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Comparison and Evaluation of Stability-Preserving Model Order Reduction Methods for Rigid Robot Manipulators: A Study on a 4-DOF Robotic Arm

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***Abstract*—Robust control of robotic systems critically depends on the stability-preserving capabilities of model order reduction (MOR) techniques. However, selecting an optimal MOR method for rigid robot manipulators remains challenging due to trade-offs between model fidelity, stability preservation, and computational efficiency. The research contribution of this study is to systematically compare three MOR methods—Balanced Truncation (BT), Positive-Real Balanced Truncation (PRBT), and Modal Truncation (MT)—applied to a 4-degree-of-freedom (4-DOF) robotic arm modeled as a linear time-invariant (LTI) system. We evaluated the methods based on error metrics, including H-infinity norm differences, and analyzed their time-domain and frequency-domain responses under standard test conditions. Our results demonstrate that BT provides superior reduction quality by maintaining stability and achieving an accurate dynamic response. PRBT, while exhibiting higher error than BT, effectively preserves both stability and passivity, making it advantageous for applications where passivity is essential, such as in mechanical and electrical circuits. In contrast, MT shows significant performance limitations with large errors and inconsistent responses, rendering it unsuitable for precision control applications. In conclusion, this study offers valuable insights into the trade-offs among MOR techniques and highlights practical implications for industrial automation. Future work will focus on expanding the analysis to a broader range of robotic systems and varying operational conditions.**

Keywords—Rigid Robot Manipulator; Model Order Reduction; Balanced Truncation; Modal Truncation; Positive-Real Balanced Truncation; Stability Preservation.

I. INTRODUCTION

Rigid robot manipulators are integral components in modern automation, performing essential tasks such as moving, positioning, and assembling objects [1]-[10]. These systems, composed of rigid links arranged in serial or branched configurations with rotational or translational joints, are widely deployed in industrial and research settings for their precision and efficiency [11]-[68]. However, the inherent complexity of their kinematics—characterized by high-dimensional state-space dynamics and tightly coupled relationships among numerous state variables—presents significant challenges in modeling, simulation, and controller design. In particular, maintaining system stability under these conditions is critical for ensuring reliable performance and precise control.

To overcome these challenges, Model Order Reduction (MOR) techniques have been developed to simplify complex models while preserving essential dynamic properties [69]-[73]. By reducing computational complexity, MOR facilitates faster simulations and more efficient system testing, evaluation, prediction, and fault detection. Despite significant progress, current MOR methods still face challenges in balancing accuracy, computational efficiency, and the preservation of key physical properties such as stability and passivity.

Several MOR algorithms have been applied in this context. The Modal Truncation (MT) method reduces model order by eliminating modes that have minimal impact on system dynamics while retaining those critical for stability [74]-[76]. Balanced Truncation (BT), as introduced in Moore's study, effectively reduces large-scale linear systems by achieving a favorable balance between accuracy and computational efficiency in applications like mechatronic systems and robotic kinematic simulations [77]-[79]. Positive-Real Balanced Truncation (PRBT) extends the BT approach to additionally preserve the positive-real property of the system, which is essential in passive systems such as electrical circuits and mechanical structures [80]-[82].

Although these techniques have been successfully applied across various fields, a systematic comparative analysis of their performance in the context of rigid robot manipulators is lacking. Specifically, there is a need to clearly define the evaluation criteria—such as error metrics, stability preservation, and computational efficiency—and to elucidate the trade-offs inherent to each method.

The research contribution of this paper is to provide a comprehensive comparison of BT, MT, and PRBT when applied to a rigid robot manipulator model [83]. This study not only streamlines the discussion of MOR techniques by focusing on their distinctive features and relevance to robotic control but also explicitly outlines the evaluation methodology and performance criteria. The insights gained will aid researchers and engineers in selecting the most appropriate MOR algorithm to optimize both model fidelity and computational efficiency in high-dimensional robotic systems.

II. METHODS

All three MOR algorithms—Balanced Truncation (BT), Positive-Real Balanced Truncation (PRBT), and Modal Truncation (MT)—begin with a common initial phase: Initialization and System Stability Check:

a) Start: Initialize the system by providing the state-space model or transfer function.

b) Stability Check: Verify if the system is stable. If the system is unstable, the respective algorithm terminates, as it requires a stable system for valid reduction.

Each algorithm involves computational steps such as solving matrix equations (Lyapunov or Riccati equations), performing matrix decompositions (Cholesky, SVD, or eigenvalue decomposition), and applying transformations. The computational complexity varies:

a) BT and PRBT: Require solving Lyapunov or positive-real Riccati equations and performing SVD, which can be computationally intensive for high-dimensional systems.

b) MT: Involves eigenvalue decomposition, which might be less demanding but may sacrifice some accuracy in capturing dynamic behavior.

Selection of Reduced Order (r): For all algorithms, the reduced order r is determined by analyzing the singular values (or positive-real singular values) of the system. A common practice is to select r such that the cumulative energy (sum of singular values) reaches a threshold (e.g., 95% of the total energy) or by discarding states with singular values below a predefined threshold. This criterion ensures a balance between model accuracy, input-output response approximation, and computational simplicity.

These three algorithms are chosen because they offer complementary advantages: BT provides an excellent balance between accuracy and efficiency; PRBT is particularly suitable for passive systems requiring the preservation of the positive-real property; and MT, while simpler, offers a direct approach by focusing on dominant dynamic modes. This selection aligns with the study's goal to comprehensively evaluate model reduction techniques in the context of high-dimensional robotic systems.

A. Balanced Truncation (BT) Algorithm

Balanced Truncation (BT) is based on balancing the input control energy and output observation energy through a non-singular transformation matrix, followed by the removal of states corresponding to small Hankel singular values, which have low energy and minimal influence on the system's dynamic behavior. The steps of the BT algorithm are illustrated in Fig. 1 and are described as follows [77]-[79]:

a) Start: Initialize the system. Provide the state-space model, including the system's matrices or transfer function.

b) System Stability Check: If the system is unstable, the BT algorithm cannot be applied directly, and the process terminates. If the system is stable:

- Compute the controllability Gramian W_c and observability Gramian W_o by solving the Lyapunov equations (1) and (2):

$$\boldsymbol{A}\boldsymbol{W}_c + \boldsymbol{W}_c\boldsymbol{A}^T = -\boldsymbol{B}\boldsymbol{B}^T \tag{1}$$

$$\boldsymbol{A}^T\boldsymbol{W}_o + \boldsymbol{W}_o\boldsymbol{A} = -\boldsymbol{C}^T\boldsymbol{C} \tag{2}$$

- Perform Cholesky decomposition on the Gramians: $\boldsymbol{W}_c = \boldsymbol{K}\boldsymbol{K}^T$ and $\boldsymbol{W}_c = \boldsymbol{J}\boldsymbol{J}^T$.

