

Design and performance analysis of ANFIS-based and deep learning controllers for tower crane systems

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Abstract- Ensuring safety, productivity, and efficiency in construction and industries is a significant task. Loads on tower cranes must be applied with high precision, and the swing angle must be carefully controlled. Intelligent controllers for tower cranes that do not need a mathematical model have been developed and evaluated in this study. Two intelligent control systems were investigated: one using a deep learning controller (DLC) and the other employing an adaptable neuro-fuzzy inference system (ANFIS). These controllers have been evaluated on tower cranes using the commonly used proportional differential (PD) controller. Simulations have been used to test how well the suggested intelligent controllers react to different working situations. The tests showed that the DLC was better at handling disturbances, accurate tracking, and responding quickly. As a result, the DLC made it easier to control the crane's swing angle and position, which improved security, reliability, and operating efficiency. The DLC is ideal for complicated crane control tasks as it can adapt to different operating conditions and disturbances.

Keywords- Tower crane; intelligent control; ANFIS-based controller; deep learning controller; PID controller.

1. Introduction

Industrial and building automation are still facing trouble with tower crane load positioning and anti-swing adjustments [1]. Tower crane behavior is unpredictable due to its nonlinear dynamic nature and variable load weights, wind velocities, and running speeds. Traditional Proportional-Integral-Derivative (PID) controllers have difficulty in handling this complexity, causing load positioning oscillations or delays [2]. This might cause damage to the crane system, security issues, and inefficient operation. Controllers using the crane mathematical model must continuously tune parameters. They also sometimes react slowly to the crane dynamics'

nonlinearity. Load swing, which happens when a load oscillates during elevation or transit, is challenging to solve [3].

The need for more sophisticated and adaptive control systems is growing. Control methods have been developed to solve control challenges in both open-loop and closed-loop crane systems [4]. Input shaping is an open-loop predictive control method that is designed to reduce crane vibrations and oscillations [5]. A mathematical model of the tower crane is required for the design of most closed-loop controllers. The PID controller is commonly used in tower crane operation. However, its

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performance requires continuous parameter updates that are determined by the crane's mathematical model. Artificial intelligence (AI) has been used to create crane controllers that work independently of the mathematical model [3]. They are also weakly sensitive to disturbances and parameter changes [6]. Xu and Ning [7] developed a tower crane system with a PID controller to deal with oscillations. Due to system characteristics and unexpected events, these controllers face several limitations, including real-time parameter modifications. Tower crane load swing angle and trolley position have been controlled using model predictive control algorithms [6]. However, Traditional and predictive controllers require the crane's mathematical model to be accurate. This is difficult owing to the crane's dynamic behavior and load characteristics [8].

Neural networks (NN) [3], fuzzy logic [9,10], and genetic algorithms [11] are some of the methods used to improve controller settings. Recent AI-driven controllers using fuzzy logic [12,13] or NNs [3,14] have been developed to solve dynamic systems modeling problems. Farage et al. [15] introduced a fuzzy logic controller for a large crane, comprising two elements: a radial fuzzy controller for detecting the trolley location and a rotary fuzzy controller for minimizing oscillations. An artificial NN controller, which is based totally on output feedback signals and functions independently of crane system parameters, was used by Chen et al. [14] to manage the vibration resistance of a crane. The controller adjusts weight using a radial basis function NN with Lyapunov stability control. Parameter uncertainty is resolved by this procedure, avoiding load vibration testing.

Soft-computing based controllers are effective and flexible for double pendulum crane management. Using the benefits of fuzzy logic and NNs, ANFIS-based controllers can be created [16,17,18]. ANFIS combines adaptive NNs with fuzzy logic to provide a self-adjusting neural technique. Research shows ANFIS can efficiently control complicated nonlinear systems [16,19]. Compared to traditional controllers, ANFIS-based controllers can handle system dynamics and external influences efficiently [10,12].

Deep learning algorithms have been used to regulate large nonlinear systems like tower cranes. Al-Aubidy et al. [20] showed that a DLC can regulate sensorless drive systems and overcome external disturbances. The DLC outperformed PID and ANFIS-based controllers. Another work by Shen et al. [21] automated container crane operations with deep learning. The results show crane performance improvements over human faults. Anderson et al. [22] used reinforcement learning (RL) to control forest cranes for energy efficiency. Despite the nonlinear dynamics of the crane and the fact that it is subject to external disturbances, the results of the tests indicate that deep reinforcement learning techniques give great performance. In the previous study [3], efforts focused on the design and performance of an ANFIS-based controller for a tower crane. The controller was designed to control

the load position and reduce the swing angle. Compared to the fuzzy logic controller and the fuzzy-tuned PID controller, the ANFIS-based controller was better at regulating position and tower crane swing angle.

