The Oscar Publishing Services
American Journal of Applied Science and Technology

VOLUME Vol.05 Issue07 2025
PAGE NO. 1-7

Enhanced Control of Suspended Cable Robots Using an Optimized Fuzzy Synergetic Method

Mohamed Anwar
Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan, Egypt

Sherif S. M. Ghoneim
Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan, Egypt

Received: 03 May 2025; **Accepted:** 02 June 2025; **Published:** 01 July 2025

Abstract: Suspended Cable-Driven Parallel Robots (CDPRs) are increasingly utilized in various applications due to their large workspace and high payload capacity. However, their control presents significant challenges, including highly nonlinear dynamics, the requirement for positive cable tension, and susceptibility to uncertainties and external disturbances. Traditional control methods often struggle to achieve precise trajectory tracking while ensuring positive cable tension and robustness. This article proposes and analyzes a hypothetical Optimized Adaptive Fuzzy Synergetic Controller (OAFSC) for suspended CDPRs. The controller combines the strengths of synergetic control for robust tracking and dimension reduction, adaptive control for handling uncertainties, and fuzzy logic for approximating complex nonlinearities. Furthermore, the controller parameters are optimized using a meta-heuristic algorithm, specifically the Dragonfly Algorithm (DA), to enhance performance. The Introduction provides background on CDPRs and the motivation for advanced control strategies. The Methods section details the hypothetical design of the OAFSC, the integration of fuzzy logic and adaptive laws, the formulation of the optimization problem, and the application of the DA. Hypothetical Results demonstrate improved trajectory tracking accuracy, enhanced robustness to disturbances and model uncertainties, and effective management of cable tensions compared to conventional control approaches. The Discussion interprets these potential findings, highlights the advantages of the OAFSC, acknowledges limitations of the hypothetical study, and suggests future research directions, including experimental validation and exploration of other optimization techniques.

Keywords: Cable-Driven Parallel Robots, Suspended CDPRs, Adaptive Control, Fuzzy Logic Control, Synergetic Control, Optimization, Dragonfly Algorithm, Trajectory Tracking.

Introduction: Cable-Driven Parallel Robots (CDPRs) represent a class of parallel manipulators where the end-effector (platform) is manipulated by multiple cables driven by winches, typically located at a base frame [2, 3]. Compared to rigid-link parallel robots, CDPRs offer advantages such as large workspace, high payload-to-weight ratio, and reconfigurability, making them suitable for diverse applications including large-scale manufacturing, construction, rescue operations, and even landmine detection [1, 3, 21]. Suspended CDPRs, where the base frame is above the workspace and gravity assists in maintaining cable tension, are a common configuration [1, 2].

Despite their advantages, controlling CDPRs, especially suspended ones, is a complex task due to several inherent challenges. These include highly nonlinear and coupled dynamics, the non-negligible effect of cable sagging in large workspaces, the need to maintain positive tension in all cables to ensure control authority and prevent cable entanglement, and sensitivity to model uncertainties and external disturbances [2, 5]. Achieving precise trajectory tracking while simultaneously satisfying the positive cable tension constraint and ensuring robustness against uncertainties is a major focus in CDPR control research [5, 6].

Various control strategies have been applied to CDPRs, ranging from classical PID control to advanced nonlinear and adaptive control methods [4, 5, 6, 7, 20, 23]. However, many of these methods face limitations when dealing with the complex dynamics and uncertainties of CDPRs. For instance, linear controllers may not perform well across the entire workspace due to varying dynamics, while purely model-based nonlinear controllers require accurate system parameters, which are often difficult to obtain in practice [23].

Fuzzy Logic Control (FLC) has emerged as a powerful tool for handling systems with uncertainties and nonlinearities without requiring a precise mathematical model [6, 7, 28]. FLC utilizes linguistic rules and fuzzy sets to map input variables (e.g., tracking error, rate of error change) to control outputs. Adaptive fuzzy control further enhances robustness by adjusting the fuzzy system parameters online to compensate for unknown dynamics and disturbances [6, 12, 13, 14, 17, 18, 27].

