the actual values. RMSE is the square root of the mean of the squared differences between predicted and actual values. MAE is the mean of the absolute differences between predicted and actual values. A higher R-squared value and lower RMSE and MAE values indicate higher accuracy and a better fit of the data-driven controller to the actual data.

The analysis of the experimental results reveals interesting trends in the R-squared values with varying data sizes. It is observed that as the data size increases, the R-squared value, which measures the goodness of fit of the LightGBM controller, improves significantly. This signifies that a larger dataset allows for better accuracy and predictive performance of the controller. Starting from 9,849 data size, a notable enhancement is observed in the R-squared value, surpassing the threshold of 0.95. This indicates that the model explains more than 95% of the variance in the robotic manipulator data. As the dataset size further scales, reaching 242,121 data points, the R-squared value exhibits remarkable stability, persistently hovering around 0.99 (99%). This sustained high R-squared value underscores the robustness of the LightGBM algorithm in discerning the underlying data patterns, resulting in highly accurate predictions of robotic manipulator behavior.

On the other hand, the Root Mean Squared Error (RMSE) and Maximum Absolute Error (MAE) values tend to decrease as the sample size increases. This observation suggests that the model's performance may increase slightly with larger sample sizes, as indicated by the smaller difference in train-test performance. However, it is important to note that the increase in RMSE and MAE values may still be within acceptable bounds, depending on the specific application and error tolerance. From Section IV-C, it is proven that we can generate a smaller M, which is equivalent to MAE, with increasing data size.

Generally, the elevated R-squared value and the observed patterns in RMSE and MAE values signify encouraging outcomes for our introduced LightGBM algorithm in the context of robotic manipulators. However, it is imperative to conduct additional scrutiny and validation to attain a comprehensive comprehension of the model's performance and possible constraints, ensuring its applicability in real-world scenarios.

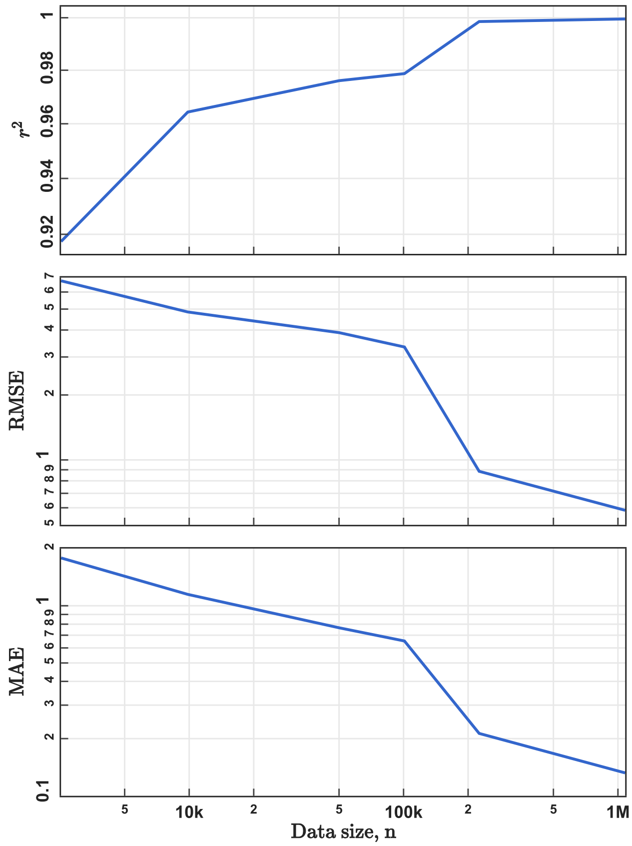

FIGURE 4. Evaluation metrics for various data size.

These findings imply that the LightGBM controller exhibits the ability to make precise predictions of torque output based on input variables with a notable level of certainty, as indicated by the robust R-squared values and minimal RMSE values. The model's proficiency improved with the expansion of the dataset. These outcomes serve to highlight the efficacy of the LightGBM controller in forecasting the dynamics of the robotic manipulator system.

B. SIMULATION OF LIGHTGBM CONTROLLER

The simulation using the LightGBM controller shows that the closed-loop system is stable as we have shown in the previous section. The simulation was conducted with different data sizes, ranging from 1 thousand to 10 Million data points. In addition to that, we also evaluate the transient property of the closed-loop dynamics in this simulation. Evaluation metrics use two parameters for the transient property. First, maximum overshoot which is defined as the percentage of the largest overshoot value with respect to the initial condition of the respective attitude, namely

$$\text{maximum overshoot} = \max_{i=1,2,3} \frac{|\zeta_{i,peak}|}{|\zeta_i(0)|} \times 100\% \tag{47}$$

TABLE 2. Maximum overshoot and settling time for various data size.

Data Size	Max Overshoot (%)	t_s (s)
2 525	-	-
9 849	-	-
50 100	8.282	0.714
100 944	4.707	0.643
242 121	5.670	0.689
1 080 900	4.132	0.528

where $|\zeta_{i,peak}|$ is the maximum absolute value sof the i-th attitude.

Second, we use 2% settling time for another evaluation metric for transient performance, t_s, which defined as follows

$$t_s = \max_{i=1,2,3} t_{s,i} \tag{48}$$

where $t_{s,i}$ is 2% settling time for attitude i, i.e. if for all $t \geq t_{s,i}$ imply $|\zeta_i(t)| \leq 2\%|\zeta_i(0)|$.