This study aims to develop a deep learning-based tower crane trolley position and swing angle controller. This research compares the performance of a tower crane with deep learning, ANFIS, and well-tuned PD controllers. The rest of the paper is structured as follows: Section 2 describes the mathematical model of a laboratory tower crane [3]. Section 3 explains crane performance using a well-tuned PD controller. Section 4 designs an ANFIS controller. Section 5 develops a deep learning-based controller, while Section 6 evaluates several control methods. Section 8 outlines the main conclusions.

2. Tower Crane Structure and Modeling

A tower crane platform comprises many elements, such as foundation, mast, jib, counterweights, and trolley, along with control and monitoring systems. This research examines the mathematical model of a Quanser 3-DOF laboratory tower crane [3, 23]. This model is illustrated in Fig. 1. The load height can be modified, the tower can be rotated in two distinct orientations, and the trolley can be traversed horizontally along the boom. These represent the three degrees of freedom accessible to the tower crane. Furthermore, the jib is equipped with a motorized trolley capable of traversing its length and rotating in both clockwise and counterclockwise orientations. Furthermore, the jib, the horizontal segment situated atop the tower, is fitted with a DC motor that drives a ball screw, therefore facilitating the movement of the trolley along a linear guide. The tower is a vertical structure that is perpendicular to the ground. The trolley is fitted with a motor-operated cable to raise and lower the cargo. Maintaining oversight of the tower crane's three motors is essential to ensure its safe functioning. The mathematical representation of a tower crane consists of a set of nonlinear equations [23]. The intricacy of the computations presents difficulties in the design of the control unit and the evaluation of performance [3].

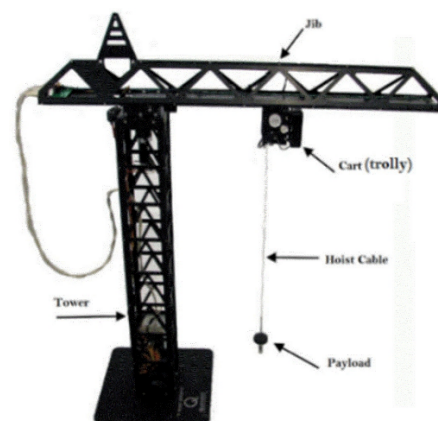


Fig. 1. Layout of the Quanser tower crane [23].

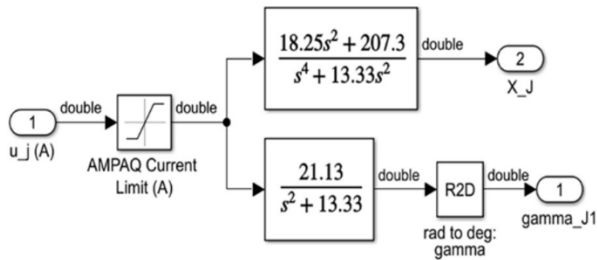


Fig. 2. Tower crane model block diagram.

To overcome these obstacles, researchers usually use simplifying assumptions to get a mathematical model of the crane that presents a decreased order. The block diagram of the mathematical model of the laboratory tower crane that was utilized in this investigation is given in Fig. 2. Using this model, it is possible to control both the position of the trolley and the load swing angle.

3. Traditional PID Controller

The traditional PID controller is one of the most used linear control techniques in crane control systems. However, these controllers may not have the capacity to manage the variety of operational situations faced in crane operations, including fluctuations in load weight and type, as well as wind disturbances. The requirement that the parameters of this controller be continuously adjusted is a significant constraint of this controller. These parameters are often taken from the mathematical model of the crane, which frequently simplify an approximation of the actual model. According to the mathematical model of the laboratory tower crane depicted in Fig. 2, a PD controller can meet the required control specifications. Fig. 3 illustrates a simulation of the tower crane regulated by a PD controller. To meet the requirements for safe crane operation, the controller parameters $K_d=1.14$ and $K_p=0.62$ were carefully chosen to enhance the system response using an automated MATLAB tuning tool. The main drawback of this controller is the need for real-time parameter modification, dependent upon fluctuations in the crane's dynamics.