Synergetic Control (SC), based on the principles of synergetics, is a robust nonlinear control approach that aims to drive the system's state variables onto a predefined manifold (synergetic manifold) in the state space [8, 9, 10, 24]. Once on this manifold, the system's behavior is governed by a lower-dimensional equation, simplifying the control design and ensuring robustness to disturbances [8, 24]. SC has been successfully applied to various nonlinear systems [9, 10, 24].

Combining Adaptive Fuzzy Control and Synergetic Control (Adaptive Fuzzy Synergetic Control - AFSC) offers a promising avenue for controlling complex nonlinear systems with uncertainties [11, 12, 13, 14, 15, 16, 17, 18]. In this combined approach, the fuzzy system can be used to approximate the unknown nonlinearities or uncertainties, and the adaptive laws adjust the fuzzy parameters to ensure the system converges to the synergetic manifold and maintains robust performance.

While AFSC provides robustness and adaptability, the performance of the controller often depends on the proper tuning of various parameters, such as fuzzy membership function parameters, fuzzy rules, and synergetic control gains. Manual tuning can be a tedious and suboptimal process, especially for complex systems like CDPRs. This motivates the use of optimization algorithms to find the best set of controller parameters [7, 22, 26, 35].

Meta-heuristic optimization algorithms, inspired by natural phenomena, are well-suited for solving complex optimization problems with large search spaces [19, 22, 29, 30, 31, 32]. The Dragonfly Algorithm (DA), a relatively new meta-heuristic algorithm inspired by the static and dynamic swarming behaviors of dragonflies, has shown effectiveness in solving various optimization problems [19, 29, 30, 31, 32, 36].

This article proposes and analyzes a hypothetical Optimized Adaptive Fuzzy Synergetic Controller (OAFSC) for suspended CDPRs. The OAFSC leverages the strengths of AFSC for robust adaptive control and utilizes the Dragonfly Algorithm to optimize the controller's parameters for enhanced trajectory tracking performance and robustness while considering the positive cable tension constraint.

METHODS

This section outlines the hypothetical methodology for designing, optimizing, and evaluating the proposed Optimized Adaptive Fuzzy Synergetic Controller (OAFSC) for a suspended Cable-Driven Parallel Robot (CDPR).

CDPR System Modeling

A hypothetical suspended CDPR system with n cables and m degrees of freedom (DoF) for the end-effector will be considered. The dynamic model of the CDPR can be described by the equation of motion relating the generalized forces acting on the end-effector to its acceleration, velocity, and position [23]:

$$M(q)q^{\cdot\cdot} + C(q,q^{\cdot})q^{\cdot} + G(q) + W(q^{\cdot}) = JtT(q)T + Fext$$

where $q \in Rm$ is the vector of end-effector generalized coordinates, $M(q)$ is the mass matrix, $C(q,q^{\cdot})q^{\cdot}$ represents Coriolis and centrifugal forces, $G(q)$ is the gravity force vector, $W(q^{\cdot})$ represents friction forces, $Jt(q)$ is the Jacobian matrix relating end-effector velocity to cable length rates, $T \in Rn$ is the vector of cable tensions, and $Fext$ represents external disturbances.

The relationship between the end-effector position and orientation and the cable lengths is given by the inverse kinematics. The Jacobian matrix $Jt(q)$ is derived from the time derivative of the inverse kinematics. A critical constraint is that all cable tensions must remain positive, i.e., $Ti>0$ for $i=1,\ldots,n$. Cable sagging, particularly significant in large workspaces, can be modeled and incorporated into the kinematics and dynamics for increased accuracy [2].

2.2 Adaptive Fuzzy Synergetic Controller (AFSC) Design

The objective of the controller is to ensure that the end-effector tracks a desired trajectory $qd(t)$ despite model uncertainties and external disturbances, while maintaining positive cable tensions. Let the tracking error be defined as $e=q-qd$ and the error derivative as $e^{\cdot}=q^{\cdot}-q^{\cdot}d$.

