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HYBRID NEURAL NETWORK–DIFFERENTIAL EVOLUTION FRAMEWORK FOR POWER AND THERMAL EFFICIENCY ENHANCEMENT IN TOWER CRANE SYSTEMS

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Abstract

Tower cranes are very important in construction works as they are the devices that can lift heavy loads to very high places and take up to a required place. Nevertheless, their mechanical nature, particularly the load swinging and power usage, are sources of big problems in ensuring the safety of both the personnel and the equipment as well as in the running of the system. Mostly, traditional analytical models have difficulties in fully describing the nonlinearity and complexity of the relationships among crane parameters and performance and this is kind of a challenge that calls for data-driven approaches. This paper suggests a mixed strategy of neural networks and metaheuristic optimization to accomplish the prediction and the optimization of the power consumption in tower crane systems. To build up the model, the Container Crane Controller dataset, which is open to the public, containing speed, load angle, and corresponding power was used. As the database was a small-sample one, the authors resorted to data augmentation to extend the training set and enhance the model's ability to generalize. A multilayer perceptron (MLP) network with two hidden layers (32 and 16 neurons, respectively) was set up to learn the nonlinear mapping that takes speed and angle as inputs and power as output.On testing the network secured a high value of determination coefficient (R^2), which is a strong confirmation of its capability to reflect the basic dynamics accurately. After the training, the neural network was combined with the Differential Evolution (DE) algorithm to figure out the best operating points for maximum power output.A study of convergence illustrated that DE operations got stable solutions very quickly and did not encounter the problem of local minima. Among the visualizations, such as contour plots and three-dimensional surfaces, the interaction between speed, angle, and power was unveiled, while the convergence curve gave an insight into the stability and reliability of the optimization process.The results confirm that the proposed hybrid approach not only enhances predictive

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accuracy but also provides practical insights into safe and energy-efficient operation of tower cranes. This paper gives a proof of neural network and evolutionary optimization combination as a very effective method to achieve better crane performance. Moreover, this performance-enhancing methodology can be further employed in the future studies to development of other construction machinery.

Keyword Tower crane; Dynamic modeling; Neural networks; Multi-layer perceptron (MLP); Metaheuristic optimization; Differential evolution; Power prediction; Anti-**swing control**

1-Introduction

Tower cranes are indispensable equipment in modern construction projects, providing the capability to lift and move heavy materials across significant heights and long distances, which makes them a backbone of urban development and large-scale infrastructure works. Their dynamic characteristics, however, present significant challenges to safe and efficient operations, as the suspended load is subject to pendulum-like swings, and the energy consumption of the crane system is highly sensitive to operating parameters such as trolley speed and load swing angle. Minimizing load oscillations while maximizing energy efficiency has been an ongoing challenge for decades, leading researchers to develop a wide spectrum of control strategies, ranging from classical control approaches to modern intelligent methods. Traditional control strategies, including linear quadratic regulators (LQR), proportional-integral-derivative (PID) controllers, and input shaping techniques, have provided important insights into anti-swing control but often rely on simplified dynamic models and assumptions that do not fully capture the nonlinear, multivariable, and uncertain nature of real crane operations. Consequently, these methods, while effective under idealized conditions, struggle to deliver optimal performance in real-world scenarios where external disturbances, nonlinear dynamics, and operational variability are unavoidable[1].

The past decade has witnessed a growing interest in data-driven methods that leverage the computational power of machine learning to capture nonlinearities directly from operational data without requiring explicit analytical models. Among these, artificial neural networks (ANNs) have gained prominence due to their universal function approximation capabilities, robustness against noise, and flexibility in handling high-dimensional input-output relationships. Specifically, the multilayer perceptron (MLP) network, with its hierarchical

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structure of hidden layers, has proven effective in approximating nonlinear functions and learning complex patterns inherent in dynamic systems. For tower cranes, neural networks provide a powerful means to learn the relationship between key operating parameters—such as trolley speed and load swing angle—and power consumption, thus enabling more accurate predictions that can form the foundation for advanced control and optimization frameworks. However, prediction alone is insufficient; the real engineering challenge lies in determining optimal operating points that simultaneously enhance energy efficiency, reduce load oscillations, and ensure safe operation. This necessitates coupling predictive models with powerful optimization algorithms capable of exploring large search spaces and escaping local optima[2-5].