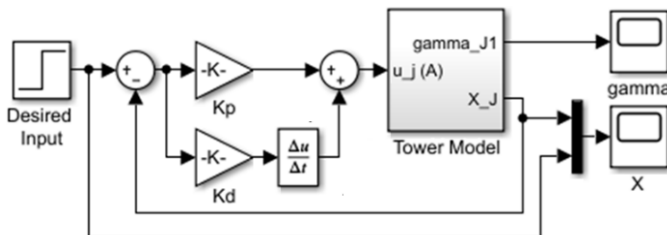


Fig. 3. Block diagram of PD controller for tower crane.

Fig. 4 shows the actual position of the Tower crane with its associated load swing angle when using the proportional differential control unit. The measured maximum overshoot was 0.2%, while the load swing angle was 20.7°.

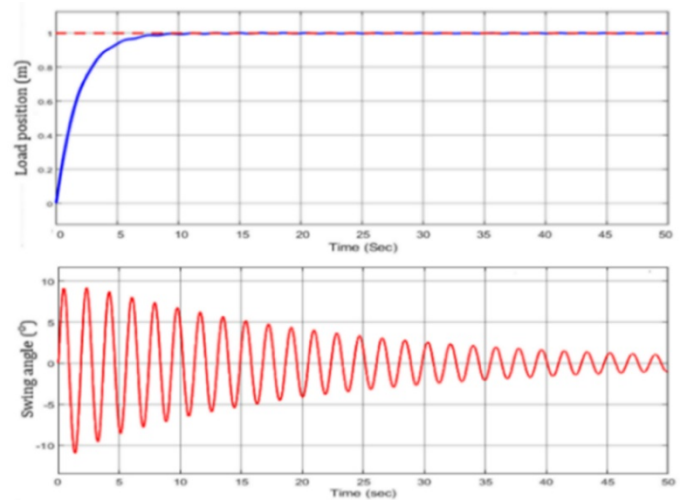


Fig. 4. Time response of load position and swing angle using PD controller.

4. ANFIS-Based Controller

The complicated dynamics of tower cranes are influenced by mechanical constraints, variations in load, and wind disturbances. The ANFIS approach has the capability to learn and modify control parameters in accordance with operational conditions. These properties can be used to create tower crane controllers for different operational and environmental settings. ANFIS-based controllers can manage the load position and swing angle of tower cranes without requiring a mathematical model, as they have the capability to learn from data.

4.1 Controller Design

The proposed ANFIS-based controller uses fuzzy rules and input-output data pairs to create an input-output mapping for the control of position and swing angle. The number of fuzzy sets employed to represent each variable is exactly proportional to the actual number of fuzzy rules. This design has 49 fuzzy rules, each having seven fuzzy sets per variable. Fig. 5 illustrates a multi-layered NN inside the ANFIS model architecture, with five layers and 49 fuzzy rules that establish the input and output connections in the controller.

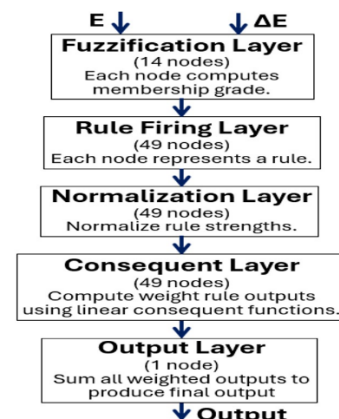


Fig. 5. Architecture of the ANFIS model.

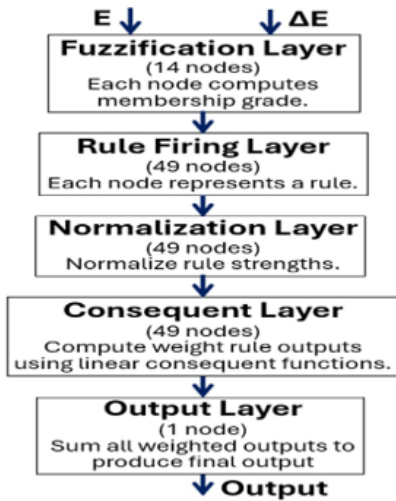


Fig. 6. Steps for the ANFIS algorithm.