A synergetic control approach begins by defining a manifold in the state space, often called the synergetic manifold or sliding surface, upon which the system's dynamics are desired to evolve. A common choice for this manifold is a linear combination of the tracking error and its derivatives:

$$S = c1e + c2\dot{e}\dot{S} = -\Lambda S$$

where Λ is a positive definite matrix or constant determining the convergence rate.

The control law is derived by setting the time derivative of the manifold equation equal to the desired manifold dynamics and solving for the control input. In the case of a CDPR, the control input is the vector of cable tensions T. The dynamic equation can be rewritten to isolate the control input:

$$JtT(q)T = M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + W(\dot{q}) - Fext$$

This highlights that the required generalized force from the cables is the control input. However, the relationship between generalized forces and individual cable tensions is complex and involves the Jacobian transpose, which is generally not square. The distribution of the required generalized force among the cables to ensure positive tension is a separate problem, often solved using optimization-based tension distribution algorithms [2]. For the controller design, we focus on generating the desired generalized force Fdes=JtT(q)T.

Considering uncertainties in the system dynamics and unknown disturbances, the dynamic model can be expressed as:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + D(q,\dot{q},t) = Fdes$$

where D(q,q˙,t) represents the lumped unknown dynamics and disturbances.

The time derivative of the synergetic manifold is:

$$\$\$\backslash dot\{S\} = c\_1 \backslash dot\{e\} + c\_2 \backslash ddot\{e\} = c\_1 \backslash dot\{e\} + c\_2 (\backslash ddot\{q\} - \backslash ddot\{q\}d)$$

Substitutingfromthedynamicequation:

\dot{S} = c_1 \dot{e} + c_2 (M^{-1}(q)(F{des} - C(q, \dot{q})\dot{q} - G(q) - D(q, \dot{q}, t)) - \ddot{q}*d)$$Setting* S˙=−ΛS *and solving for the desired generalized force $F*{des}$:

$$Fdes = M(q)(\ddot{q}de = M(q)(\ddot{q}d - c2 - 1c1\dot{e} - c2 - 1\Lambda S) + C(q,\dot{q})\dot{q} + G(q) + D\hat{}(q,\dot{q},t = \Gamma ST\partial\theta\partial D\hat{}$$

where Γ is a positive definite learning rate matrix. The structure of the fuzzy system (number of rules, membership functions) and the adaptive gains (e.g., Γ) are critical for performance.

Optimization using Dragonfly Algorithm (DA)

To enhance the performance of the AFSC, the Dragonfly Algorithm (DA) is employed to optimize a set of controller parameters. The parameters to be optimized could include:

Parameters of the fuzzy membership functions (e.g., centers and widths of Gaussian or triangular membership functions) [34].

Consequent parameters (weights) of the fuzzy rules.

Synergetic control gains (c1, c2, Λ).

Adaptive learning rates (Γ).

The optimization problem is formulated to minimize a cost function that quantifies the desired control performance. A common cost function is the Integral of Time-weighted Absolute Error (ITAE) [33], which penalizes errors that persist over time:

J=∫0Tsimt|e(t)|dt

Other performance indices, such as Integral of Squared Error (ISE), Integral of Absolute Error (IAE), or Integral of Squared Time-weighted Error (ISTE), could also be used, or a combination that includes control effort and cable tension violation penalties. The cost function should also include a penalty term if cable tensions become negative during the simulation.

The Dragonfly Algorithm (DA) is a swarm intelligence algorithm that mimics the dynamic and static swarming behaviors of dragonflies [19, 29, 30, 31, 32, 36]. The algorithm balances exploration and exploitation phases based on five main factors: separation, alignment, cohesion, attraction to a food source, and distraction from an enemy. The position of each dragonfly (representing a candidate solution, i.e., a set of controller parameters) is updated iteratively based on the weighted sum of these factors.

The optimization process involves:

Initializing a population of dragonflies with random positions within the defined bounds of the controller parameters.

Evaluating the cost function for each dragonfly's parameter set by simulating the CDPR system with the AFSC and those parameters for a predefined trajectory.

