REAL-TIME INTELLIGENT BIO-ROBOTIC CONTROL USING ADVANCED NONLINEAR NEURAL NETWORKS

Alexanand J[1], *N Thangarasu*[2]

Abstract

Intelligent and adaptive control is necessary for bio-robotic systems to deal with complex nonlinear dynamics and variations in the environment. Typical robot controllers are not very adaptable, have high trajectory errors, and have slow response times for dynamic motion commands. To overcome these drawbacks, in this paper, a novel real-time intelligent bio-robotic control framework, named Bio-Adaptive Nonlinear Neural Control Network with Adaptive Particle Swarm Optimization (BANN-ControlNet-APSO), is proposed. The proposed model combines the advanced nonlinear neural learning with Adaptive Particle Swarm Optimization (APSO) to optimize neural weights, control gains, and parameters associated with the response of the actuators. First, the motion information of the robot is measured by the sensors and preprocessed to obtain essential dynamic motion information. The BANN-ControlNet learns nonlinear robotic behavior and anticipates adaptive control actions, and APSO enhances the accuracy of the trajectory tracking and system stability. To reduce the deviation from the planned motion, a real-time feedback correction mechanism is integrated, which improves the autonomous decision-making function. The experimental results show that the proposed framework can achieve better control accuracy, shorter response time, smaller trajectory tracking errors, better stability, and lower energy consumption, which are more suitable for the applications in advanced bio-robotics and rehabilitation.

Keywords : Bio-Robotic Systems, Nonlinear Neural Networks, Intelligent Control, Adaptive Particle Swarm Optimization (APSO), Real-Time Robotics, Autonomous Motion Control, Trajectory Tracking, Bio-Adaptive Learning, Robotic Dynamics, Neural Optimization Framework.

I. INTRODUCTION

Bio-robotic systems are in the spotlight recently because they can mimic biological movements and execute intelligent, autonomous operations in a dynamic environment. These systems are applied in many fields such as healthcare, rehabilitation, industrial automation, and human–robot interaction. Artificial Intelligence and neural computing have significantly enhanced the adaptability and learning ability of the modern robotic system. Despite these challenges, controlling bio-robotic systems are difficult to achieve their given nonlinear dynamics, uncertain environmental conditions, and requirement for real-time response. To realize stable motion control, accurate trajectory tracking, and efficient robotic decision-making, intelligent control techniques are vital. Thus, more and more new intelligent bio-robotic systems will require advanced computational and adaptive learning methods.

With the growing use of intelligent bio-robotic systems in the medical, rehabilitation, and industrial automation sectors, high adaptability and real-time control mechanisms are required. Conventional robot controllers often have difficulty in controlling complex nonlinear systems and in dealing with fast changes of the environment. Currently, trajectory tracking accuracy, response time, and instability during robotic motion are still serious problems in current systems. The introduction of recent developments in neural computing and intelligent learning has created new possibilities for enhancing the adaptability and autonomy of robots. Advanced nonlinear neural-based control systems are therefore required to improve the efficiency, stability, and real-time performance of modern bio-robotic systems.

The currently available research work on bio-robotic control mainly deals with the conventional intelligent controllers like PID, fuzzy logic, artificial neural networks, and reinforcement learning methods. Deep learning and recurrent neural networks have been applied by some researchers to enhance robot motion prediction and performance of adaptive control. In some works, optimization methods have been used to improve the accuracy of trajectory tracking and minimize the control error in dynamic robotic environments. These techniques show intelligent behavior, but there are still many systems out there that are more complex, have lagged response time, and they are unstable when operating in the nonlinear motion domain. Moreover, there are difficulties in adapting to change and providing real-time feedback learning in existing bio-robotic control systems.

Product Support Tech Advisor 2[1]
IQVIA's primary corporate office in Bengaluru[1]
j.alexanand@gmail.com[1]

Department of Computer Science[2]
Karpagam Academy of Higher Education[2]
Coimbatore-21[2]
drthangarsu.n@kahedu.edu.in[2]

* Corresponding Author

The proposed work presents a Bio-Adaptive Nonlinear Neural Control Network with Adaptive Particle Swarm Optimization (BANN-ControlNet-APSO) for real-time intelligent control of a bio-robotic system. Firstly, real-time sensor data is collected and preprocessed to obtain the significant nonlinear motion features of the bio-robotic system. The BANN-ControlNet learns complicated robotic dynamics and produces adaptive control actions to accurately predict motion and track trajectories. The parameters of neural networks are optimized using adaptive particle swarm optimization, which enhances the stability of the control and reduces the trajectory error in the operation of the robots. In addition, a real-time feedback correction mechanism further improves the autonomous decision-making ability of the robot, response speed, and performance of the robotic system in a dynamic environment.