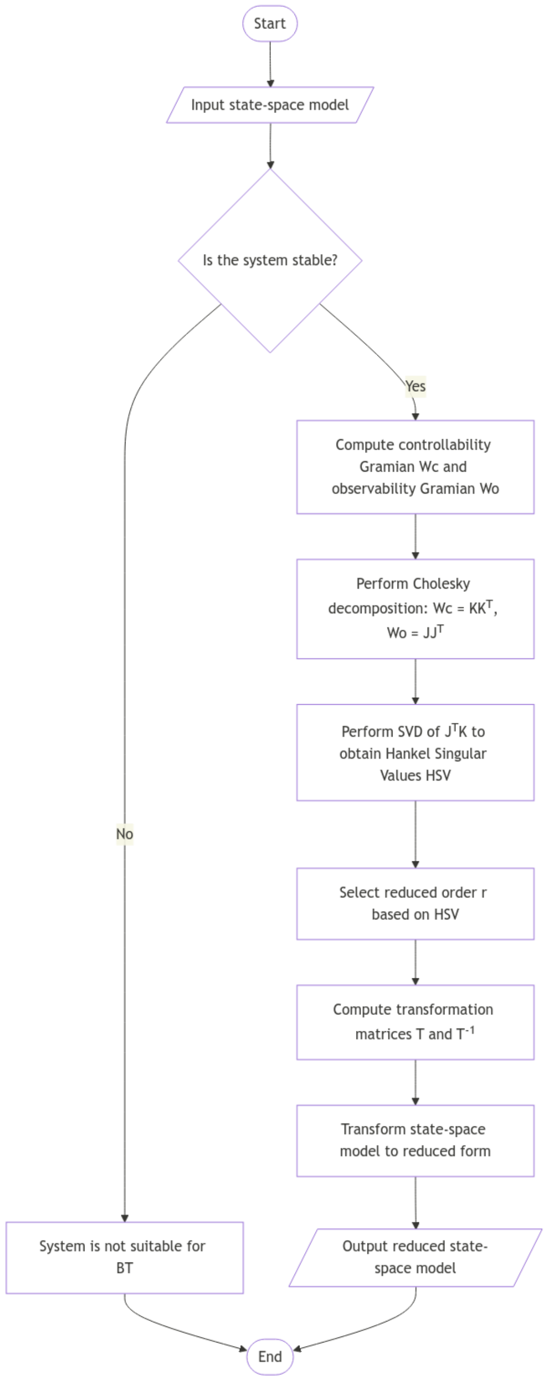

Fig. 1. Flowchart of the BT model reduction algorithm

– Conduct Singular Value Decomposition (SVD) of $\boldsymbol{J}^T\boldsymbol{K}$ to determine the Hankel singular values.

– Select the desired reduced order r: Based on the singular values, determine the reduced order that ensures a balance between error accuracy, input-output response approximation, and model simplicity.

– Compute the transformation matrices $\boldsymbol{T}$ to transform the system into the balanced Gramian state-space form.

– Apply the transformation to obtain the reduced-order state-space matrices by eliminating states corresponding to the small Hankel singular values for the desired reduced order.

– End: Complete the model reduction process using the BT algorithm.

B. Positive-Real Balanced Truncation (PRBT) Algorithm

The PRBT algorithm is a model reduction technique specifically designed for stable and passive systems, aiming to preserve the positive-real property while reducing system complexity. PRBT operates by balancing the energy between the system's controllability and observability, then eliminating less significant states based on Positive Real Singular Values (PRSVs). The steps of the PRBT algorithm are illustrated in the flowchart in Fig. 2 and are described as follows [77]-[79]:

a) Start: Initialize the system. Provide the system matrices or transfer function.

b) System Stability Check: If the system is unstable, the PRBT algorithm cannot be applied directly, and the process terminates. If the system is stable:

– Compute the controllability Gramian R_c and observability Gramian R_o by solving the positive-real Riccati equations (3) and (4):

$$\boldsymbol{A}^T\boldsymbol{R}_c + \boldsymbol{R}_c\boldsymbol{A} + (\boldsymbol{R}_c\boldsymbol{B} - \boldsymbol{C}^T)(\boldsymbol{D} + \boldsymbol{D}^T)^{-1}(\boldsymbol{B}^T\boldsymbol{R}_c - \boldsymbol{C}) = \boldsymbol{0} \tag{3}$$

$$\boldsymbol{A}\boldsymbol{R}_o + \boldsymbol{R}_o\boldsymbol{A}^T + (\boldsymbol{R}_o\boldsymbol{C}^T - \boldsymbol{B})(\boldsymbol{D} + \boldsymbol{D}^T)^{-1}(\boldsymbol{C}\boldsymbol{R}_o - \boldsymbol{B}^T) = \boldsymbol{0} \tag{4}$$

– Perform Cholesky decomposition on the Gramians: $\boldsymbol{R}_c = \boldsymbol{R}\boldsymbol{R}^T$ and $\boldsymbol{R}_o = \boldsymbol{S}\boldsymbol{S}^T$.

– Conduct SVD of $\boldsymbol{S}^T\boldsymbol{R}$ to determine the positive-real Hankel singular values.

– Select the desired reduced order r: Based on the positive-real singular values, determine the reduced order to balance error accuracy, input-output response approximation, and model simplicity.

– Compute the transformation matrices $\boldsymbol{T}_z$ and $\boldsymbol{T}_z^{-1}$ to transform the system into the positive-real balanced Gramian state-space form.

– Apply the transformation to obtain the reduced-order state-space matrices by eliminating states corresponding to small positive-real Hankel singular values for the desired reduced order.

– End: Complete the model reduction process using the PRBT algorithm.