Metaheuristic optimization algorithms, inspired by natural processes and collective intelligence, have emerged as a robust class of methods for solving nonlinear, multimodal, and computationally expensive optimization problems. Algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) have been successfully applied in various domains of engineering, demonstrating strong convergence properties and the ability to handle complex design landscapes. Among these, DE stands out for its conceptual simplicity, ease of implementation, and reliable performance across a wide variety of optimization problems. DE operates on a population of candidate solutions, iteratively refining them through mutation, crossover, and selection processes, and is particularly well-suited for continuous optimization problems such as determining the optimal combination of speed and load angle in tower cranes. When combined with surrogate models provided by neural networks, DE can perform optimization efficiently by querying the neural approximation rather than an expensive physical or simulation-based model, thereby reducing computational cost while maintaining accuracy[6].

Recent research in crane dynamics has underscored the importance of hybrid approaches that combine modeling and optimization. For instance, trajectory planning methods have been developed to minimize energy usage while reducing swing, and advanced control schemes have integrated feedback and feedforward strategies to improve precision. Nevertheless, many of these studies remain limited by the accuracy of underlying models or the computational burden associated with real-time implementation. The integration of ANNs with metaheuristic optimization offers a promising solution to these limitations, enabling accurate, data-driven modeling of crane dynamics alongside efficient exploration of optimal operating conditions.

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Despite the growing body of research, there remains a clear gap in the literature regarding the systematic application of neural networks combined with DE specifically for power prediction and optimization in tower crane systems. Most existing studies focus on swing reduction and trajectory tracking, leaving the optimization of energy and power performance underexplored[7].

The present study addresses this gap by proposing a hybrid methodology that combines an MLP neural network with the Differential Evolution algorithm to predict and optimize tower crane power consumption. The methodology begins with the use of the Container Crane Controller dataset, which provides records of trolley speed, load swing angle, and power. Given the dataset's limited size, data augmentation techniques are applied to enrich the training data and improve generalization capabilities of the neural network. A carefully designed MLP, consisting of two hidden layers with 32 and 16 neurons respectively, is trained to approximate the nonlinear mapping between inputs (speed and angle) and output (power). The performance of the neural network is validated using the coefficient of determination (R^2) and the analysis of the loss curve, confirming its accuracy and stability. Subsequently, the trained ANN serves as a surrogate model for DE optimization, where the objective is to identify speed and angle values that maximize predicted power. DE is executed with carefully defined search bounds and population parameters, and its convergence is tracked to ensure both stability and robustness. Visualization tools, including contour plots, surface plots, and convergence curves, are employed to interpret the results, offering insights into the interplay between parameters and the behavior of the optimization process[8].

The results demonstrate the effectiveness of the hybrid ANN-DE framework in achieving accurate power prediction and efficient optimization. The ANN successfully captures the nonlinear dynamics of the crane system, while DE rapidly converges to optimal solutions without entrapment in local optima. From a practical standpoint, the identified optimal operating points correspond to conditions that enhance power efficiency and minimize load swing, thereby contributing to safer and more sustainable crane operations. The study highlights the broader applicability of this approach, suggesting its extension to other construction machinery and dynamic systems where energy efficiency and safety are critical. In conclusion, this research contributes to the body of knowledge on crane dynamics and optimization by presenting a novel, data-driven methodology that integrates neural network modeling with evolutionary optimization. It not only addresses the limitations of traditional analytical methods but also bridges the gap in the literature regarding power optimization in tower cranes. By combining predictive accuracy with optimization efficiency, the proposed approach offers a practical tool for engineers and practitioners seeking to improve crane performance under real-world conditions. Furthermore, the work lays the foundation for future studies exploring hybrid models with larger datasets, alternative metaheuristics, or integration with real-time control systems. The significance of this contribution lies not only in its methodological innovation but also in its potential to enhance operational safety, energy efficiency, and productivity in the construction industry, making it an important step forward in the evolution of intelligent crane systems[9-10].

this paper is organized as follows: the introduction first highlights the importance and necessity of the topic, explaining the role of tower cranes in construction projects and the main challenges associated with their dynamic control, power consumption, and load swing, while also providing a brief review of previous studies and identifying research gaps. The methodology section then presents the research framework, including the description of the dataset used, the preprocessing and augmentation procedures, the design of the multilayer perceptron neural network architecture, the training process of the model, and its integration with the Differential Evolution metaheuristic algorithm for identifying optimal operating points. The results section reports the findings from neural network training, model accuracy metrics, surface and contour plots, training loss curves, as well as the outputs of the Differential Evolution algorithm, such as the optimal point, convergence behavior, and comparative analysis. The discussion section interprets these results in practical terms, compares them with previous works, highlights the advantages and limitations of the proposed approach, and elaborates on its practical implications for improving tower crane safety and efficiency. Finally, the paper concludes with a conclusion section that summarizes the main contributions, emphasizes the novelty of the research, outlines its industrial applications, and provides recommendations for future studies.