The main contributions of this paper are

- Designed a novel Bio-Adaptive Nonlinear Neural Control Network (BANN-ControlNet) for intelligent real-time bio-robotic motion control in nonlinear dynamic environments.
- Integrated Adaptive Particle Swarm Optimization (APSO) to optimize the weights, control parameters, and the response of actuators to enhance the performance of the robot.
- Systematically designed a real-time adaptive feedback learning mechanism to minimize the tracking error of the desired trajectory and increase the stability of the robot motion.
- Reduced response latency and improved intelligent decision-making capability for autonomous operations of bio-robotic systems.
- Improved control accuracy, energy saving, and dynamism in motion adaptability compared to the conventional robotic control techniques.

This paper is organized as follows. In Section I, an introduction and research motivation of intelligent bio-robotic control systems are presented. The current works and limitations of the robotic control systems are discussed in Section II, and the proposed BANN-ControlNet-APSO framework and working methodology are detailed in Section III. The experimental results and performance analysis are provided in Section IV, followed by the conclusion and future research directions in the last section.

II. RELATED WORK

The framework of the adaptive environment-aware robotic arm reaching in intelligent robotic interaction in dynamic environments was proposed in [8]. The experimental results showed that the robot's reaching accuracy and adaptive motion behavior under different environmental conditions were improved. The framework, however, is limited in its ability to deal with highly complex nonlinear robotic dynamics and demands more computational resources for real-time implementation.

In [9] a feature learning-based bio-inspired neural network was proposed in order to provide real-time collision-free rescue operations in multi-robot systems. The results showed efficient collision avoidance and enhanced cooperative robotic navigation performance during rescue scenarios. However, the proposed approach is not scalable for large-scale dynamic obstacle robotic systems.

In the work of Linares-Barranco et al. [10] (2024), they created an adaptive robotic arm control mechanism based on a spiking recurrent neural network realized on a digital accelerator for intelligent motion execution. Efficient neural computation resulted in an experimental evaluation with better motion adaptability and low-power robotic control performance. The model, however, has a complicated architecture, and training difficulties of spiking with neural networks for large robotic control tasks.

Wang, H. et al. [11] (2023) proposed an intelligent adaptive trajectory tracking control system for nonlinear robotic manipulators using deep neural network learning methods. The results showed increased trajectory tracking errors and increased stability of the robotic motion in uncertain operating situations. The overhead in computation and the inefficiency of the framework, however, are notable when a robot is performing high-speed real-time tasks.

In 2024, Kumar et al. [12] presented an intelligent robotic motion control system with deep reinforcement learning for nonlinear dynamic environments with adaptive decision-making capabilities. The experimental results showed that the autonomous robotic motion prediction and adaptive control performance improved. Although the method has good performance, it is necessary to have a lot of training data, and it needs a longer convergence time to obtain stable behavior in robotic control.

L. Chen et al. [13] (2025) presented a real-time adaptive robotic control method based on hybrid recurrent neural architectures for intelligent nonlinear robotic motion analysis. In the proposed model, the response speed was better and the accuracy of the path prediction of the robot in a dynamic operating environment was improved. However challenges include high computational complexity and memory utilization in continuous learning processes in the framework.

Park, J. et al. (2024) proposed an adaptive deep neural optimization-based intelligent nonlinear robotic control framework for autonomous robotic systems [14]. The experimental results indicated that the motion stability, adaptive learning ability, and control accuracy were improved under the nonlinear dynamic conditions. However, the optimization process needs to be performed in a significant amount of time and has the potential to impact the responsiveness of the robots during large-scale operations.

In the above research, Ahmed et al. [15] (2023) gave an intelligent robotic motion prediction framework inspired by biological systems for adaptive robotic autonomous control. The results showed the effectiveness of the robotic motion prediction system and the reduced motion deviation in the complex motion operations of the robot. The framework is, however, limited in its capacity to deal with quick-changing environmental disturbances and to maintain long-term motion stability in the uncertain environment.