The basic ANFIS-based controller design includes six phases, as illustrated in Fig. 6. The final prediction error of the ANFIS model after it has been trained for 1,000 full learning cycles is illustrated in Fig. 7. A closed-loop control system with an ANFIS-based controller to control the swing angle and load location is shown in Fig. 8. The ANFIS system's NN component allows the system to continually enhance its performance by adjusting the fuzzy rule parameters in response to the difference between the desired input and the actual output.

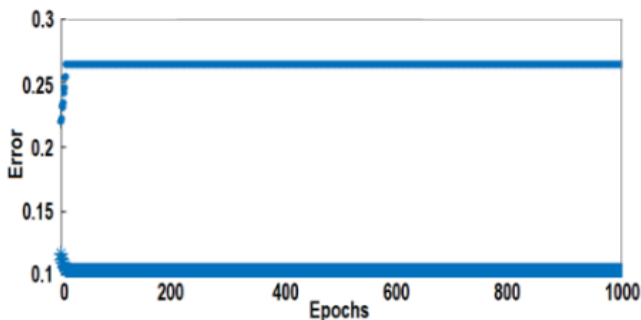


Fig. 7. ANFIS controller error.

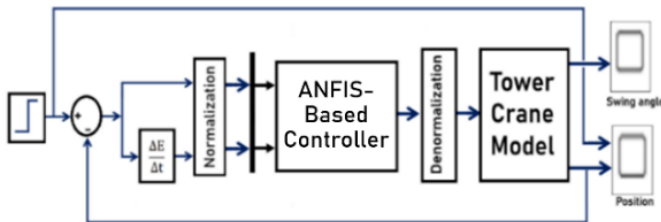


Fig. 8. ANFIS-based controller layout.

4.2 Controller Tests

The simulation results given in Fig. 9 show that the use of an ANFIS-based controller with a tower crane generated a significant enhancement in performance.

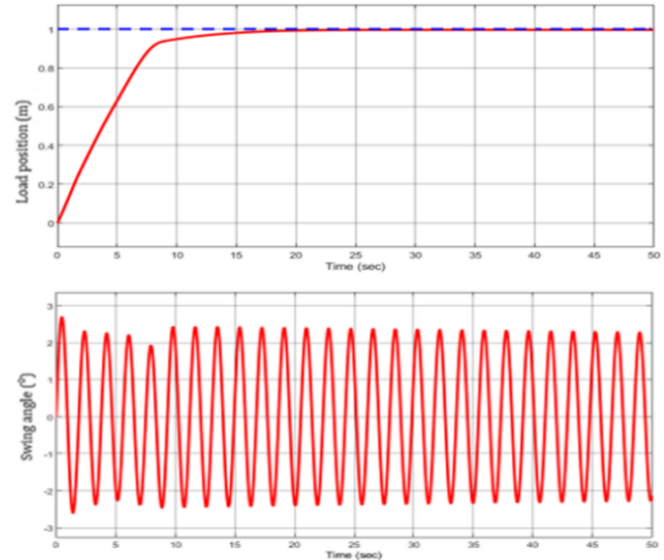


Fig. 9. Time response of load position and swing angle using ANFIS-based controller.

A major reduction in the swing angle $[-2.28^\circ$ to $+2.28^\circ]$ was achieved in comparison to the PD controller $[-10.90^\circ$ to $+9.10^\circ]$. The enhancement in performance has been linked to the combination of fuzzy logic with adaptive learning ANN. This hybrid approach provides effective and reliable crane operation, considering that the dynamics are a challenging requirement of real-world scenarios.

5. Deep Learning-Based Controller

Deep learning is a machine learning approach derived from the architecture of the human brain, using multi-layered NNs. Deep learning algorithms automatically learn complex nonlinear relationships using several layers to gradually extract facts. Due to these features, deep learning algorithms are now recognized as an attractive option for solving control problems. This study will use deep learning to control a tower crane, focusing on the load's position and swing angle. The main goal is to enhance positioning accuracy and minimize load oscillations to improve system performance.