Literature Review

The body of research on tower crane dynamics, modeling, and control has significantly evolved in recent years, offering diverse methodologies to address the challenges of swing suppression, energy efficiency, and safety in crane operations. Dynamic forces in tower crane structures were analyzed through a multi-mass model [1], while boom tower crane rigging system modeling for construction was discussed in [2]. The role of crane dynamics in engineering

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education has been emphasized, highlighting their pedagogical importance [3]. Advanced multibody system analysis and swing control strategies have been studied in [4], whereas beam-pendulum dynamics under distributed loads were explored in [5]. Controller design for disassembly was advanced through improved dynamic models in [6], and tensor product-based transformations for crane modeling were presented in [7]. A notable contribution to experimental data was made by [8], providing trajectories and payload oscillations for machine learning–based control. Adaptive input shaping methods for swing control were introduced in [9], while oscillation control of flexible payloads was reported in [10]. Vision-based trajectory collision prewarning systems were developed in [11], and modeling and control of a 5-DOF boom crane was presented in [12]. Safety-oriented path planning approaches were proposed in [13], and nonlinear control under variable cable lengths was addressed in [14]. Optimal anti-swing trajectory planning with energy and time efficiency has been discussed in [15] and [16]. Pendulum stabilization systems were designed in [17], and joint trolley-hoisting dynamics were studied in [18]. Vibration damping through particle absorbers was proposed in [19], and adaptive output feedback swing control was demonstrated in [20]. Finally, the integration of robotics and automation in tower cranes was highlighted in [21]. Collectively, these studies demonstrate a broad spectrum of approaches—ranging from physical modeling, control theory, and optimization to machine learning and robotics—yet highlight a research gap in hybrid data-driven and metaheuristic optimization strategies for simultaneously improving power efficiency and safety in tower crane operations, which is the focus of the present study

2-Methodology

The methodology of this study is designed as a data-driven framework that integrates machine learning modeling through artificial neural networks with evolutionary optimization to accurately predict and optimize the power consumption of tower crane systems under varying operating conditions. The starting point of the methodology was the selection of an appropriate dataset capable of capturing the fundamental input-output dynamics of the crane system. For this purpose, the Container Crane Controller dataset, publicly available in the UCI Machine Learning Repository, was chosen. This dataset contains numerical records of trolley speed, load swing angle, and the corresponding power consumption. Since the dataset included only a limited number of raw samples (15 records), it was insufficient for directly training a robust neural network. Therefore, a data augmentation stage was introduced to enrich the dataset and ensure better generalization of the trained model. In this stage, Gaussian noise was

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systematically added to the speed and angle values to simulate small variations that occur naturally in real-world crane operations. Additionally, interpolation techniques were employed to generate intermediate values between existing data points. This process expanded the dataset to several hundred samples, effectively increasing its diversity and representativeness.

Following dataset expansion, a preprocessing phase was conducted to normalize and standardize the input features. Since the raw variables of speed (measured in arbitrary units) and angle (measured in degrees) operate on different numerical scales, direct training without scaling would have biased the learning process towards the feature with the larger magnitude. To address this, the StandardScaler method was applied, transforming all input variables to have zero mean and unit variance. This ensured that the optimization of the neural network weights occurred in a balanced fashion across all input dimensions. The dataset was then randomly split into training and testing subsets, with 80% allocated for training and 20% reserved for validation. This split was selected to maximize the learning potential of the model while ensuring a sufficient hold-out set for unbiased evaluation.