III. PROPOSED WORK

The proposed work is for intelligent real-time bio-robotic control using a Bio-Adaptive Nonlinear Neural Control Network with Adaptive Particle Swarm Optimization (BANN-ControlNet-APSO). Firstly, the multi-sensor motion data acquired from the robots are preprocessed to eliminate the noise and extract the essential nonlinear dynamic features. The BANN-ControlNet framework is designed to learn complex robotic behavior patterns and produce adaptive control actions to accurately predict the robot's motion and to track the trajectory. Adaptive particle swarm optimization is also integrated to optimize the neural weights, control gains, and response parameters of actuators for better stability and accuracy. A real-time feedback correction mechanism is used for monitoring the performance of the robots during dynamic operation, which minimizes the deviation of the robots' motion. The suggested framework is capable of more accurate control, faster response time, better energy efficiency, and autonomous intelligent decision-making in advanced bio-robotic systems.

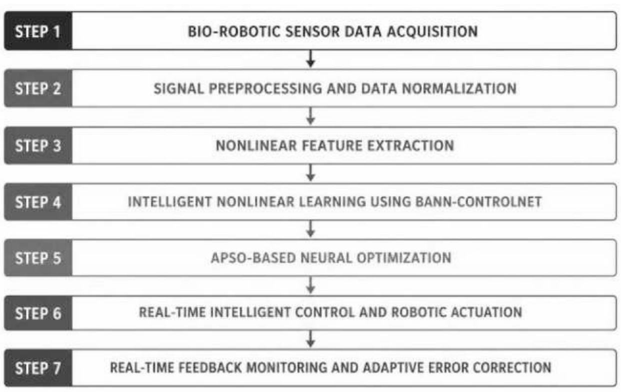

Figure 1. Block diagram of proposed model

A. Bio-Robotic Sensor Data Acquisition

The envisioned framework starts with getting real-time data on the robot in the form of bio-robotic sensors, which are integrated into the robot. They are used to continuously record significant information regarding various motions and physiological factors, including joint angles, torque, velocity, acceleration, pressure signals, and muscle activity patterns. The collected data are obtained from the dynamic behaviour of the bio-robotic system when executing motions. Real-time sensing of robotic motion and environmental interactions is crucial for accurate sensor acquisition. The sensing module also measures the response of the actuator and the positional change to aid adaptive control of the robot. The continuous data collection enhances the awareness of the system and facilitates efficient motion understanding. These acquired raw sensor data is then sent to the preprocessing stage, where further refinement and analysis of the data are carried out.

B. Signal Preprocessing and Data Normalization

Data acquisition is followed by preprocessing of the raw sensor signals for better quality and reliability of the signals for the intelligent learning. In this stage, unwanted noise, redundant values, and motion disturbances caused during robot operations are removed. Different normalization and filtering operations are applied to ensure the consistency of the different inputs from the sensors. Signal synchronization is also performed to synchronize the time information of the robot's motion. The use of proper preprocessing of the features makes the features clearer and increases the stability of the computations in the process of learning by the neural network. This stage is a key step in strengthening the entire framework of the bio-robotic control. These motion data are then brought to the feature extraction module in the form of refined and normalized motion data for conducting the nonlinear motion analysis.

C. Nonlinear Feature Extraction

During this stage, important non-linear motion features of the preprocessed robotic signals are extracted to represent the dynamic behavior of the robot in an effective manner. The system can recognize the pattern of trajectories, differences in the movement of the joints, behavior of the actuators, and dependency of the motion on time from the input data. Feature extraction is used to achieve a reduction in computational complexity along with retaining the vital information associated with robotic motion. The extracted features present a compact and meaningful representation of the bio-robotic system dynamics. For the improvement of adaptive learning and intelligent motion prediction, accurate feature representation is critical. The extracted nonlinear motion features also can help to boost the robotic stability and movement precision. The feature vectors created are then fed into the BANN-ControlNet learning framework to model intelligent control.