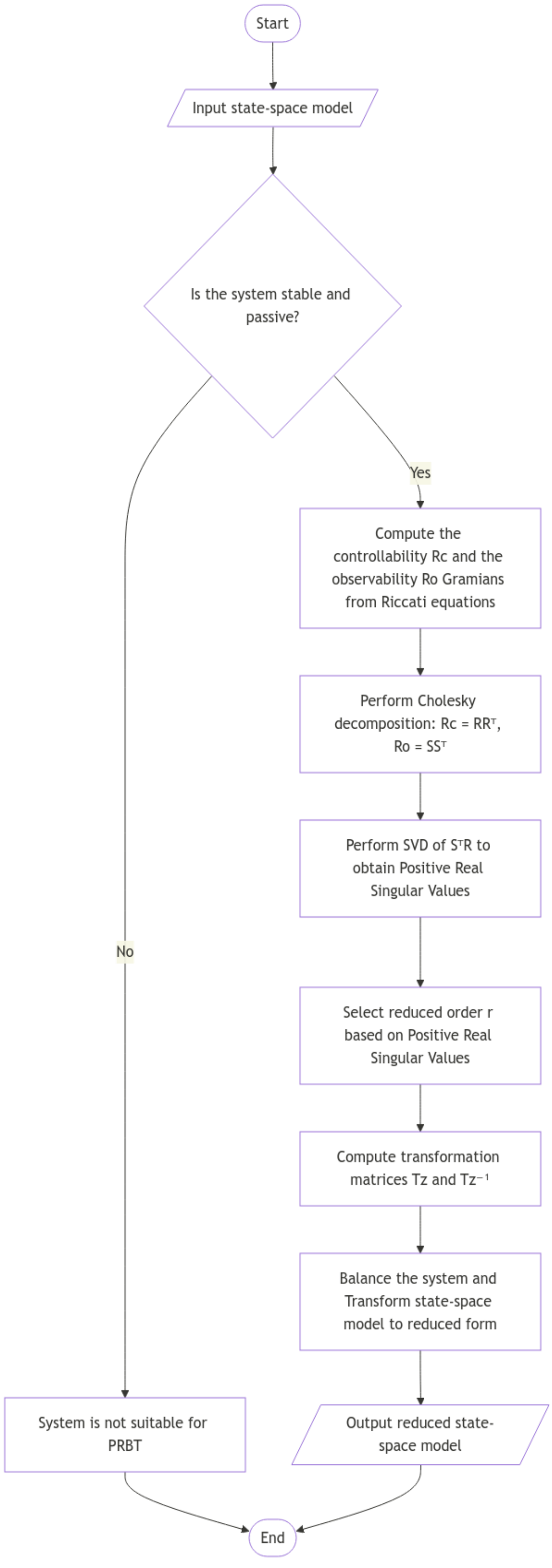

Fig. 2. Flowchart of the PRBT model reduction algorithm

C. *Modal Truncation (MT) Algorithm*

Modal Truncation (MT) is a model reduction method based on retaining the system's most significant modes (eigenvalues). The steps of the MT algorithm are illustrated in the flowchart in Fig. 3 and are described as follows [74]-[76]:

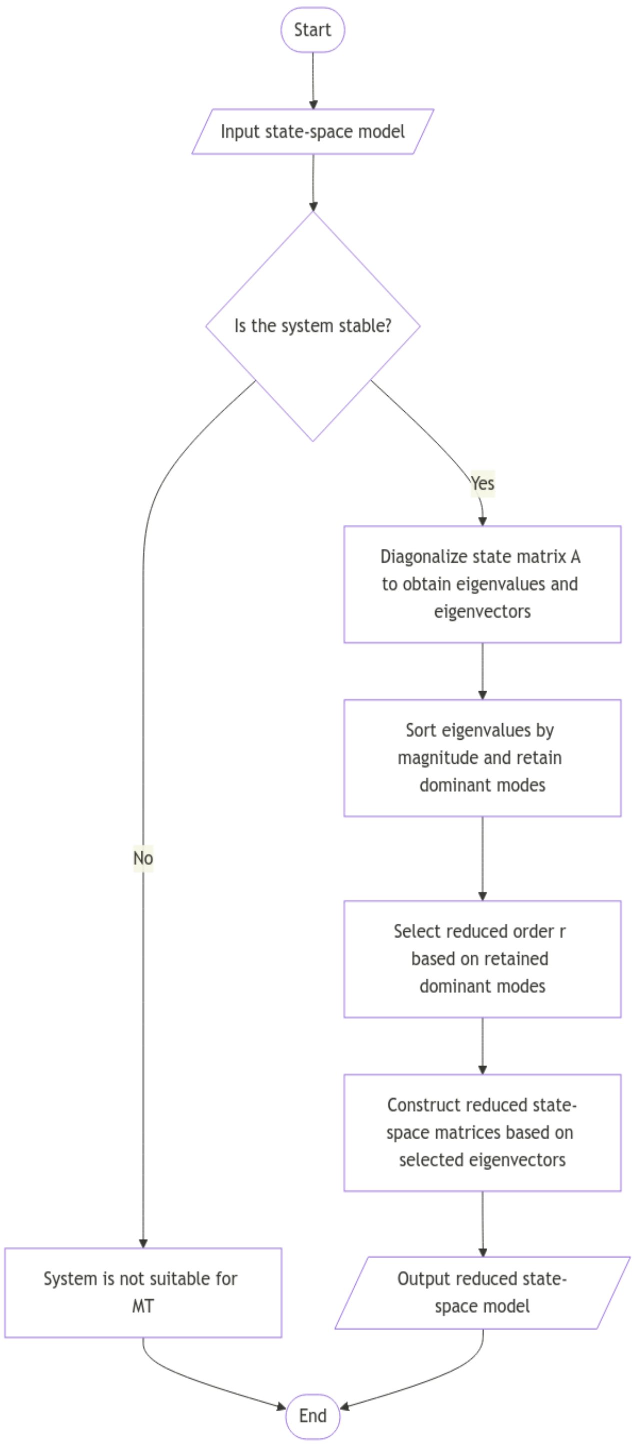

Fig. 3. Flowchart of the MT model reduction algorithm

a) Step 1. Start: Initialize the system. Provide the system matrices or transfer function.

b) Step 2. System Stability Check: If the system is unstable, the MT algorithm cannot be applied directly, and the process terminates. If the system is stable:

– Diagoalize the state matrix A, calculate its eigenvalues and eigenvectors, representing the system's modes.

– Sort the eigenvalues by magnitude and identify the most significant modes, which contribute the most to the system’s dynamics.

– Determine the number of significant modes rr to retain, ensuring a balance between accuracy and model simplicity.

– Reconstruct the reduced-order state-space model matrices based on the eigenvectors corresponding to the retained modes.

– End: Complete the process with a lower-order model that preserves the original eigenvalues and system stability.

III. RESULTS AND DISCUSSION

Consider the dynamic model of a Rigid Robot Manipulator as described in [83]. This model is commonly used for analyzing and controlling robotic arms in industrial applications, aiming to optimize motion while ensuring high accuracy and stability. It is designed for performing rotational and translational movements in space, serving tasks such as picking, transporting, or assembling in industrial environments.

The robotic arm has 4 degrees of freedom (4 DOF), corresponding to 4 independently controlled rotary joints. The system exhibits stability, controllability, observability, and passivity. The dynamic model of the Rigid Robot Manipulator is expressed in the form of linear time-invariant (LTI) state-space differential equations as shown in (5):

$$\begin{aligned} \dot{\boldsymbol{x}}(t) &= \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) \\ \boldsymbol{y}(t) &= \boldsymbol{C}\boldsymbol{x}(t) \end{aligned} \tag{5}$$

where:

a) State vectors: The state variables include the positions (angles) and angular velocities of the rotary joints: $\boldsymbol{x}^T(t) = [q \quad \dot{q}]$, where $q \in \mathbb{R}^4$ is the vector of joint angles, and $\dot{q} \in \mathbb{R}^4$ is the vector of angular velocities; $\boldsymbol{u}(t)$: Input (control torques at the joints); $\boldsymbol{y}(t)$: Output (measured signals).