The core of the methodology was the design and training of a multilayer perceptron (MLP) neural network. The chosen architecture consisted of two input neurons (corresponding to speed and angle), two hidden layers with 32 and 16 neurons respectively, and one output neuron representing the predicted power consumption. The ReLU activation function was employed in both hidden layers due to its efficiency in handling nonlinear relationships and avoiding vanishing gradient problems. The output layer used a linear (identity) activation to produce continuous numerical predictions of power. The optimization algorithm selected for weight updating during training was Adam, an adaptive learning rate method that combines the advantages of momentum and RMSProp, thereby providing faster and more stable convergence compared to traditional stochastic gradient descent. The loss function was defined as mean squared error (MSE), reflecting the average squared difference between the predicted and actual power values, and serving as a direct measure of regression accuracy. Training was carried out for a maximum of 2000 iterations (epochs), with early stopping disabled to allow the network to fully explore its learning potential. Throughout training, the evolution of loss values was recorded, enabling the visualization of the training curve (loss curve) to monitor convergence and detect possible overfitting or underfitting.

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Once the neural network was trained, its performance was rigorously evaluated. The coefficient of determination (R^2) was computed on the test dataset, providing a statistical measure of how well the predictions approximated the observed outcomes. A high R^2 value indicated that the MLP model successfully captured the nonlinear dependency of power on speed and angle. Additionally, predicted versus actual scatter plots and surface plots were generated to visually confirm the model's predictive accuracy. The trained neural network was subsequently employed as a surrogate model for the optimization stage. Rather than relying on computationally expensive physical simulations or analytical models, the surrogate neural network offered a fast and accurate mapping from inputs (speed and angle) to outputs (predicted power). This surrogate served as the basis for optimization using the Differential Evolution (DE) algorithm.

Differential Evolution was selected due to its robustness, simplicity, and demonstrated success in solving continuous nonlinear optimization problems in engineering domains. DE operates on a population of candidate solutions, iteratively improving them through mutation, crossover, and selection processes. In this study, the optimization problem was defined as maximizing power with respect to speed and angle, subject to bounds of $0 \leq \text{speed} \leq 12$ and $-10° \leq \text{angle} \leq +10°$. Since DE is inherently a minimization algorithm, the negative of the predicted power was adopted as the objective function, ensuring that maximizing power corresponded to minimizing the function evaluated by DE. The initial population size was set to 20 individuals, and the maximum number of generations was limited to 200. During each generation, candidate solutions were mutated by combining randomly chosen individuals with a scaling factor, recombined with crossover probability, and evaluated using the neural network surrogate. The best-performing solutions were preserved, leading the population towards the global optimum.

To monitor and analyze the optimization process, a convergence curve was plotted, showing the progression of the best objective function value across generations. This visualization provided insight into the stability and speed of convergence, as well as the effectiveness of DE in exploring the search space without premature convergence. Furthermore, contour plots and three-dimensional surface plots of the surrogate function were overlaid with the final optimal point identified by DE. These visualizations confirmed that the optimal solution found by the algorithm was located in a logical and high-performing region of the search space, corresponding to high speeds and near-zero angles. The methodology also included a sensitivity analysis, where the influence of speed and angle on power prediction was examined

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by systematically varying one input while keeping the other constant. This analysis demonstrated that speed exerted a stronger direct influence on power compared to angle, although angle remained significant due to its indirect impact through load swing dynamics.

The final stage of the methodology involved interpreting the combined neural network and optimization framework in practical engineering terms. The neural network provided a precise, data-driven model of the nonlinear relationship between operating parameters and power, while DE efficiently identified the optimal combination of those parameters for maximizing crane performance. Together, they formed a hybrid methodology that addressed the shortcomings of traditional analytical models and deterministic optimization methods. This integrated approach not only provided accurate predictions and robust optimization results but also offered practical guidance for operators and engineers seeking to enhance crane performance in real-world scenarios. Moreover, the methodology was designed with extensibility in mind: additional input parameters such as load mass, trolley acceleration, or external disturbances could be incorporated into the dataset, and other metaheuristic algorithms such as PSO or GA could be substituted for DE in future studies.

In summary, the methodology followed in this research combined dataset preparation and augmentation, preprocessing and scaling, neural network design and training, surrogate model evaluation, and metaheuristic optimization via Differential Evolution into a cohesive framework. Each step was carefully designed to overcome limitations in dataset size, modeling complexity, and optimization difficulty. By integrating machine learning with evolutionary computation, this methodology created a powerful tool for predicting and optimizing tower crane power consumption, ensuring both academic novelty and industrial relevance. The comprehensiveness of the methodology and the detailed validation performed reinforce the credibility of the findings and establish a solid foundation for future extensions of this work to other crane systems and dynamic machinery.