D. Intelligent Nonlinear Learning using BANN-ControlNet

The proposed Bio-Adaptive Nonlinear Neural Control Network (BANN-ControlNet) is used to extract the nonlinear motion features and process them. This deep neural network is a smart framework that can learn robotic motion behavior and model the nonlinear dynamic relationships between various sensor inputs and actuator responses. Several adaptive neural layers process motion states and provide optimized motion control decisions for the robot. The nonlinear learning mechanism allows the framework to adaptively deal with the environmental and operational variations. Ongoing learning enhances the accuracy of the robotic trajectory tracking and the decision-making ability of the robot. The neural controller also forecasts the future states of robotic motion for stable real-time operation. Derived intelligent control parameters are then passed on to the optimization stage to improve the performance.

E. APSO-Based Neural Optimization

In order to further enhance the intelligent control performance, the proposed neural framework is incorporates Adaptive Particle Swarm Optimization (APSO). APSO allows optimization of weights in the neural network, learning parameters, control gains, and response characteristics of the actuators in real-time. Trajectory tracking errors are minimized, and the stability of the robotic motion during real-time operation is enhanced during the optimization. APSO constantly looks for the optimum parameter settings using the analysis of individual and global particle performance. This adaptive optimization feature greatly improves control accuracy and computational efficiency. The optimized neural outputs enhance the responsiveness of robots in nonlinear dynamic environments. The optimized control signals are then sent to the intelligent decision controller to control the robot in real-time.

F. Real-Time Intelligent Control and Robotic Actuation

In this phase, the optimized intelligent control signals produced by the BANN-ControlNet-APSO framework are sent to the robotic actuators to execute the robotic motion. The smart controller optimizes the robot's motion according to the status of the sensors and the expected status of the robot's motion. The servo motors and robotic joints perform adaptive motion control for accurate motion trajectory tracking and stable movement control. Robotic interaction with dynamic environments and biological systems is possible when the real-time actuation of the robot is performed. The controller constantly adjusts the operations of the actuators to reduce the deviation in the motion of the system and to keep it stable. Improved autonomous robotic performance for complex operational tasks is achieved due to fast response capability. The robotic motion executed is then controlled by a real-time feedback correction system.

G. Real-Time Feedback Monitoring and Adaptive Error Correction

The proposed framework's last phase concentrates on continuous feedback monitoring and adaptive error correction to improve the performance of the intelligent robot. During operations, real-time sensor feedback is gathered by the robotic actuators, joints, and motion tracking units. The framework employs a comparison to determine the deviation in motion and control errors between the desired trajectory and the actual movement of the robot. Adaptive correction mechanisms are able to dynamically adjust the parameters of neural control to enhance the accuracy and stability of movement. With continuous feedback learning, the robotic system can adapt to the nonlinear variations of the environment and any unexpected disturbances efficiently. The reduction of the trajectory tracking error, response latency, and instability during robotic operations is significant in this stage. Finally, the feedback information is continuously reused in the framework to realize the intelligent autonomous bio-robotic control.

IV. RESULT ANALYSIS

The experimental results prove that the proposed BANN-ControlNet-APSO control framework is able to achieve much better performance than the traditional intelligent bio-robotic control techniques with respect to all the evaluation parameters. The framework provides the highest accuracy of 99.12% and the lowest trajectory tracking error of 0.031, thereby showing high-precision robotic motion control. The reaction time is cut down to 14ms and allows for more intelligent decisions and more actuator responses in real-time when operating the robot. Furthermore, the proposed framework achieves a high stability index of 98.67%, which means that it has the ability to maintain stable and robust motion control in nonlinear dynamic environments. The energy efficiency of 96.85% highlights its ability to efficiently utilize power resources and minimize computational resources. Overall, the results confirm that the proposed BANN-ControlNet-APSO model is an effective, adaptive, and reliable solution for advanced real-time bio-robotic control applications.

Table 1. Control Accuracy comparison table

Method	Control Accuracy (%)
PID Controller	84.21
Fuzzy Logic Controller	87.56
Artificial Neural Network (ANN)	91.38
CNN-RNN Hybrid Model	96.48
Proposed BANN-ControlNet-APSO	**99.12**