b) System matrices **A**, **B**, **C**:

a) The state matrix **A** describes the system's overall dynamics, linking positions, velocities, and accelerations with applied forces. It reflects the relationships between equilibrium of positions and velocities and the effects of inertial mass and damping forces $\boldsymbol{A} = \begin{bmatrix} \boldsymbol{0} & \boldsymbol{M}^{-1} \\ -\boldsymbol{I}_4 & -\boldsymbol{F}\boldsymbol{M}^{-1} \end{bmatrix}$, where $\boldsymbol{I}_4$ is a 4×4 identity matrix; the inertial matrix $\boldsymbol{M} = \frac{1}{2}\boldsymbol{I}_4$ represents the relationship between joint accelerations and torques, and being diagonal assumes inertial independence between joints. The damping matrix $\boldsymbol{F} =$

$\begin{bmatrix} 2 & -1 & 0 & 0 \\ -1 & 4 & -2 & 0 \\ 0 & -2 & 4 & -1 \\ 0 & 0 & -1 & 2 \end{bmatrix}$ models the resistance forces due to joint friction. Its symmetric positive-definite property ensures energy dissipation, reflecting the system's sustainability.

b) The input matrix $\boldsymbol{B}^T = [0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0]$ determines how input torques affect the joints. In this case, forces act specifically on individual joints.

c) The output matrix $\boldsymbol{C} = \boldsymbol{B}^T \cdot \begin{bmatrix} \boldsymbol{I} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{M}^{-1} \end{bmatrix}$ relates the system states (angles, velocities) to the measured signals or desired outputs.

The order of this robotic arm model (n = 8) is reduced to lower orders using the BT, PRBT, and MT algorithms. The deviations between the original system and reduced-order systems of order r (with r ranging from 1 to n^{-1}) in terms of the H_∞-norm are summarized in Table I, with error plots shown in Fig. 4.

TABLE I. ERRORS BETWEEN THE ORIGINAL AND REDUCED-ORDER SYSTEMS USING BT, PRBT, MT

Order	Err of BT	Err of PRBT	Err of MT
1	0.6060606060606	0.6044493035126	0.7309146392584
2	0.0218653259230	0.0951432964074	0.7309146392584
3	0.0218647940185	0.0951359605571	0.7309146392584
4	0.0010159300171	0.0072259695212	0.7309146392584
5	0.0009638489032	0.0072259477188	0.7309146392584
6	0.0000520811139	0.0004616388483	0.7309146392584
7	0.0000520811139	0.0004616364865	0.7309146392584

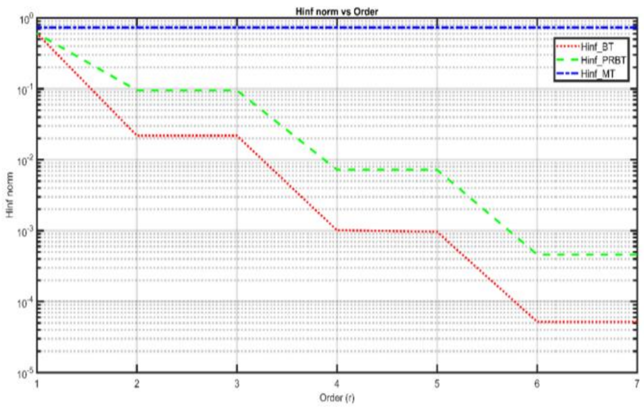

Fig. 4. H∞-norm errors for orders rr using BT, PRBT, and MT

From Table I and Fig. 4, the following observations can be made:

a) BT consistently achieves the smallest error, with PRBT slightly higher. In contrast, MT maintains a high error level (approximately 0.73) regardless of r, indicating that its methodology does not capture the system's coupled dynamics adequately.

b) The error using BT (red curve) is consistently the smallest, followed by PRBT (green curve), with MT (blue curve) exhibiting the largest deviation.

c) Across all reduced orders, MT shows negligible change in error, indicating poor reduction quality and unsuitability for this robot model.

d) BT and PRBT exhibit similar errors for orders r = 2 and r = 3, r = 4 and r = 5, r = 6 and r = 7.

To evaluate the input-output responses of the reduced-order systems compared to the original system in both time and frequency domains, the model is reduced to order r = 2. The Bode and impulse response plots for the reduced systems using BT, PRBT, and MT are shown in Fig. 5 and Fig. 6.

From the frequency response in Fig. 5:

a) The reduced-order system using BT (red curve) matches the original system in both phase and magnitude across all frequencies.

b) PRBT (green curve) shows approximate alignment with the original system, while MT (blue curve) deviates significantly.

c) A reduced-order model of r = 3 using BT or PRBT can effectively replace the original n = 8 model in frequency-domain applications, reducing complexity.

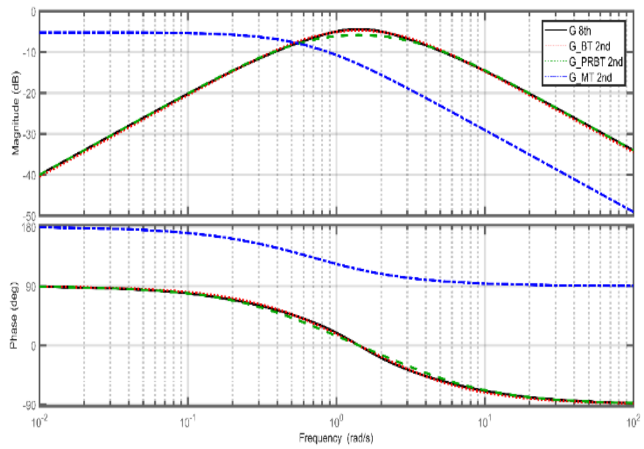

Fig. 5. Bode plots for the original and reduced-order systems using BT, PRBT, MT

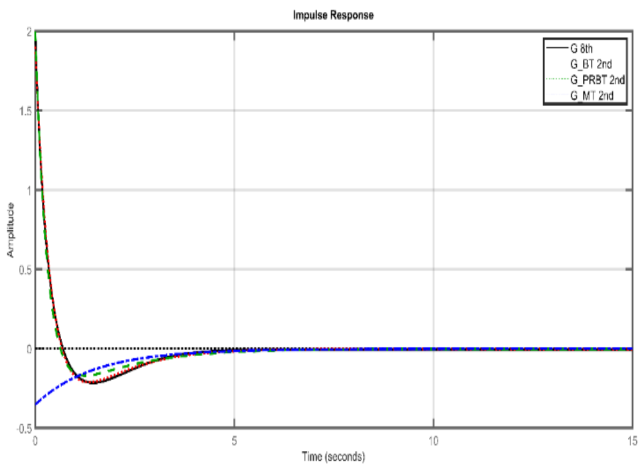

Fig. 6. Impulse responses for original and reduced-order systems using BT, PRBT, and MT

Fig. 6. Impulse responses for original and reduced-order systems using BT, PRBT, and MT.

From the time-domain responses in Fig. 6:

a) The r = 2 reduced system using BT (red curve) aligns closely with the original system, followed by PRBT (green curve).

b) From 0 to 5 seconds, MT deviates from the original system, but after 5 seconds, it approximates the original response.

c) A reduced-order model of r = 2 using BT or PRBT can effectively replace the original n = 8 model in time-domain applications, enhancing processing speed.