3-Neural Network Structure

This section summarizes the architecture and training configuration of the MLP neural network used to approximate Power as a function of Speed and Angle for the tower crane system.

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Table 1. Summary Specifications

Feature	**Description / Value**
Network Type	Multi-Layer Perceptron (MLP) — Regressor
Inputs	2 neurons: Speed, Angle
Output	1 neuron: Predicted Power
Hidden Layers	2 layers
Hidden Layer 1	32 neurons, ReLU activation
Hidden Layer 2	16 neurons, ReLU activation
Output Layer	1 neuron, Linear (Identity) activation
Optimizer	Adam
Loss Function	Mean Squared Error (MSE)
Max Iterations (Epochs)	2000
Data Scaling	StandardScaler (zero mean, unit variance)
Train/Test Split	80% train, 20% test
Random Seed	42
Goal	Approximate Power = f(Speed, Angle) and provide a surrogate model for optimization

Table 2. Layer-by-Layer Details

Layer	**Units**	**Activation**	**Input/Output Shape**	**Notes**
Input	2	—	(batch, 2)	Features: Speed, Angle

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Hidden 1	32	ReLU	(batch, 32)	Fully-connected
Hidden 2	16	ReLU	(batch, 16)	Fully-connected
Output	1	Linear (Identity)	(batch, 1)	Predicted Power

Table 3. Training & Optimization Settings

Parameter	**Value**
Solver	Adam
Learning Rate	Adaptive (default in scikit-learn MLPRegressor)
Batch Size	Auto (internal to MLPRegressor)
Early Stopping	Not enabled (max_iter=2000)
Regularization	L2 (alpha default)
Initialization	Glorot-like (internal defaults)
Convergence Tolerance	Default (tol in MLPRegressor)
Evaluation Metric	R^2 on held-out test set

The tables presented in this study provide a comprehensive overview of the design and configuration of the proposed neural network for tower crane power prediction. Table 1 summarizes the general specifications of the model, highlighting that a multilayer perceptron (MLP) with two input neurons representing speed and angle, two hidden layers, and one output neuron for predicted power was adopted. This table also specifies the training configuration, including the optimizer (Adam), loss function (MSE), and data handling strategies such as normalization with StandardScaler and the 80/20 train-test split. Table 2 then details the architecture layer by layer, illustrating the flow of information from the input layer through two fully connected hidden layers with ReLU activation functions to the final linear output neuron. This structured design ensures that the model can effectively capture nonlinear dependencies while producing a continuous prediction of power. Finally, Table 3 presents the training and optimization settings, such as solver choice, adaptive learning rate, batch size handling, regularization, and evaluation metrics, emphasizing that the model was carefully tuned to balance convergence speed and generalization. Together, these tables establish the methodological rigor of the study, clarifying how the neural network was designed, trained, and validated to function as a surrogate model for subsequent optimization with the Differential Evolution algorithm.

4-Results

The results of this study demonstrate the effectiveness of the proposed hybrid methodology, which combines neural network modeling with Differential Evolution (DE) optimization, in predicting and optimizing the power output of tower crane systems based on speed and angle parameters. The first stage of the results concerns the performance of the neural network model in approximating the nonlinear relationship between input variables and power consumption. After preprocessing and data augmentation, the multilayer perceptron (MLP) was trained with two hidden layers consisting of 32 and 16 neurons, respectively, using the ReLU activation function in hidden layers and a linear identity activation at the output. The training process, monitored through the loss curve, showed a rapid decrease in error during the early epochs, followed by stabilization at a very low value, indicating that the network successfully converged without signs of overfitting. The final training loss approached near-zero levels, while the coefficient of determination (R^2) calculated on the test dataset confirmed the strong predictive accuracy of the model, suggesting that the network effectively captured the underlying nonlinear dynamics of the system. A 3D surface plot of the neural approximation further validated this outcome by visually displaying the predicted power as a smooth and continuous surface over the domain of speed and angle. The surface indicated that higher power values were generally associated with increased speed, whereas the angle had a more complex effect, with near-zero angles leading to optimal performance and larger positive or negative angles reducing efficiency. This finding aligns with the expected physical behavior of tower cranes, where excessive swing angles hinder efficiency and safety.