The analysis of the simulation results with various data sizes, ranging from 2,225 to 1,080,900, reveals interesting trends in the maximum overshoot and settling time with varying data sizes, as shown in Table 2. The analysis reveals that as the data size increases, the LightGBM controller demonstrates enhanced performance in terms of maximum overshoot and settling time. This indicates that a larger dataset allows for better learning and generalization of the controller. However, it's noteworthy that data sizes 2,525 and 9,849 exhibits less stable results.

C. SIMULATION OF LIGHTGBM CONTROLLER WITH UNCERTAINTY AND DISTURBANCE

The LightGBM controller's capability to manage disturbances and increased inertia is crucial in practical applications where robotic systems face uncertainties and disturbances. The demonstrated robustness of the controller, evident in its capacity to sustain effective control amid uncertainties and disturbances, emphasizes its dependability and applicability for real-world deployment in robotic manipulator systems. The robotic manipulator system using LightGBM controller with uncertainty and disturbance is defined in Section IV-C.

This section delves into the robustness of the proposed LightGBM controller approach. To demonstrate its robustness, simulations are performed under conditions involving a 5% increase in inertia. Torque disturbance is simulated using white noise generated by a normal Gaussian distribution with a mean value of zero and a standard deviation of 3%. The simulations utilize a dataset containing 1,080,900 data points, and the outcomes are presented in Fig. 5.

The results demonstrate the controller's effective handling of uncertainty and noise, showcasing robust performance. A 5% increase in inertia and the 3% Gaussian white noise lead to a 26.10% increase in settling time and quite similar overshoot values, compared to robotic manipulators without uncertainty and disturbance. However, as illustrated in Fig. 5, the system with uncertainty and disturbance maintains stability. The analysis offers crucial insights into the controller's performance and its ability to counteract the detrimental effects of uncertainty and disturbance. Future investigations could delve into exploring the controller's performance across various types and levels of uncertainty and disturbance, as well as comparing its effectiveness with other control methods under similar conditions.

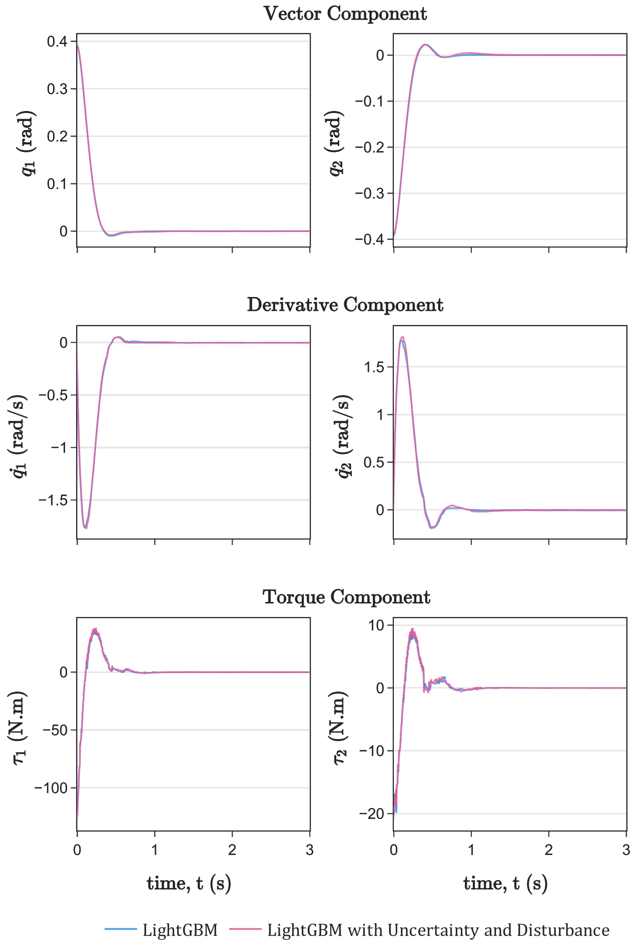

FIGURE 5. Robotic manipulator system using LightGBM controller without and with uncertainty and disturbance.

In summary, the results highlight the favorable prospects of employing the LightGBM controller as a data-driven method for robotic manipulators when facing perturbances like uncertainty in inertia and torque disturbance.

VI. CONCLUSION

Based on the points discussed in our paper, we can conclude that our proposed data-driven LightGBM controller for robotic manipulators presents a promising approach for addressing the constraints associated with traditional model-based controllers. Utilizing feedback linearization with robotic manipulator data, the synthesis procedure facilitates robust and scalable control performance.

Extensive simulations and real-world experiments validate the practical applicability of the proposed controller across diverse industrial applications, affirming its effectiveness in real-world scenarios. Through extensive simulations and real-world experiments, the proposed LightGBM controller demonstrated superior performance with evaluation metrics such as Root Mean Squared Error (RMSE) of 0.584, Mean Absolute Error (MAE) of 0.132, and R-squared of 0.999. The controller also demonstrates a settling time of 0.528 seconds and an overshoot of 4.132%. This comprehensive assessment underscores the controller's effectiveness and reliability.

Furthermore, by using the Lyapunov stability approach and adopting the concepts of nominal motion [25], practical stability [11], and total stability [25], we establish that the tracking error dynamics exhibit notable stability properties, namely practical stability and total stability. This research contributes to the development of robust, intelligent, and adaptive control strategies for robotic manipulators, paving the way for enhanced performance and applicability in diverse operational environments.

Moreover, the outcomes derived from the application of the proposed LightGBM controller highlight its effectiveness in handling challenging conditions characterized by uncertainty and disturbance. The controller exhibits robust performance, affirming its capacity to adeptly manage instances of uncertainty and disturbance within a robotic manipulator system.

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