*1) **Some discussion:***

The H_∞-norm error between the full-order model $G(s)$ and the reduced-order model $G_r(s)$ is defined as shown in (6):

$$\|G(s) - G_r(s)\|_\infty = \sup_{\omega \in \mathbb{R}} \sigma_{\max}(G(j\omega) - G_r(j\omega)) \tag{6}$$

where $\sigma_{max}(\cdot)$ is the maximum singular value. This metric measures the worst-case gain of the error system across all frequencies.

A low H_∞ error means that, even under worst-case conditions (i.e., at the frequency where the error is maximized), the discrepancy between the full and reduced models is minimal. This is crucial in robust control where safety and performance margins must be preserved. For applications such as robotic manipulators, ensuring a small H_∞-norm error implies that the essential dynamic behaviors (e.g., stability margins and resonance peaks) are well maintained in the reduced model, thereby ensuring reliable control performance in practical, real-world settings.

The impulse response reflects the system's time-domain reaction to a Dirac delta input. Key characteristics include rise time, overshoot, settling time, and damping behavior. An impulse response that closely matches the full-order system indicates that the transient behavior—how the system reacts immediately to a disturbance—is accurately captured. For example, similar overshoot and settling times suggest that the reduced model will behave similarly to the full model when subjected to sudden changes. In real-time control, transient response characteristics determine how quickly and accurately a system can respond to disturbances. A reduced model with a well-preserved impulse response ensures that the controller designed using this model will perform reliably during rapid dynamic changes.

Bode plots graph the magnitude and phase of a system's frequency response. They are instrumental in evaluating stability margins, gain crossover frequency, and phase crossover frequency. f the Bode plot of the reduced model closely replicates that of the full model, then the stability margins (gain margin, phase margin) are preserved. This is critical for ensuring that the control system remains robust to variations and external disturbances. Maintaining similar frequency responses ensures that the reduced model captures the essential dynamics over the frequency range of interest. Deviations in critical frequency bands might lead to performance degradation (e.g., reduced tracking accuracy or increased sensitivity to noise) when the model is used for control design

Considering the overall requirements for model order reduction based on three main criteria—reduction error, preservation of the original system's physical properties, and computational cost—we can summarize the findings as follows:

a) Reduction Quality: Among the three algorithms (BT, PRBT, and MT), the BT algorithm yields the highest reduction quality. It produces the smallest reduction error and generates time- and frequency-domain responses that most accurately replicate those of the original system. PRBT follows closely, while MT shows the largest deviation.

b) Computational Cost: The MT algorithm exhibits the lowest computational complexity because it primarily relies on eigenvalue decomposition (matrix diagonalization). In contrast, the BT method requires solving two Lyapunov equations, performing Cholesky decomposition, and executing singular value decomposition (SVD). The PRBT algorithm is computationally the most demanding, as it involves solving two Riccati equations along with Cholesky decomposition and SVD.

c) Preservation of System Properties: With respect to retaining the inherent properties of the original system, PRBT is superior, particularly in maintaining stability and passivity. This is followed by BT and then MT.

d) Retention of Key System Features: In terms of safeguarding critical system characteristics, PRBT preserves the positive-real singular values, BT retains the Hankel singular values, and MT maintains the eigenvalues (poles) of the original system.

Criteria for Choosing Reduction Error:

a) The selection of the acceptable reduction error may be guided by several factors:

b) The user-specified target reduced order.

c) The magnitude of the reduction error.

d) The level of approximation required in the time-domain and/or frequency-domain responses.

e) The necessity to preserve certain properties of the original system in the reduced model.

Based on these considerations, simulation results, and performance evaluations of the BT, PRBT, and MT algorithms, the choice of a model reduction method should be tailored to the specific application requirements, scope, and target objectives.

IV. CONCLUSION

This study presents a comprehensive analysis and comparison of three Model Order Reduction (MOR) techniques—Balanced Truncation (BT), Positive-Real Balanced Truncation (PRBT), and Modal Truncation (MT)—applied to a rigid-link robotic arm model. The results indicate that the BT algorithm delivers the best overall performance by achieving the lowest reduction error and closely replicating the time-domain impulse response and frequency-domain characteristics of the original system. PRBT, although exhibiting slightly higher errors, excels in preserving both stability and passivity, which is crucial for physical systems where energy dissipation is critical. In contrast, MT underperforms because its reliance on eigenvalue preservation alone fails to capture the intricate coupled dynamics of the robotic arm.

It is important to note that our analysis is based on a linear time-invariant (LTI) model under specific idealized conditions, such as a diagonal inertia matrix and symmetric damping. These assumptions may limit the generalizability of the findings to more complex or nonlinear systems. Future research should address these limitations by extending the investigation to nonlinear or time-varying models and by exploring enhanced reduction techniques that further minimize error while preserving key system properties. Additionally, practical implementations in real-world industrial applications should be validated through experiments that evaluate computational savings and performance improvements in real-time control scenarios.

The theoretical contributions of this work lie in the establishment of quantitative performance metrics and guidelines for selecting an appropriate MOR algorithm based on reduction error, preservation of physical properties, and computational cost. By providing a detailed comparison of BT, PRBT, and MT, this study contributes new insights into the trade-offs inherent in model reduction and lays the groundwork for future advancements in high-performance robotic system design and industrial automation.

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References

[1] M. Marsono, Y. Yoto, A. Suyetno, and R. Nurmalasari, "Design and programming of 5 axis manipulator robot with GrblGru open source software on preparing vocational students' robotic skills," *Journal of Robotics and Control (JRC)*, vol. 2, no. 6, pp. 539–545, 2021.

[2] B. Sánchez-García, F. Reyes-Cortés, B. M. Al-Hadithi, and O. Félix-Beltrán, "Global saturated regulator with variable gains for robot manipulators," *Journal of Robotics and Control (JRC)*, vol. 2, no. 6, pp. 571-581, 2021.

[3] H. Q. T. Ngo and M. H. Nguyen, "Enhancement of the tracking performance for robot manipulator by using the feed-forward scheme and reasonable switching mechanism," *Journal of Robotics and Control (JRC)*, vol. 3, no. 3, pp. 328–337, 2022.

[4] Z. Anjum, S. Samo, A. Nighat, A. U. Nisa, M. A. Soomro, and R. Alayi, "Design and modeling of 9 degrees of freedom redundant robotic manipulator," *Journal of Robotics and Control (JRC)*, vol. 3, no. 6, pp. 800–808, 2022.

[5] C. E. Martínez Ochoa, I. O. Benítez González, A. O. Cepero Díaz, J. R. Nuñez-Alvarez, C. G. Miguélez-Machado, and Y. Llosas Albuerne, "Active disturbance rejection control for robot manipulator," *Journal of Robotics and Control (JRC)*, vol. 3, no. 5, pp. 622–632, 2022.

[6] A. S. Reddy, V. S. Chembuly, and V. K. Rao, "Modelling and simulation of a redundant agricultural manipulator with virtual prototyping," *Journal of Robotics and Control (JRC)*, vol. 4, no. 1, pp. 83–94, 2023.