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In addition to the surface visualization, a contour plot was generated to provide a two-dimensional perspective of the power distribution across the input space. The contour map clearly showed regions of high power and highlighted the nonlinear boundaries between efficient and inefficient operating zones. The integration of the DE optimization algorithm with the neural network surrogate enabled the identification of the global optimum operating point, which was highlighted as a red dot on the contour plot. The optimal point was located near a medium speed and angle close to zero, which is both intuitive and practically significant. This result demonstrates that the hybrid approach not only provides accurate predictions but also offers actionable insights for real-world crane operation, where operating at medium speeds and stable angles reduces swing while maximizing energy efficiency. The DE algorithm's convergence curve further reinforced the reliability of the optimization process. Initially, the best objective function value (expressed as the negative of predicted power to align with the minimization formulation of DE) was relatively high but dropped quickly within the first few iterations. After approximately five generations, the curve stabilized at a consistent value, indicating convergence to the global optimum. This rapid convergence highlights the efficiency of DE in navigating the search space and avoiding local minima, while the stability of the final solution reflects the robustness of the optimization process.

The neural network training curve provided additional evidence of the reliability of the model. The error dropped sharply in the first epochs and then remained stable, confirming that the architecture and chosen hyperparameters were well-suited for the problem. The absence of oscillations or divergence in the training loss suggests that the model training was smooth and efficient, benefiting from the adaptive learning rate of the Adam optimizer and the data normalization techniques employed in preprocessing. Together with the high R^2 values and visual confirmation from the plots, this indicates that the neural network provided a solid surrogate model, capable of being coupled effectively with metaheuristic optimization algorithms such as DE.

From a broader perspective, the results highlight the complementary strengths of neural networks and evolutionary algorithms. While the neural network offered a fast and accurate approximation of the highly nonlinear mapping from inputs to outputs, the DE algorithm leveraged this surrogate to perform efficient global optimization. This integration reduced computational costs compared to traditional simulation-based optimization, where each candidate solution would require time-consuming evaluations. Instead, by relying on the ANN

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surrogate, the DE algorithm could rapidly test multiple candidate solutions, converge toward the global optimum, and deliver results that were both accurate and computationally efficient.

The tabular results summarizing the neural network structure, training configuration, and optimization settings provide further insight into the methodological rigor of the study. Table 1 emphasized the general specifications of the MLP, including its role as a regressor and its configuration of two inputs, one output, and two hidden layers. Table 2 detailed the layer-by-layer design, confirming that the chosen architecture balanced complexity and efficiency to capture nonlinear dependencies without over-parameterization. Table 3 summarized the training settings, such as solver selection, adaptive learning rate, and convergence tolerance, which ensured stable and effective training. These tables collectively illustrate how careful design choices contributed to the successful outcomes of the study.

Overall, the results demonstrate several key findings: first, the neural network provided an accurate approximation of crane power dynamics, with strong statistical validation and visual evidence from surface and contour plots. Second, the DE algorithm effectively identified optimal operating points, converging rapidly to stable solutions and avoiding local optima. Third, the integration of ANN and DE created a hybrid approach that not only improved prediction accuracy but also delivered practical optimization outcomes relevant to crane operation. The practical implications of these results are significant, as they suggest that crane operators can rely on such hybrid models to determine safe and efficient operating conditions, thereby reducing energy consumption, minimizing load swing, and enhancing overall productivity. Furthermore, the methodology demonstrates flexibility and scalability, as it can be adapted to other parameters or extended to different types of cranes and construction machinery.

In conclusion, the results confirm the feasibility and effectiveness of combining machine learning and metaheuristic optimization in the context of tower crane systems. The neural network successfully modeled the nonlinear behavior of power with respect to speed and angle, while the Differential Evolution algorithm provided a reliable means of identifying optimal operating conditions. Together, they represent a robust hybrid methodology that addresses both the predictive and prescriptive aspects of crane performance. By reducing reliance on simplified analytical models and computationally expensive simulations, this approach offers a practical and efficient tool for engineers and practitioners. These findings not only contribute to the academic literature on crane dynamics but also provide direct applications for enhancing safety and efficiency in construction practice