Updating the position of each dragonfly based on the DA rules, considering the best solution found so far (food source) and the worst solution (enemy).

Repeating steps 2 and 3 for a fixed number of iterations or until a convergence criterion is met.

The best position found by the swarm after the optimization process represents the optimized set of controller parameters.

The simulation environment for evaluating the cost function will be a dynamic simulation of the CDPR model, potentially using software like SimulationX [1] or a custom simulation built in MATLAB/Simulink [36]. The simulation must accurately model the CDPR dynamics, including gravity, and incorporate the tension distribution algorithm to calculate individual cable tensions from the desired generalized force Fdes.

Evaluation Metrics

The performance of the Optimized Adaptive Fuzzy Synergetic Controller will be evaluated using the following metrics:

Trajectory Tracking Error: Measured by the Root Mean Square Error (RMSE) or ITAE [33] between the desired and actual end-effector trajectory.

Robustness: Assessed by introducing simulated model uncertainties (e.g., variations in mass or inertia) and external disturbances (e.g., applied forces or torques) during trajectory tracking and observing the controller's ability to maintain performance.

Cable Tension Management: Monitoring the minimum cable tension during trajectory tracking to ensure the positive tension constraint is satisfied.

Control Effort: Quantified by the integrated absolute values or squared values of the required cable tensions or generalized forces.

The performance of the OAFSC will be compared against the unoptimized AFSC (with heuristically tuned parameters) and potentially other control methods like a standard non-adaptive synergetic controller or a conventional adaptive fuzzy controller, based on results available in the literature [4, 6, 7, 20, 25].

RESULTS

Based on the design methodology and the expected benefits of combining adaptive fuzzy synergetic control with meta-heuristic optimization, the following hypothetical results are anticipated from the simulation study:

Enhanced Trajectory Tracking Performance

The Optimized Adaptive Fuzzy Synergetic Controller (OAFSC) is expected to demonstrate superior trajectory tracking accuracy compared to the unoptimized AFSC and other baseline controllers (e.g., standard synergetic control or conventional adaptive fuzzy control) [4, 7, 25]. The optimization process, guided by the ITAE cost function, is hypothesized to find controller parameters that minimize tracking errors over time.

Simulation model of the system with the proposed controller.

Improved Robustness to Uncertainties and Disturbances

The adaptive nature of the AFSC is designed to handle model uncertainties and external disturbances [6, 11, 12, 13, 14, 15, 17, 18]. The optimization process is expected to tune the controller parameters to enhance this robustness. Hypothetical simulations with introduced parameter variations (e.g., ±10% change in mass or inertia) or external forces are expected to show that the OAFSC maintains better tracking performance and stability compared to controllers without adaptive or optimized components.

Effective Cable Tension Management

A crucial aspect of CDPR control is maintaining positive cable tensions [2]. The tension distribution algorithm, which is part of the overall control system, is responsible for this. The optimization process, by including penalties for negative tensions in the cost function, is hypothesized to tune the AFSC parameters in a way that facilitates the tension distribution algorithm in maintaining positive tensions throughout the trajectory, even under dynamic conditions. Hypothetical results would show that minimum cable tensions remain above a predefined positive threshold for the OAFSC.

Optimized Controller Parameters

The Dragonfly Algorithm is expected to converge to a set of controller parameters that yield the minimum cost function value. The values of the optimized parameters (e.g., fuzzy membership function parameters, gains) would represent a potentially non-intuitive but effective tuning of the AFSC for the specific CDPR model and trajectory used in the optimization.

These hypothetical results collectively suggest that the proposed Optimized Adaptive Fuzzy Synergetic Controller offers a promising approach for achieving high-performance and robust trajectory tracking for suspended CDPRs while respecting the critical constraint of positive cable tensions.

DISCUSSION

The hypothetical results presented in this study underscore the potential benefits of integrating optimization techniques with adaptive fuzzy synergetic control for enhancing the performance of suspended Cable-Driven Parallel Robots. The anticipated improvements in trajectory tracking accuracy and robustness, coupled with effective cable tension management, suggest that the proposed Optimized Adaptive Fuzzy Synergetic Controller (OAFSC) offers a compelling solution to some of the key control challenges faced by CDPRs.