[7] T. Q. Ngo, T. T. H. Le, B. M. Lam, and T. K. Pham, "Adaptive single-input recurrent WCMAC-based supervisory control for de-icing robot manipulator," *Journal of Robotics and Control (JRC)*, vol. 4, no. 4, pp. 438–451, 2023.

[8] N. X. Khoat, C. T. V. Hoa, N. B. N. Khoa, and N. M. Dung, "Trajectory planning and tracking control for 6-DOF Yaskawa manipulator based on differential inverse kinematics," *Journal of Robotics and Control (JRC)*, vol. 5, no. 6, pp. 2035–2047, 2024.

[9] Q. N. Xuan, C. N. Cong, and N. N. Ba, "Robust adaptive trajectory tracking sliding mode control for industrial robot manipulator using fuzzy neural network," *Journal of Robotics and Control (JRC)*, vol. 5, no. 2, pp. 490–499, 2024.

[10] T. Q. Ngo and T. H. Tran, "Robust adaptive iterative learning control for de-icing robot manipulator," *Journal of Robotics and Control (JRC)*, vol. 5, no. 3, pp. 746–755, 2024.

[11] T. Triwiyanto, W. Caesarendra, V. Abdullayev, A. A. Ahmed, and H. Herianto, "Single Lead EMG signal to Control an Upper Limb Exoskeleton Using Embedded Machine Learning on Raspberry Pi," *Journal of Robotics and Control (JRC)*, vol. 4, no. 1, pp. 35-45, 2023.

[12] F. Umam, M. Fuad, I. Suwarno, A. Ma'arif, and W. Caesarendra, "Obstacle avoidance based on stereo vision navigation system for omni-directional robot," *Journal of Robotics and Control (JRC)*, vol. 4, no. 2, pp. 227-242, 2023.

[13] . D. Cong, "Path following and avoiding obstacle for mobile robot under dynamic environments using reinforcement learning," *Journal of Robotics and Control (JRC)*, vol. 4, no. 2, pp. 157-164, 2023.

[14] P. Chotikunnan *et al.*, "Evaluation of single and dual image object detection through image segmentation using ResNet18 in robotic vision applications," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 263-277, 2023.

[15] F. Z. Baghli, Y. Lakhal, and Y. A. El Kadi, "The Efficiency of an Optimized PID Controller Based on Ant Colony Algorithm (ACO-PID) for the Position Control of a Multi-articulated System," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 289-298, 2023.

[16] A. A. Abed, A. Al-Ibadi, and I. A. Abed, "Vision-Based Soft Mobile Robot Inspired by Silkworm Body and Movement Behavior," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 299-307, 2023.

[17] A. A. Shetty, N. T. Hegde, A. C. Vaz, and C. R. Srinivasan, "Multi Cost Function Fuzzy Stereo Matching Algorithm for Object Detection and Robot Motion Control," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 356-370, 2023.

[18] N. T. T. Van, N. M. Tien, N. C. Luong, and H. T. K. Duyen, "Energy Consumption Minimization for Autonomous Mobile Robot: A Convex Approximation Approach," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 403-412, 2023.

[19] A. Ubaidillah and H. Sukri, "Application of Odometry and Dijkstra Algorithm as Navigation and Shortest Path Determination System of Warehouse Mobile Robot," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 413-423, 2023.

[20] H. L. Tran and T. V. Dang, "An Ultra Fast Semantic Segmentation Model for AMR's Path Planning," *Journal of Robotics and Control (JRC)*, vol. 4, no. 3, pp. 424-430, 2023.

[21] J. Díaz-Téllez *et al.*, "ROS-based controller for a two-wheeled self-balancing robot," *Journal of Robotics and Control (JRC)*, vol. 4, no. 4, pp. 491-499, 2023.

[22] T. Q. Ngo, T. H. Tran, T. T. H. Le, and B. M. Lam, "An application of modified T2FHC algorithm in two-link robot controller," *Journal of Robotics and Control (JRC)*, vol. 4, no. 4, pp. 509-520, 2023.

[23] N. S. Abu, W. M. Bukhari, M. H. Adli, and A. Ma'arif, "Optimization of an autonomous mobile robot path planning based on improved genetic algorithms," *Journal of Robotics and Control (JRC)*, vol. 4, no. 4, pp. 557-571, 2023.

[24] M. Shamseldin, "Real-time inverse dynamic deep neural network tracking control for Delta robot based on a COVID-19 optimization," *Journal of Robotics and Control (JRC)*, vol. 4, no. 5, pp. 643-649, 2023.

[25] H. Hidayat, A. Buono, K. Priandana, and S. Wahjuni, "Modified Q-Learning Algorithm for Mobile Robot Path Planning Variation using

Motivation Model," *Journal of Robotics and Control (JRC)*, vol. 4, no. 5, pp. 696-707, 2023.

[26] V. V. Kravchenko *et al*., "Comparison of Spider-Robot Information Models," *Journal of Robotics and Control (JRC)*, vol. 4, no. 5, pp. 719-725, 2023.

[27] D. T. Tran, N. M. Hoang, N. H. Loc, Q. T. Truong, and N. T. Nha, "A fuzzy LQR PID control for a two-legged wheel robot with uncertainties and variant height," *Journal of Robotics and Control (JRC)*, vol. 4, no. 5, pp. 612-620, 2023.

[28] E. A. Nugroho, J. D. Setiawan, and M. Munadi, "Handling four DOF robot to move objects based on color and weight using fuzzy logic control," *Journal of Robotics and Control (JRC)*, vol. 4, no. 6, pp. 769-779, 2023.

[29] R. Pyla, V. Pandalaneni, and P. J. N. Raju, "Design and Development of swarm AGV's alliance for Search and Rescue operations," *Journal of Robotics and Control (JRC)*, vol. 4, no. 6, pp. 791-807, 2023.

[30] K. Yamtuan, T. Radomngam, and P. Prempraneerach, "Visual servo kinematic control of delta robot using YOLOv5 algorithm," *Journal of Robotics and Control (JRC)*, vol. 4, no. 6, pp. 818-831, 2023.

[31] V. V. Kravchenko *et al*., "Mathematical model of a robot-spider for group control synthesis: derivation and validation," *Journal of Robotics and Control (JRC)*, vol. 4, no. 6, pp. 849-855, 2023.

[32] M. Fuad *et al*., "Towards controlling mobile robot using upper human body gesture based on convolutional neural network," *Journal of Robotics and Control (JRC)*, vol. 4, no. 6, pp. 856-867, 2023.

[33] I. A. Hassan, I. A. Abed, and W. A. Al-Hussaibi, "Path planning and trajectory tracking control for two-wheel mobile robot," *Journal of Robotics and Control (JRC)*, vol. 5, no. 1, pp. 1-15, 2024.

[34] N. Jayasekara *et al*., "Revolutionizing Accessibility: Smart Wheelchair Robot and Mobile Application for Mobility, Assistance, and Home Management," *Journal of Robotics and Control (JRC)*, vol. 5, no. 1, pp. 27-53, 2024.