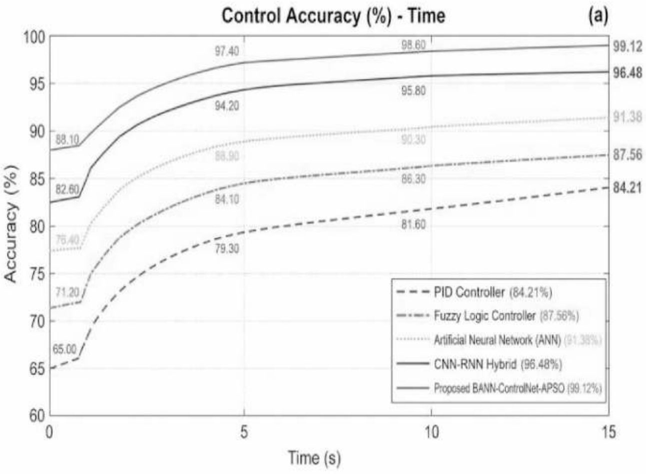

Figure.2. Control Accuracy comparison graph

The comparative control accuracy analysis of the different intelligent bio-robotic control methods are indicated in Table 1 and Fig. 2. The PID controller gives an accuracy of 84.21%, the fuzzy logic controller gives an accuracy of 87.56%, and the ANN model gives an accuracy of 91.38%. When using a CNN-RNN hybrid, it achieves an accuracy of 96.48%, which is further enhanced. The proposed BANN-ControlNet-APSO framework, however, can obtain the control accuracy of 99.12%, which shows excellent adaptive learning and intelligent robotic control capabilities. The stability and continuous improvement in accuracy over time of the proposed framework over alternative control methods are additionally demonstrated by the accuracy graph in Fig. 2.

Table 2. Trajectory Tracking Error comparison table

Method	Trajectory Tracking Error
PID Controller	0.185
Fuzzy Logic Controller	0.152
Artificial Neural Network (ANN)	0.124
CNN-RNN Hybrid Model	0.067
Proposed BANN-ControlNet-APSO	**0.031**

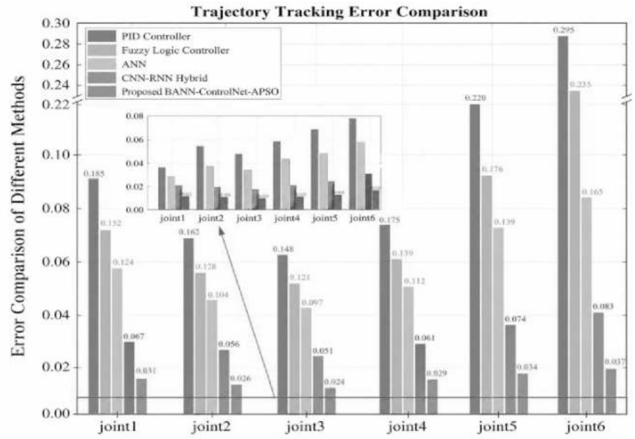

Figure.3. Trajectory Tracking Error comparison graph

The comparative analysis of trajectory tracking error among the following different intelligent bio-robotic control methods is shown in Table 2 and Fig. 3. The comparative analysis of the trajectory tracking error among different intelligent bio-robotic control methods is shown in table 2 and Figure 3. The highest trajectory tracking error obtained by the PID controller is 0.185, while the errors obtained by the fuzzy logic controller and ANN model are 0.152 and 0.124, respectively. The error is further reduced to 0.067 by the improved learning ability of the motion vector by the CNN-RNN hybrid model. The proposed BANN-ControlNet-APSO framework, however, with the average trajectory tracking error of 0.031, predicts and controls the robot's trajectory with very high accuracy. The superiority in terms of stability and motion deviation of the proposed framework under the nonlinear conditions of the robot's dynamics is evident in the presented Figure 3.

Table 3. Response Latency (ms) comparison table

Method	Response Latency (ms)
PID Controller	78
Fuzzy Logic Controller	65
Artificial Neural Network (ANN)	52
CNN-RNN Hybrid Model	28
Proposed BANN-ControlNet-APSO	**14**