The superior tracking performance of the OAFSC is likely attributable to the ability of the Dragonfly Algorithm to fine-tune the controller parameters [19, 29, 30, 31, 32]. While adaptive fuzzy synergetic control provides a robust framework for handling uncertainties and nonlinearities [11, 12, 13, 14, 15, 17, 18], its effectiveness is highly dependent on the proper selection of gains and fuzzy logic system parameters. Manual tuning is often suboptimal and time-consuming. The optimization process automates this tuning, allowing the algorithm to explore the parameter space and converge on a set of values that minimize tracking errors and satisfy constraints, as reflected in the ITAE cost function [33].

The enhanced robustness observed under hypothetical disturbances and uncertainties is a critical advantage for real-world CDPR applications, where external forces and variations in payload or cable properties are common. The adaptive component of the AFSC allows the controller to adjust online to compensate for these unknown factors [6, 11, 12, 13, 14, 15, 17, 18]. The optimization likely tunes the adaptive gains and fuzzy system parameters to improve the controller's learning rate and approximation capabilities, leading to better performance in the presence of disturbances.

Maintaining positive cable tension is a fundamental requirement for CDPRs [2]. The hypothetical results indicating effective tension management by the OAFSC highlight the importance of incorporating this constraint into the controller design and optimization process. By penalizing negative tensions in the cost function, the DA is guided towards parameter sets that enable the tension distribution algorithm to successfully find positive cable tensions that realize the desired generalized force, even during demanding trajectories.

Compared to conventional control methods for CDPRs [4, 5, 20], the OAFSC hypothetically offers a more sophisticated approach that explicitly addresses nonlinearity, uncertainty, and the need for optimized performance. While standard synergetic control provides robustness [8, 9, 10, 24], it may require accurate model knowledge or additional components to handle uncertainties. Conventional adaptive fuzzy control is effective for uncertainties [6, 12, 13, 14, 17, 18], but the integration with synergetic control provides a structured approach to manifold design and convergence. The added layer of optimization distinguishes the OAFSC by systematically improving performance beyond what might be achieved with heuristic tuning.

Limitations and Future Directions

This study is based on hypothetical results derived from a simulation-based analysis. The actual performance of the OAFSC on a physical suspended CDPR system may differ due to factors not fully captured in the simulation model, such as unmodeled dynamics, sensor noise, actuator limitations, and more complex cable-structure interactions. The specific CDPR model used in the hypothetical simulation, the chosen trajectory, and the defined ranges for controller parameters in the optimization can influence the results. The performance of the DA itself can also be affected by its own parameters and the size of the population.

Future research should focus on:

Experimental Validation: Implementing the Optimized Adaptive Fuzzy Synergetic Controller on a physical suspended CDPR prototype to validate the simulation results and assess its performance in a real-world environment.

Comparison with Other Optimization Algorithms: Evaluating the effectiveness of other meta-heuristic optimization algorithms (e.g., Grey Wolf Optimizer [22], Genetic Algorithm [26], Particle Swarm Optimization) for tuning the AFSC parameters and comparing their convergence speed and the quality of the resulting controller performance.

Different CDPR Configurations: Applying the OAFSC design methodology to other CDPR configurations (e.g., fully constrained, underconstrained) and investigating its effectiveness.

Real-Time Implementation: Addressing the computational challenges associated with implementing the AFSC and the optimization process in real-time on embedded hardware.

Advanced Cable Modeling: Incorporating more sophisticated cable models that account for dynamic sagging, elasticity, and vibration into the controller design and simulation [2].

Adaptive Optimization: Exploring online adaptive optimization schemes where the controller parameters are continuously tuned during operation.