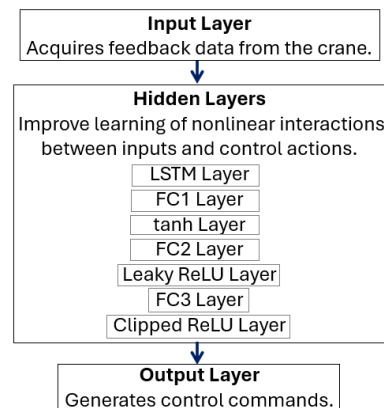


Fig. 10. Deep Learning structure.

5.1 Controller Design

The DLC can acquire the tower crane's dynamics from data to predict the load's swing angle and then generate control actions that minimize oscillations. This can be achieved by using the abilities of deep NNs, as illustrated in Fig.10. This network comprises an input layer, seven hidden layers, and an output layer. The chosen design uses LSTM and fully linked layers to utilize the crane system's time dynamics and nonlinear mapping. The crane is a nonlinear dynamic system with memory (velocity, sway, acceleration). LSTM captures timing dependencies, while fully linked layers map features to control actions. Table 1 lists the hyperparameters of the selected architecture.

Table 1. Hyperparameters of the DLC.

Component	Value
LSTM	100 units
FC layer 1	20 neurons
FC layer 2	20 neurons
FC layer 3	20 neurons
Activation	tanh + ReLU + leaky ReLU
Optimizer	Adam
Learning rate	0.001
Batch size	1
Epochs	300
Loss function	Mean Squared Error (MSE)

The input layer acquires feedback data from the crane's sensors, including the trolley's position, velocity, sway angle, and angular velocity. The hidden layers improve learning of nonlinear interactions between inputs and control actions. The hidden layers include a Long Short-Term Memory (LSTM) layer, three fully connected (FC) layers, a Hyperbolic Tangent activation (tanh) layer, a Rectified Linear Unit (ReLU) layer, and a truncated ReLU layer. The output layer generates control commands. The NNs were trained with 5,000 input/output data pairs obtained from the operation of a tower crane. The data pairs were divided into three subsets: 60% allocated for training, 20% for testing, and the final 20% for verification.

5.2 Controller Test

Crane operation scenarios with position changes and disturbance effects were used to generate the dataset. The DLC was trained, verified, and tested on the produced dataset, as illustrated in Fig.11. This dataset is not static; rather, it represents high-quality dynamic simulation examples. The DLC was then implemented on a tower crane model, as indicated in Fig.12. The DLC obtained a minimal overshoot of 0.003%, 0% steady-state error, and a swing angle range of $[-0.45^\circ, +0.45^\circ]$, as shown in Fig.13. It is obvious that the DLC performs better than the PD and ANFIS-based controllers.

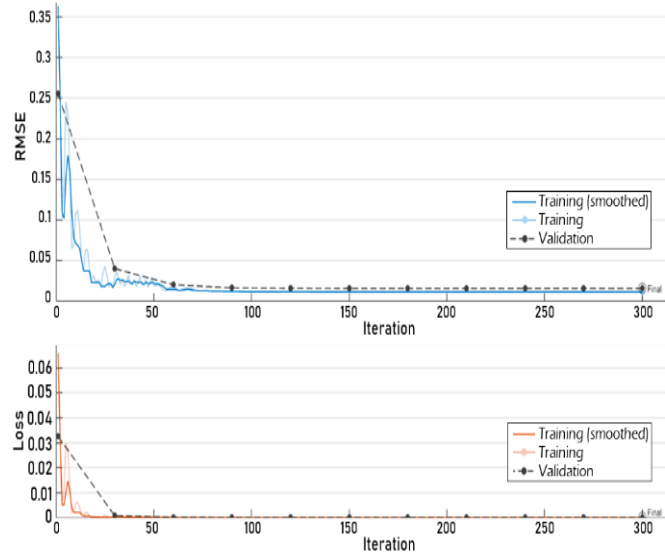


Fig. 11. Training and validation of the DLC.

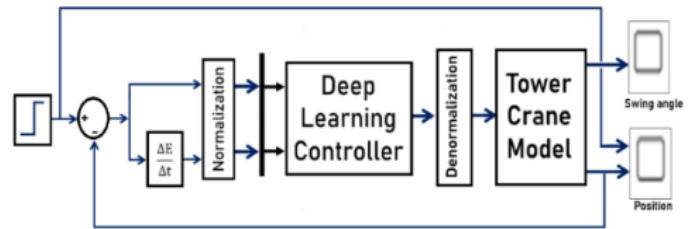


Fig. 12. Deep learning-based controller simulation block diagram.