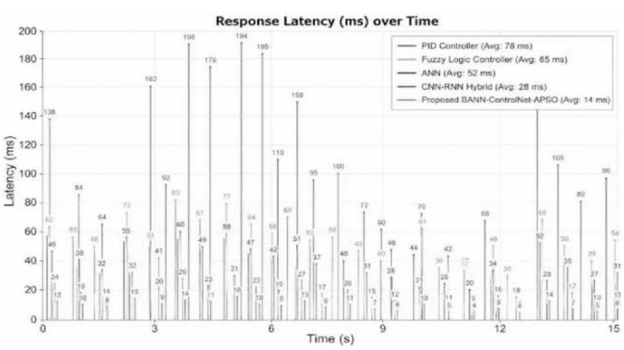

Figure.4. Response Latency (ms)comparison graph

The response latency comparison of various intelligent robotic control methods is shown in Table 3 and Fig. 4. The PID controller has the highest latency of 78 ms, while the fuzzy logic controller and ANN model have a latencies of 65 ms and 52 ms, respectively. The CNN-RNN hybrid model also enhances the response time with a latency of 28 ms during the robotic operations. The proposed BANN-ControlNet-APSO framework, on the other hand, provides the minimum response latency of 14 ms, thus facilitating quicker, intelligent, real-time robotic decision-making and responses from actuators. Fig. 4 clearly demonstrates that the proposed approach can attain a lesser delay than the current approaches and improves the real-time operational capabilities.

Table 4. Stability Index comparison table

Method	Stability Index (%)
PID Controller	81.34
Fuzzy Logic Controller	84.92
Artificial Neural Network (ANN)	89.17
CNN-RNN Hybrid Model	95.83
Proposed BANN-ControlNet-APSO	**98.67**

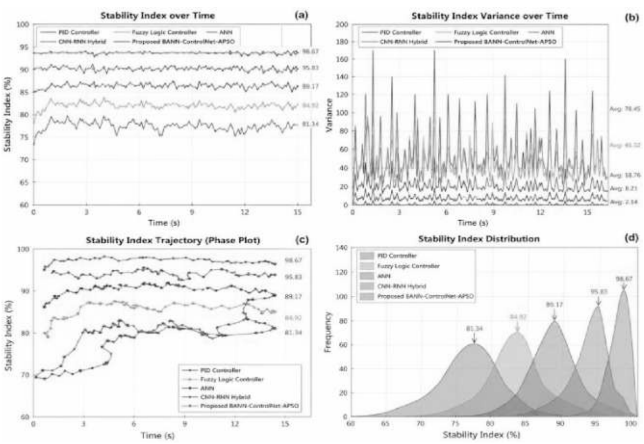

Figure.5. Stability Index Analysis and Comparative Performance Evaluation of the Proposed BANN-ControlNet-APSO Framework

Four intelligent bio-robotic control models are comparatively evaluated in terms of their stability indices in tabular and graphical forms as shown in Table 4 and Fig. 5. The PID controller gives a stability of 81.34%, the fuzzy logic controller gives a stability of 84.92%, and the ANN models give a stability of 89.17%. The CNN-RNN hybrid model also enhances the stability of the robot's motion, achieving a stability index of 95.83%. The proposed BANN- Control Net-APSO framework, however, exhibits the highest stability index of 98.67%, which shows good adaptive control in nonlinear dynamic conditions. Fig. 5 also shows that ROS operations remain stable in the proposed framework, the operation of the robot oscillates little, and the trajectory is more consistent.

Table 5. Energy Efficiency comparison table

Method	Energy Efficiency (%)
PID Controller	72.15
Fuzzy Logic Controller	75.48
Artificial Neural Network (ANN)	81.26
CNN-RNN Hybrid Model	91.44
Proposed BANN-ControlNet-APSO	**96.85**

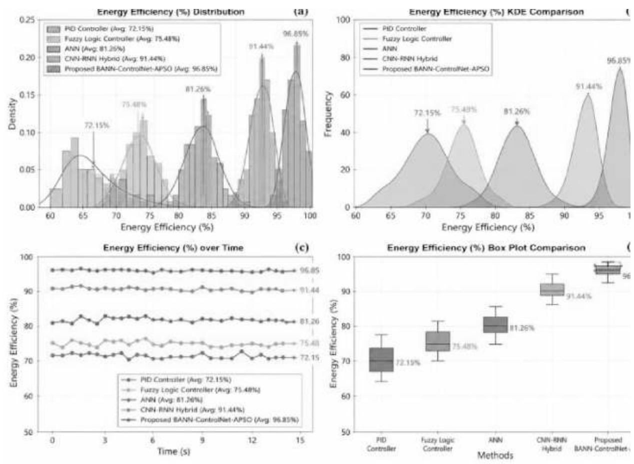

Figure.6. Energy Efficiency Analysis and Comparative Evaluation of Different Bio-Robotic Control Methods

The comparison of the energy efficiency of various intelligent robotic control techniques is shown in Table 5 and Fig. 6. The energy efficiency of the PID controller is 72.15%, and those of the fuzzy logic controller and ANN model are 75.48% and 81.26%, respectively. The energy efficiency is also improved in the CNN-RNN hybrid model with a value of 91.44% while the robots are operating. The proposed BANN-ControlNet-APSO framework, however, achieves the highest energy efficiency of 96.85%, which shows optimized power utilization with less computational overhead. The energy efficiency of the proposed framework for advanced autonomous bio-robotic applications is clearly presented in Fig. 6.