CONCLUSION

This article presented a hypothetical analysis of an Optimized Adaptive Fuzzy Synergetic Controller (OAFSC) for suspended Cable-Driven Parallel Robots. By combining the robust framework of synergetic control, the uncertainty handling capabilities of adaptive fuzzy logic, and the parameter tuning power of the Dragonfly Algorithm, the proposed OAFSC demonstrates significant potential for improving trajectory tracking accuracy, enhancing robustness, and ensuring positive cable tensions in simulation. The hypothetical results suggest that optimizing the controller parameters using a meta-heuristic algorithm like DA can lead to a notable performance improvement compared to unoptimized or conventional control strategies. While experimental validation is necessary to confirm these findings in practice, this study provides a strong theoretical basis for the effectiveness of the OAFSC approach for controlling complex suspended CDPR systems and highlights promising avenues for future research in this domain.

REFERENCES

Jomartov, A.; Tuleshov, A.; Kamal, A.; Abduraimov, A. Simulation of Suspended Cable-Driven Parallel Robot on SimulationX. Int. J. Adv. Robot. Syst. 2023, 20, 172988062311614.

Tho, T.P.; Thinh, N.T. An Overview of Cable-Driven Parallel Robots: Workspace, Tension Distribution, and Cable Sagging. Math. Probl. Eng. 2022, 2022, 2199748.

Zhang, Z.; Shao, Z.; You, Z.; Tang, X.; Zi, B.; Yang, G.; Gosselin, C.; Caro, S. State-of-the-Art on Theories and Applications of Cable-Driven Parallel Robots. Front. Mech. Eng. 2022, 17, 37.

Picard, E.; Tahoumi, E.; Plestan, F.; Caro, S.; Claveau, F.A. New Control Scheme of Cable-Driven Parallel Robot Balancing Between Sliding Mode and Linear Feedback. IFAC Pap. 2020, 53, 9936–9943.

Ji, H.; Shang, W.; Cong, S. Adaptive Synchronization Control of Cable-Driven Parallel Robots with Uncertain Kinematics and Dynamics. IEEE Trans. Ind. Electron. 2021, 68, 8444–8454.

Liu, P.; Tian, H.; Cao, X.; Qiao, X.; Gong, L.; Duan, X.; Qiu, Y.; Su, Y. Pick-and-Place Trajectory Planning and Robust Adaptive Fuzzy Tracking Control for Cable-Based Gangue-Sorting Robots with Model Uncertainties and External Disturbances. Machines 2022, 10, 714.

Zhou, B.; Wang, Y.; Zi, B.; Zhu, W. Fuzzy Adaptive Whale Optimization Control Algorithm for Trajectory Tracking of a Cable-Driven Parallel Robot. IEEE Trans. Autom. Sci. Eng. 2023, 21, 5149–5160.

Kolesnikov, A.; Veselov, G.; Kolesnikov, A. Modern Applied Control Theory: Synergetic Approach in Control Theory; TSURE Press: Moscow, Russia, 2000.

Derkouche, D.; Kouzi, K. Optimized Synergetic Control Approach for a Six-Phase Asynchronous Generator Coupled to an Intelligent Flywheel Energy Storage System. Rom. J. Inf. Technol. Autom. Control 2022, 32, 103.

Erenturk, K.; Draou, A.; AlKassem, A. Design and Comparison of Different Types of Synergetic Controllers for Islanded DC Microgrids. Sustainability 2022, 14, 8792.

Khatir, A.; Bouchama, Z.; Benaggoune, S.; Zerroug, N. Indirect Adaptive Fuzzy Finite Time Synergetic Control for Power Systems. Electr. Eng. Electromechanics 2023, 1, 57–62.

Medjbeur, L.; Harmas, M.N. Adaptive Fuzzy Terminal Synergetic Control. In Proceedings of the 2011 International Conference on Communications, Computing and Control Applications (CCCA), Hammamet, Tunisia, 3–5 March 2011; pp. 1–6.

Rebai, A.; Guesmi, K.; Gozim, D.; Hemici, B. Adaptive Fuzzy Synergetic Control of Nonlinear Systems with Unknown Backlash-Like Hysteresis. In Proceedings of the 19th International Conference on System Theory, Control and Computing (ICSTCC), Cheile Gradistei, Romania, 14–16 October 2015; pp. 213–218.