6. Results and Discussion

Multiple tests were performed on a laboratory tower crane using three types of controllers: a proportional-derivative controller, an ANFIS-based controller, and a DLC. The main objective of these tests was to demonstrate the controllers' ability to control the load position and swing angle of the crane. Traditional controllers, such as the PD controller, need an accurate mathematical model of the tower crane to adjust the controller settings. The parameters of the crane's mathematical model are affected by variations in crane dynamics, load layout, and load weight.

On the other hand, the ANFIS-based controller and the DLC do not need a precise mathematical model of the crane. This is a considerable benefit of having intelligent controllers that are independent of a mathematical model of the crane. Moreover, only one controller was used to manage both the load position and the swing angle.

The performance evaluation of the three controllers under the same conditions is presented in Table 2. The deep learning-based controller outperformed the other controllers. This response was distinguished by a rise time of 3.162 seconds and a settling time of 7.438 seconds, along with a minimum swing amplitude of 0.9° .

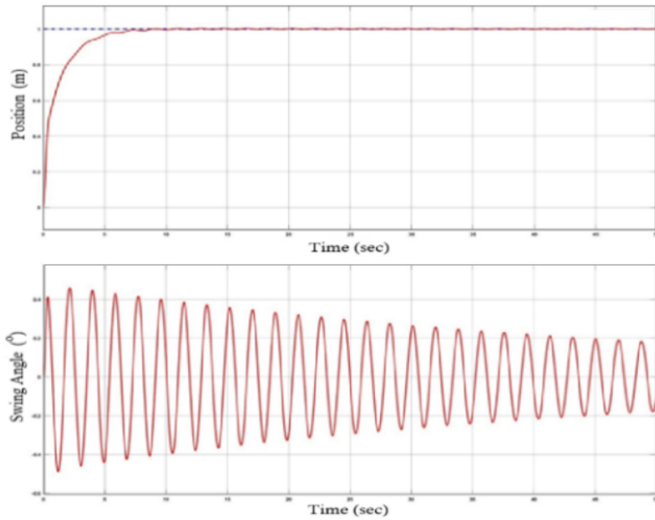


Fig. 13. Time response of load position, swing angle, and control signal using DL based controller.

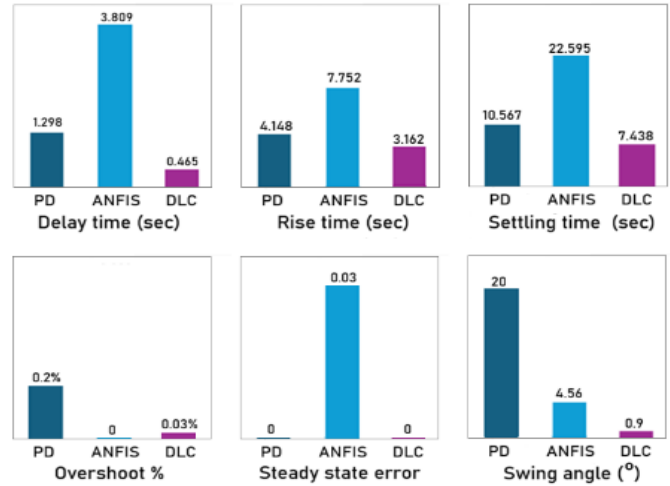


Fig. 14. Performance indicators of the three implemented controllers.

Table 2. Time response parameters for different controllers.

Position			
Parameters	PD	ANFIS	DLC
Delay time (sec)	1.298	3.809	0.465
Rising time (sec)	4.148	7.752	3.162
Settling time (sec)	10.567	22.595	7.438
Overshoot %	0.20%	0	0.03%
Steady-state error	0	0.003	0
Swing Angle			
Gamma (°):	[-10.90 ~ +9.10]	[-2.28 ~ +2.28]	[-0.45 ~ +0.45]

The performance indicators of the three controllers are compared in Fig.14, where the deep learning-based controller outperforms the others, particularly regarding swing angle, steady-state error, and overshoot percentage. The ANFIS-based controller became an alternative for position control and swing angle reduction since its swing angle amplitude is less than that of the PD controller. It is achievable to investigate how disturbances impact tower crane performance with the three controllers under evaluation.