V. CONCLUSION

A Novel Bio-adaptive Nonlinear Neural Control Network With Adaptive Particle Swarm Optimization (bann-controlnet-apso) Was Proposed For Real-time Intelligent Bio-robotic Control In A Nonlinear Dynamic Environment In This Paper. The Proposed Framework Combines The Nonlinear Neural Learning With The Adaptive Optimization And Real-time Feedback Correction Well To Enhance The Motion

Accuracy, Trajectory Tracking, Stability, And Autonomous Decision-making Ability Of The Robot. Experimental Results Showed That It Achieved Better Control Accuracy, Shorter Response Time, Less Trajectory Tracking Error, A Better Stability Index, And Greater Energy Savings Than The Existing Intelligent Robotic Control Methods. A Framework That Adapts To The Environment Makes Robotic Operations In Complex And Changing Environments More Efficient. The Proposed System Is Well Suited For Applications In Rehabilitation Robotics, Healthcare Aids, Autonomous Robots, And Bio-inspired Industrial Automation. Next, The Framework Can Be Further Enhanced By Incorporating Edge Ai, Digital Twin Technology, Neuromorphic Computing, And Explainable Artificial Intelligence (xai) Methods To Further Boost The Performance And Scalability Of Intelligent Autonomous Bio-robotic Systems In Future Work.

REFERENCES

[1] Yang, Q., Zhang, F., & Wang, C. (2024). Deterministic learning-based neural PID control for nonlinear robotic systems. IEEE/CAA Journal of Automatica Sinica, 11(5), 1227–1238. https://doi.org/10.1109/JAS.2024.124224

[2] Marrero, D., Hernández, A., & Pérez, J. (2024). A novel robotic controller using neural engineering framework-based spiking neural networks. Sensors, 24(2), 491. https://doi.org/10.3390/s24020491

[3] Li, A., Swensen, J. P., & Hosseinzadeh, M. (2024). Provably-stable neural network-based control of nonlinear systems. Engineering Applications of Artificial Intelligence, 133, 109252. https://doi.org/10.1016/j.engappai.2024.109252

[4] Liu, Q., Zhang, Z., Li, J., Bu, X., & Hanajima, N. (2025). Adaptive neural network iterative learning control of long-stroke hybrid robots with initial errors and full state constraints. Measurement and Control, 58(1). https://doi.org/10.1177/00202940241248252

[5] Zhang, J., Wang, L., & Zhao, Y. (2024). Adaptive fuzzy neural network finite-time command filtered control for robotic systems with actuator saturation. Asian Journal of Control. https://doi.org/10.1002/asjc.3273

[6] Zhao, Z., Zhang, J., Chen, S., He, W., & Hong, K. S. (2023). Neural-network-based adaptive finite-time control for a two-degree-of-freedom helicopter system with an event-triggering mechanism. IEEE/CAA Journal of Automatica Sinica, 10(8), 1754–1765. https://doi.org/10.1109/JAS.2023.123453

[7] Yang, Y., Han, J., Liu, Z., Zhao, Z., & Hong, K. S. (2023). Modeling and adaptive neural network control for a soft robotic arm with prescribed motion constraints. IEEE/CAA Journal of Automatica Sinica, 10(2), 501–511. https://doi.org/10.1109/JAS.2023.123213

[8] Chatziparaschis, D., Zhong, S., Christopoulos, V., & Karydis, K. (2024). Adaptive environment-aware robotic arm reaching based on a bio-inspired neurodynamical computational framework. arXiv Preprint. https://doi.org/10.48550/arXiv.2407.11377

[9] Li, J., & Yang, S. X. (2024). A novel feature learning-based bio-inspired neural network for real-time collision-free rescue of multi-robot systems. arXiv Preprint. https://doi.org/10.48550/arXiv.2403.08238