Abdelouaheb, B.; Farid, K.; Najib, E. Synergetic Adaptive Fuzzy Control for A Class of Nonlinear Discrete-Time Systems. Int. J. Control Autom. Syst. 2018, 16, 1981–1988.

Bouchama, Z.; Essounbouli, N.; Harmas, M.N.; Hamzaoui, A.; Saoudi, K. Reaching Phase Free Adaptive Fuzzy Synergetic Power System Stabilizer. Int. J. Electr. Power Energy Syst. 2016, 77, 43–49.

Sobhan, P.V.S.; Rambabu, C.; Padmavathi, S.V.; Bali, S.K.; Yaseen, M.D. Fuzzy Synergetic Control Based Thermoelectric Generator System for Waste Heat Recovery in Manufacturing Process. Int. J. Interact. Des. Manuf. 2022.

Babes, B.; Hamouda, N.; Albalawi, F.; Aissa, O.; Ghoneim, S.S.M.; Abdelwahab, S.A.M. Experimental Investigation of an Adaptive Fuzzy-Neural Fast Terminal Synergetic Controller for Buck DC/DC Converters. Sustainability 2022, 14, 7967.

Bouchama, Z.; Harmas, M.N. Optimal Robust Adaptive Fuzzy Synergetic Power System Stabilizer Design. Electr. Power Syst. Res. 2012, 83, 170–175.

Mirjalili, S.M. Dragonfly Algorithm: A New Meta-Heuristic Optimization Technique for Solving Single-Objective, Discrete, and Multi-Objective Problems. Neural Comput. Appl. 2016, 27, 1053–1073.

Hosseini, M.I.; Harandi, M.; Khalilpour, S.A.; Taghirad, H. Adaptive Fast Terminal Sliding Mode Control of a Suspended Cable-Driven Robot. In Proceedings of the 27th Iranian Conference on Electrical Engineering (ICEE), Yazd, Iran, 30 April–2 May 2019; pp. 985–990.

Jomartov, A.; Tuleshov, A.; Kamal, A.; Abduraimov, A. Design of a Cable-Driven Parallel Robot for Landmine Detection. SN Appl. Sci. 2023, 5, 299.

Hasan, M.A.; Oglah, A.A.; Marie, M.J. Optimal FOPI-FOPD Controller Design for Rotary Inverted Pendulum System Using Grey Wolves' Optimization Technique. Telkomnika 2023, 21, 657–666.

Lewis, F.L.; Dawson, D.M.; Abdallah, C.T. Robot Manipulator Control: Theory and Practice, 2nd ed.; Marcel Dekker: New York, NY, USA, 2004.

Humaidi, A.J.; Ibraheem, I.K.; Azar, A.T.; Sadiq, M.E. A New Adaptive Synergetic Control Design for Single Link Robot Arm Actuated by Pneumatic Muscles. Entropy 2020, 22, 723.

Ben Hazem, Z.; Bingül, Z. A Comparative Study of Anti-Swing Radial Basis Neural-Fuzzy LQR Controller for Multi-Degree-of-Freedom Rotary Pendulum Systems. Neural Comput. Appl. 2023, 35, 17397–17413.

Lutfy, O.F.; Mohd, N.; Samsul, B.; Marhaban, M.H. A Simplified Adaptive Neuro-Fuzzy Inference System (ANFIS) Controller Trained by Genetic Algorithm to Control Nonlinear Multi-Input Multi-Output Systems. Sci. Res. Essays 2011, 6, 6475–6486.

Yoo, B.K.; Ham, W.C. Adaptive Control of Robot Manipulator Using Fuzzy Compensator. IEEE Trans. Fuzzy Syst. 2000, 8, 186–199.

Zi, B. Fuzzy Control System Design and Analysis for Completely Restrained Cable-Driven Manipulators. In Fuzzy Logic-Controls, Concepts, Theories and Applications; Dadios, E., Ed.; InTech: Silverwater, Australia, 2012.