The computation of maximum overshoot in load position and sway angles for each controller of a tower crane that was subjected to disturbance during the steady-state phase is illustrated in Fig. 15. The deep learning-based controller had the lowest swing angle of 1.04°, while the ANFIS-based controller had the lowest overshoot of 5.1% at the load position and a swing angle of 11.8°. Because it enhances the control of position and swing angle, the deep learning-based controller is appropriate for tower cranes.

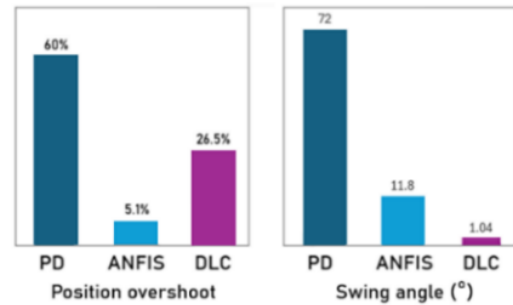


Fig. 15. Load position and swing angle evaluation.

7. Conclusion

Nonlinear dynamics affect tower crane load position management and swing angle adjustment. Because tower cranes need a precise mathematical model to create control signals and set controller parameters, traditional control methods typically fail. Intelligent controllers were built, tested, and assessed to minimize swing angles and enhance load positioning accuracy without a tower crane mathematical model. A deep learning-based tower crane load position and sway angle controller was built and tested. The ANFIS, deep learning, and PD controllers were tested under identical settings. The test results show the deep learning-based controller performed well. Compared to the PD controller, the DLC reduced load position overshoot by a factor of more than five times, and the swing angle was lowered to 1.04° from 72°. For tower cranes, the deep learning-based controller can successfully manage disturbances, improve load position, and control the swing angle. The feasibility of implementing the proposed controllers in a real tower crane will be examined in a future study.