[35] R. D. Puriyanto and A. K. Mustofa, "Design and Implementation of Fuzzy Logic for Obstacle Avoidance in Differential Drive Mobile Robot," *Journal of Robotics and Control (JRC)*, vol. 5, no. 1, pp. 132-141, 2024.

[36] O. Y. Ismael, M. Almaged, and A. I. Abdulla, "Nonlinear model predictive control-based collision avoidance for mobile robot," *Journal of Robotics and Control (JRC)*, vol. 5, no. 1, pp. 142-151, 2024.

[37] H. Yadavari, V. T. Aghaei, and S. I. GLU, "Addressing challenges in dynamic modeling of stewart platform using reinforcement learning-based control approach," *Journal of Robotics and Control (JRC)*, vol. 5, no. 1, pp. 117-131, 2024.

[38] V. G. Nair, "Efficient Path Planning Algorithm for Mobile Robots Performing Floor Cleaning Like Operations," *Journal of Robotics and Control (JRC)*, vol. 5, no. 1, pp. 287-300, 2024.

[39] W. Al-Mayahi and H. Al-Fahaam, "Soft Actuator Based on a Novel Variable Stiffness Compound Extensor Bending-Pneumatic Artificial Muscle (CEB-PAM): Design and Mathematical Model," *Journal of Robotics and Control (JRC)*, vol. 5, no. 2, pp. 321-335, 2024.

[40] S. Yeslyamov, "Application of Software Robots Using Artificial Intelligence Technologies in the Educational Process of the University," *Journal of Robotics and Control (JRC)*, vol. 5, no. 2, pp. 359-369, 2024.

[41] G. N. P. Pratama, I. Hidayatulloh, H. D. Surjono, and T. Sukardiyono, "Enhance Deep Reinforcement Learning with Denoising Autoencoder for Self-Driving Mobile Robot," *Journal of Robotics and Control (JRC)*, vol. 5, no. 3, pp. 667-676, 2024.

[42] T. Q. Ngo, T. H. Tran, and T. T. H. Le, "Robust Adaptive Tracking Control for Uncertain Five-Bar Parallel Robot Using Fuzzy CMAC in Order to Improve Accuracy," *Journal of Robotics and Control (JRC)*, vol. 5, no. 3, pp. 766-774, 2024.

[43] E. H. E. Suryadarma, P. W. Laksono, I. Priadythama, and L. Herdiman, "Controlling Robots Using Gaze Estimation: A Systematic Bibliometric and Research Trend Analysis," *Journal of Robotics and Control (JRC)*, vol. 5, no. 3, pp. 786-803, 2024.

[44] H. Jati, N. A. Ilyasa, and D. D. Dominic, "Enhancing Humanoid Robot Soccer Ball Tracking, Goal Alignment, and Robot Avoidance Using YOLO-NAS," *Journal of Robotics and Control (JRC)*, vol. 5, no. 3, pp. 829-838, 2024.

[45] V. H. Le, "Visual Slam and Visual Odometry Based on RGB-D Images Using Deep Learning: A Survey," *Journal of Robotics and Control (JRC)*, vol. 5, no. 4, 2024.

[46] T. T. H. Le, T. Q. Ngo, and T. H. Tran, "Developing an Advanced Control System to Enhance Precision in Uncertain Conditions for Five-Bar Parallel Robot Through a Combination of Robust Adaptive Tracking Control Using CMAC," *Journal of Robotics and Control (JRC)*, vol. 5, no. 4, pp. 954-963, 2024.

[47] N. Nawress, A. N. L. Gharbi, and N. B. Braiek, "Sliding Mode Control based on Neural State and Disturbance Observers: Application to a Unicycle Robot Using ROS2," *Journal of Robotics and Control (JRC)*, vol. 5, no. 4, pp. 964-980, 2024.

[48] E. Marliana, A. Wahjudi, L. Nurahmi, I. M. L. Batan, and G. Wei, "Optimizing the Tuning of Fuzzy-PID Controllers for Motion Control of Friction Stir Welding Robots," *Journal of Robotics and Control (JRC)*, vol. 5, no. 4, pp. 1002-1017, 2024.

[49] W. A. Salah, A. A. Sneineh, and A. A. Shabaneh, "Smartphone Sensor-based Development and Implementation of a Remotely Controlled Robot Arm," *Journal of Robotics and Control (JRC)*, vol. 5, no. 4, pp. 1180-1188, 2024.

[50] W. A. H. Sandanika *et al*., "Ros-based multi-robot system for efficient indoor exploration using a combined path planning technique," *Journal of Robotics and Control (JRC)*, vol. 5, no. 5, pp. 1241-1260, 2024.

[51] S. Z. Saeed, M. A. A. Alobaidy, and Z. M. Yosif, "Errors Detection Based on SDWT and BNN Applied for Position, Velocity and Acceleration Signals of a Wheeled Mobile Robot," *Journal of Robotics and Control (JRC)*, vol. 5, no. 5, pp. 1291-1298, 2024.

[52] A. K. Abbas and S. K. Kadhim, "Dynamic Motion Control of Two-Link Robots with Adaptive Synergetic Algorithms," *Journal of Robotics and Control (JRC)*, vol. 5, no. 5, pp. 1536-1548, 2024.

[53] I. Al-Tameemi, D. Doan, A. Patanwala, and M. Agheli, "Momentum-Based Push Recovery Control of Bipedal Robots Using a New Variable Power Reaching Law for Sliding Mode Control," *Journal of Robotics and Control (JRC)*, vol. 5, no. 5, pp. 1570-1581, 2024.

[54] M. D. Nguyen, M. T. Ngo, H. Do Quang, and N. D. Phuong, "Reinforcement Learning-Based Trajectory Control for Mecanum Robot with Mass Eccentricity Considerations," *Journal of Robotics and Control (JRC)*, vol. 5, no. 5, pp. 1436-1443, 2024.

[55] S. Supriadi, A. Wajiansyah, M. Zainuddin, and A. B. W. Putra, "Optimization of Proportional Integral Derivative Controller for Omni Robot Wheel Drive by Using Integrator Wind-up Reduction Based on Arduino Nano," *Journal of Robotics and Control (JRC)*, vol. 5, no. 6, pp. 1690-1701, 2024.

[56] Y. Al Mashhadany, A. K. Abbas, S. Algburi, and B. A. Taha, "Design and Analysis of a Hybrid Intelligent SCARA Robot Controller Based on a Virtual Reality Model," *Journal of Robotics and Control (JRC)*, vol. 5, no. 6, pp. 1722-1735, 2024.

[57] M. Bashabsheh, "Autonomous Robotic Systems with Artificial Intelligence Technology Using a Deep Q Network-Based Approach for Goal-Oriented 2D Arm Control," *Journal of Robotics and Control (JRC)*, vol. 5, no. 6, pp. 1872-1887, 2024.