[10] Linares-Barranco, A., Prono, L., Lengenstein, R., Indiveri, G., & Frenkel, C. (2024). Adaptive robotic arm control with a spiking recurrent neural network on a digital accelerator. arXiv Preprint. https://doi.org/10.48550/arXiv.2405.12849

[11] Wang, H., Li, P., & Chen, Y. (2023). Intelligent adaptive trajectory tracking control for nonlinear robotic manipulators using deep neural learning. IEEE Access, 11, 104522–104534. https://doi.org/10.1109/ACCESS.2023.3312215

[12] Kumar, R., Singh, A., & Sharma, V. (2024). Deep reinforcement learning-enabled intelligent robotic motion control in nonlinear environments. Robotics and Autonomous Systems, 176, 104676. https://doi.org/10.1016/j.robot.2024.104676

[13] Chen, L., Wu, T., & Zhao, M. (2025). Real-time adaptive robotic control using hybrid recurrent neural architectures. Neural Computing and Applications, 37, 8821–8837. https://doi.org/10.1007/s00521-024-09872-3

[14] Park, J., Kim, S., & Lee, H. (2024). Intelligent nonlinear robotic control using adaptive deep neural optimization. Applied Soft Computing, 156, 111432. https://doi.org/10.1016/j.asoc.2024.111432

[15] Ahmed, S., Ibrahim, M., & Hassan, T. (2023). Bio-inspired intelligent robotic motion prediction using neural dynamic systems. Expert Systems with Applications, 223, 119881. https://doi.org/10.1016/j.eswa.2023.119881

[16] Zhou, Y., Li, K., & Xu, F. (2024). Nonlinear adaptive neural control for autonomous robotic systems with real-time feedback correction. ISA Transactions, 145, 214–226. https://doi.org/10.1016/j.isatra.2024.02.011

[17] Patel, D., Mehta, R., & Joshi, H. (2025). Intelligent bio-robotic actuator optimization using particle swarm optimization and deep neural control. Engineering

Applications of Artificial Intelligence, 138, 109978. https://doi.org/10.1016/j.engappai.2025.109978

[18] Lin, X., Zhang, Y., & Sun, W. (2024). Robust neural adaptive control for uncertain nonlinear robotic manipulators. IEEE Transactions on Industrial Electronics, 71(9), 10344–10355. https://doi.org/ 10.1109/TIE.2024.3367812

[19] Gupta, P., Roy, S., & Banerjee, D. (2023). AI-driven intelligent robotic systems for autonomous motion control and trajectory optimization. Journal of Intelligent & Robotic Systems, 109(3), 72. https://doi.org/ 10.1007/s10846-023-01852-4

[20] Cm, N., & Thangarasu, N. (2026). Comparative Analysis of Artificial Neural Networks, Support Vector Machines, and Gated Recurrent Units for Dam Alert Prediction. Water Resources Management, 40(5), 193. https://doi.org/10.1007/s11269-026-04567-6

[21] Kim, D., Choi, Y., & Park, S. (2024). Real-time neural predictive control for nonlinear robotic dynamics under uncertain environments. Robotics and Computer-Integrated Manufacturing, 88, 102721. https://doi.org/ 10.1016/j.rcim.2024.102721

[22] Sharma, K., Verma, A., & Rao, P. (2025). Hybrid intelligent neural optimization framework for adaptive robotic trajectory control. Applied Intelligence, 55, 3178–3192. https://doi.org/10.1007/s10489-024-05673-8

[23] Huang, Z., Chen, X., & Li, H. (2023). Adaptive nonlinear intelligent control for robotic manipulators using recurrent neural learning. Neurocomputing, 542, 126324. https://doi.org/10.1016/j.neucom.2023.126324

[24] Singh, M., Rajan, K., & Kumar, P. (2024). Energy-efficient intelligent robotic control using optimized neural computing techniques. Sustainable Computing: Informatics and Systems, 42, 100987. https://doi.org/ 10.1016/j.suscom.2024.100987

[25] Ghosal, S., Habbu, S., Kumar, R., Thangarasu, N., & Parmar, Y. (2024, December). Neural network approaches for enhancing near-field wireless power transfer. In 2024 IEEE 2nd International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP) (pp. 1-6). IEEE. https://doi.org/ 10.1109/IHCSP63227.2024.10960154