References

- [1] A. T. Le and S.-G. Lee, "3D cooperative control of tower cranes using robust adaptive techniques," *Journal of the Franklin Institute*, vol. 355, no. 4, pp. 1913–1937, Mar. 2018, doi: 10.1016/j.jfranklin.2017.10.026.
- [2] R. Čápková and A. Kozáková, "Experimental modelling and control of a tower crane," in *Proc. 22nd Int. Conf. Process Control (PC)*, 2019, pp. 97–101, doi: 10.1109/PC.2019.8815327.
- [3] S. B. Al-Tuhaifi and K. M. Al-Aubidy, "Neuro-fuzzy-based anti-swing control of automatic tower crane," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 21, no. 4, pp. 891–900, Aug. 2023, doi: 10.12928/TELKOMNIKA.v21i4.24044.
- [4] H. Ouyang, H. Zhu, and H. Xi, "Trajectory planning and anti-swing for rotary crane considering physical constraints and obstacle avoidance," *IEEE/ASME Transactions on Mechatronics*, early access, Aug. 2025, doi: 10.1109/TMECH.2025.3593606.
- [5] A. M. Abdullahi et al., "Adaptive output-based command shaping for sway control of a 3D overhead crane with payload hoisting and wind disturbance," *Mechanical Systems and Signal Processing*, vol. 98, pp. 157–172, Jan. 2018, doi: 10.1016/j.ymssp.2017.04.034.
- [6] J. Wang, Z. Tian, J. Sun, J. Yang, and S. Li, "Event-triggered safety-critical model predictive control for underactuated overhead cranes," *IEEE Transactions on Industrial Informatics*, vol. 21, no. 9, pp. 6857–6867, Sep. 2025, doi: 10.1109/TII.2025.3567405.
- [7] C. Xu and H. Ning, "Simulation analysis of crane anti-sway control system based on PID," *Scientific Journal of Intelligent Systems Research*, vol. 3, no. 4, pp. 271–276, 2021. [Online]. Available: <http://www.sjisr.org/download/sjisr-3-4-271-276.pdf>
- [8] G. Feng, "A survey on analysis and design of model-based fuzzy control systems," *IEEE Trans. Fuzzy Syst.*, vol. 14, no. 5, pp. 676–697, Oct. 2006, doi: 10.1109/TFUZZ.2006.883415.
- [9] M. I. Solihin, Wahyudi, and A. Legowo, "Fuzzy-tuned PID anti-swing control of automatic gantry crane," *J. Vib. Control*, vol. 16, no. 1, pp. 127–145, 2010, doi: 10.1177/1077546309103421.
- [10] M. M. Abdulghani and K. M. Al-Aubidy, "Design and evaluation of a MIMO ANFIS using MATLAB and V-REP," *GRENZE Int. J. Eng. Technol.*, vol. 6, no. 2, pp. 129–136, Jul. 2020.
- [11] M. Marzouk and A. Abubakr, "Decision support for tower crane selection with building information models and genetic algorithms," *Autom. Constr.*, vol. 61, pp. 1–15, 2016, doi: 10.1016/j.autcon.2015.09.008.
- [12] A. F. Al-Saoudi, K. M. Al-Aubidy, and A. J. Al-Mahasneh, "Comparison of PID, fuzzy logic, ANFIS and model predictive controllers for cruise control system," in *Proc. 21st IEEE Int. Multi-Conf. Syst., Signals, Devices (SSD)*, Erbil, Iraq, Apr. 22–25, 2024.
- [13] D. Zhao, K. Wang, X. Zhou, X. Ma, and L. Jia, "Output-constrained controller with fuzzy-tuned parameters for overhead cranes," *arXiv preprint arXiv:2512.03680*, 2025, doi: 10.48550/arXiv.2512.03680.
- [14] Q. Chen, W. Cheng, L. Gao, and J. Fottner, "A pure neural network controller for double-pendulum crane anti-sway control: Based on Lyapunov stability theory," *Asian J. Control*, vol. 23, no. 1, pp. 387–398, 2021, doi: 10.1002/asjc.2226.
- [15] S. A. Farag, S. G. Foda, and A. Alenany, "Fuzzy control of a large crane structure," *Indones. J. Electr. Eng. Informatics (IJEI)*, vol. 5, no. 1, pp. 85–98, 2017, doi: 10.11591/ijeii.v5i1.256.
- [16] B. Selma, S. Chouraoui, and H. Abouaïssa, "Optimization of ANFIS controllers using improved ant colony to control an UAV trajectory tracking task," *SN Appl. Sci.*, vol. 2, Art. no. 878, 2020, doi: 10.1007/s42452-020-2236-z.
- [17] B. Benhellal, M. Hamerlain, and Y. Rahmani, "Decoupled adaptive neuro-fuzzy sliding mode control applied in a 3D crane system," *Arab. J. Sci. Eng.*, vol. 43, no. 6, pp. 2725–2733, Jul. 2017, doi: 10.1007/s13369-017-2747-0.
- [18] M. Abulaila, K. M. Al-Aubidy, and I. M. Alsudi, "Speed control of permanent magnet synchronous machines: ANFIS design and performance evaluation," in *Proc. 22nd Int. Conf. Research and Education in Mechatronics (REM)*, Jordan, Sep. 24–26, 2024, pp. 326–340, doi: 10.1109/REM63063.2024.10735555.
- [19] D. Ilir and L. Shpetim, "Rotational motion of tower crane—Dynamic analysis and regulation using schematic modeling," *Int. Sci. J. Math. Model.*, vol. 2, no. 1, pp. 21–25, 2018. [Online]. Available: <https://stumejournals.com/journals/mm/2018/1/21.full.pdf>
- [20] K. M. Al-Aubidy, I. M. Alsudi, and M. Abulaila, "Deep learning-based control of sensorless drives for robotics and automation," *Eurasian J. Sci. Eng.*, vol. 10, no. 3, pp. 63–74, 2024, doi: 10.23918/eajse.v10i3p7.
- [21] H. S. Shin, S. P. Lee, Y. S. Ha, and H. S. Kim, "Designing container crane control learning model using deep learning," *J. Adv. Mar. Eng. Technol.*, vol. 47, no. 6, pp. 367–378, Dec. 2023, doi: 10.5916/jamet.2023.47.6.367.
- [22] J. Andersson, K. Bodin, D. Lindmark, M. Servin, and E. Wallin, "Reinforcement learning control of a forestry crane manipulator," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Czech Republic, Sep. 27–Oct. 1, 2021, doi: 10.1109/IROS51168.2021.9636219.
- [23] Quanser, "3DOF Crane User Manual," [Online]. Available: <https://www.quanser.com/products/3-dof-crane/> (accessed Apr. 4, 2023).