[58] K. D. Wahyuadnyana, K. Indriawati, P. A. Darwito, A. N. Aufa, and H. Tnunay, "Performance Analysis of PID and SMC Control Algorithms on AUV under the Influence of Internal Solitary Wave in the Bali Deep Sea," *Journal of Robotics and Control (JRC)*, vol. 5, no. 6, pp. 1957-1972, 2024.

[59] R. Mardiati, H. Firdaus, A. E. Setiawan, and D. Zulherman, "Combining Finite State Machine and Fuzzy Logic Control for Accuracy Enhancing Performance of a Tomato-Handling Robot Gripper," *Journal of Robotics and Control (JRC)*, vol. 5, no. 6, pp. 2027-2034, 2024.

[60] M. A. Basal and M. F. Ahmed, "Mathematical Modeling of a Unicycle Robot and Use of Advanced Control Methodologies for Multi-Paths Tracking Taking into Account Surface Friction Factors," *Journal of Robotics and Control (JRC)*, vol. 6, no. 1, pp. 142-154, 2025.

[61] N. L. Tao, D. H. Pham, and M. K. Pham, "Optimization of Hierarchical Sliding Mode Control Parameters for a Two-Wheeled Balancing Mobile Robot Using the Firefly Algorithm," *Journal of Robotics and Control (JRC)*, vol. 6, no. 1, pp. 76-88, 2025.

[62] J. P. A. Ogenga, W. Njeri, and J. Muguro, "Development of a Virtual Environment-Based Electrooculogram Control System for Safe

Electric Wheelchair Mobility for Individuals with Severe Physical Disabilities," *Journal of Robotics and Control (JRC)*, 2023.

[63] W. Rahmaniar and A. E. Rakhmania, "Online digital image stabilization for an unmanned aerial vehicle (UAV)," *Journal of Robotics and Control (JRC)*, vol. 2, no. 4, pp. 234–239, 2021.

[64] R. Pyla, V. Pandalaneni, and P. J. N. Raju, "Design and development of swarm AGV's alliance for search and rescue operations," *Journal of Robotics and Control (JRC)*, vol. 4, no. 6, pp. 791–807, 2023.

[65] H. F. Al-Qrimli, L. D'souza, and O. D. Hussein, "An innovative approach to a hybrid quadrotor design," *Journal of Robotics and Control (JRC)*, vol. 2, no. 1, pp. 19–23, 2021.

[66] W. Rahmaniar and A. E. Rakhmania, "Mobile robot path planning in a trajectory with multiple obstacles using genetic algorithms," *Journal of Robotics and Control (JRC)*, vol. 3, no. 1, pp. 1–7, 2022.

[67] B. AlKhlidi, A. T. Abdulsadda, and A. Al Bakri, "Optimal robotic path planning using intelligent search algorithms," *Journal of Robotics and Control (JRC)*, vol. 2, no. 6, pp. 519–526, 2021.

[68] H. Suwoyo, A. Adriansyah, J. Andika, A. U. Shamsudin, and Y. Tian, "An effective way for repositioning the beacon nodes of fast RRT results utilizing grey wolf optimization," *Journal of Robotics and Control (JRC)*, vol. 6, no. 1, pp. 272–284, 2025.

[69] S. Hiruma and H. Igarashi, "Fast Time-Domain Analysis of Darwin Model of Maxwell's Equations Using Arnoldi-Based Model Order Reduction," in *IEEE Transactions on Magnetics*, vol. 58, no. 9, pp. 1-4, Sept. 2022.

[70] N. Akram, M. Alam, R. Hussain and Y. Massoud, "Statistically Inspired Passivity Preserving Model Order Reduction," in *IEEE Access*, vol. 11, pp. 52226-52235, 2023.

[71] A. Marjamäki, R. Schneckenleitner, R. Elkhadrawy and P. Rasilo, "High-Frequency Modeling of Granular Soft Magnetic Materials With Local Model Order Reduction," in *IEEE Transactions on Magnetics*, vol. 60, no. 3, pp. 1-4, March 2024.

[72] Y. Li, D. Karunathilake, D. M. Vilathgamuwa, Y. Mishra, T. W. Farrell, and C. Zou, "Model order reduction techniques for physics-based lithium-ion battery management: A survey," *IEEE Ind. Electron. Mag.*, vol. 16, no. 3, pp. 36–51, 2021.

[73] A. Opreni, A. Vizzaccaro, A. Frangi, and C. Touzé, "Model order reduction based on direct normal form: Application to large finite element MEMS structures featuring internal resonance," *Nonlinear Dyn.*, vol. 105, no. 2, pp. 1237–1272, 2021.

[74] P. Vuillemin, A. Maillard, and C. Poussot-Vassal, "Optimal modal truncation," *Systems & Control Letters*, vol. 156, p. 105011, 2021.

[75] R. K. Németh and B. B. Geleji, "Modal truncation damping in reduced modal analysis of piecewise linear continuum structures," *Mechanics Based Design of Structures and Machines*, vol. 51, no. 3, pp. 1582-1605, 2023.

[76] G. Sui and Y. Zhang, "A complete SRSS format for the response spectrum method of high-cycle fatigue life assessment considering modal truncation error correction," *International Journal of Fatigue*, vol. 175, p. 107834, 2023.

[77] P. Benner, P. Goyal and I. P. Duff, "Gramians, Energy Functionals, and Balanced Truncation for Linear Dynamical Systems With Quadratic Outputs," in *IEEE Transactions on Automatic Control*, vol. 67, no. 2, pp. 886-893, Feb. 2022.

[78] A. M. Burohman, B. Besselink, J. M. A. Scherpen and M. K. Camlibel, "From Data to Reduced-Order Models via Generalized Balanced Truncation," in *IEEE Transactions on Automatic Control*, vol. 68, no. 10, pp. 6160-6175, Oct. 2023.

[79] M. S. Hossain and S. Trenn, "Midpoint-Based Balanced Truncation for Switched Linear Systems With Known Switching Signal," in *IEEE Transactions on Automatic Control*, vol. 69, no. 1, pp. 535-542, Jan. 2024.

[80] Z. Salehi, P. Karimaghaee, and M. H. Khooban, "Model order reduction of positive real systems based on mixed gramian balanced truncation with error bounds," *Circuits, Systems, and Signal Processing*, vol. 40, no. 11, pp. 5309-5327, 2021.

[81] Z. Salehi, P. Karimaghaee, and M. H. Khooban, "A new passivity preserving model order reduction method: conic positive real balanced truncation method," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, no. 5, pp. 2945-2953, 2021.

[82] T. T. Nguyen, N. K. Vu, and H. D. Dao, "A Comparative of Positive Real Truncation and H-Infinity Reduction Techniques for Model Simplification in Electrical Circuits and Power Systems," in *International Conference on Advances in Information and Communication Technology*, pp. 9-17, 2023.

[83] X. Cheng, J. M. A. Scherpen, and B. Besselink, "Balanced truncation of networked linear passive systems," *Automatica*, vol. 104, pp. 17–25, 2019.