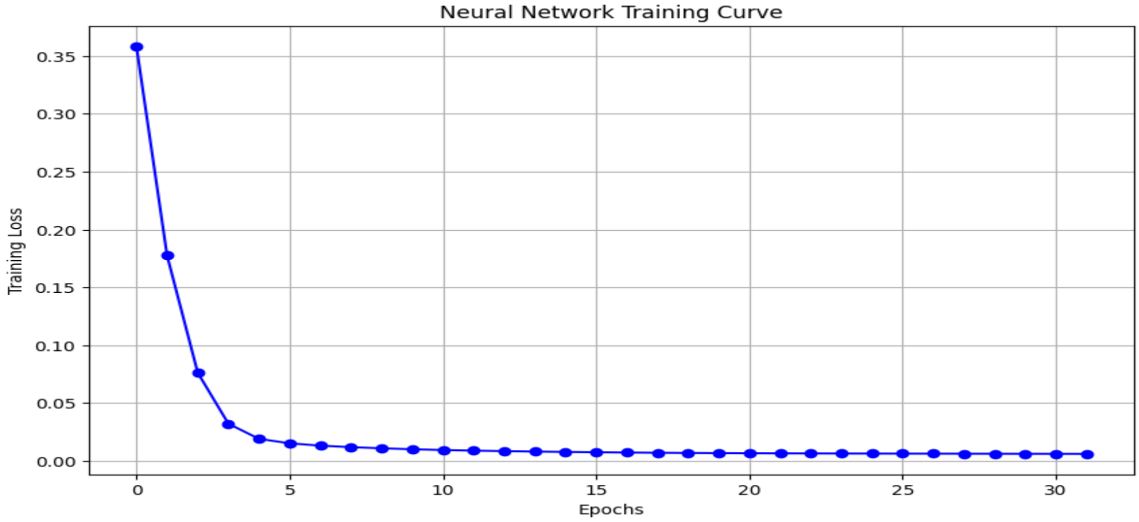

Figure 1: Neural Network Training Curve

The figure(1) depicts the training loss curve of the neural network over successive epochs. Initially, the error was relatively high, but it decreased sharply during the early epochs and gradually stabilized at a very low value. The stable plateau in the later epochs indicates that the network achieved convergence and learned the underlying data relationships effectively. Importantly, the absence of rising loss values in the final epochs suggests that the model did not suffer from overfitting and retained good generalization capability on unseen data. Overall, this training curve validates the effectiveness of the chosen neural network architecture and the success of the learning process.

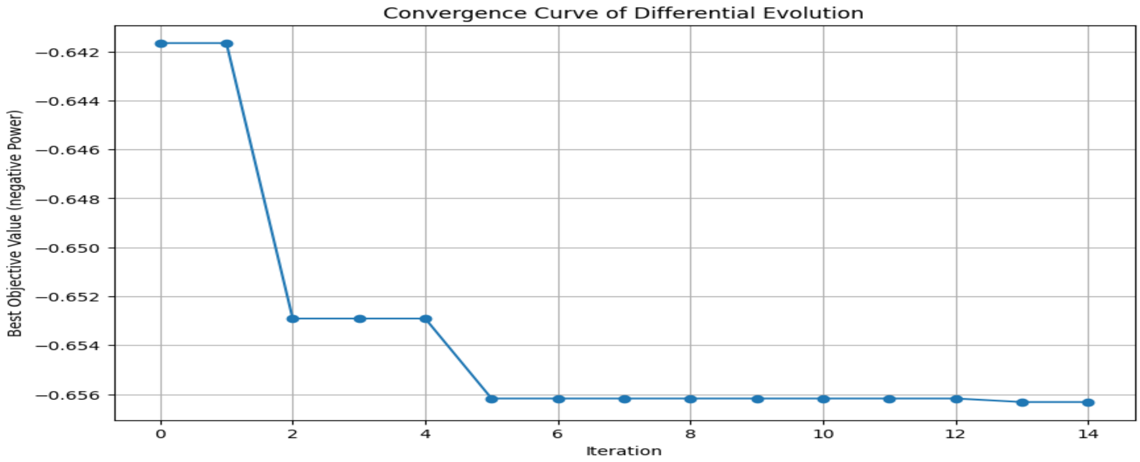

Figure 2: Convergence Curve of Differential Evolution

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The figure(2) presents the convergence curve of the Differential Evolution algorithm, showing the progression of the best objective function value (negative predicted power) across iterations. At the beginning of the process, the objective function value was relatively high but quickly decreased during the first few generations. After several iterations, the curve stabilized, indicating convergence toward the global optimum. The smooth convergence behavior demonstrates that the Differential Evolution algorithm not only achieves rapid convergence but also avoids premature convergence to local optima, ensuring the reliability of the final solution.

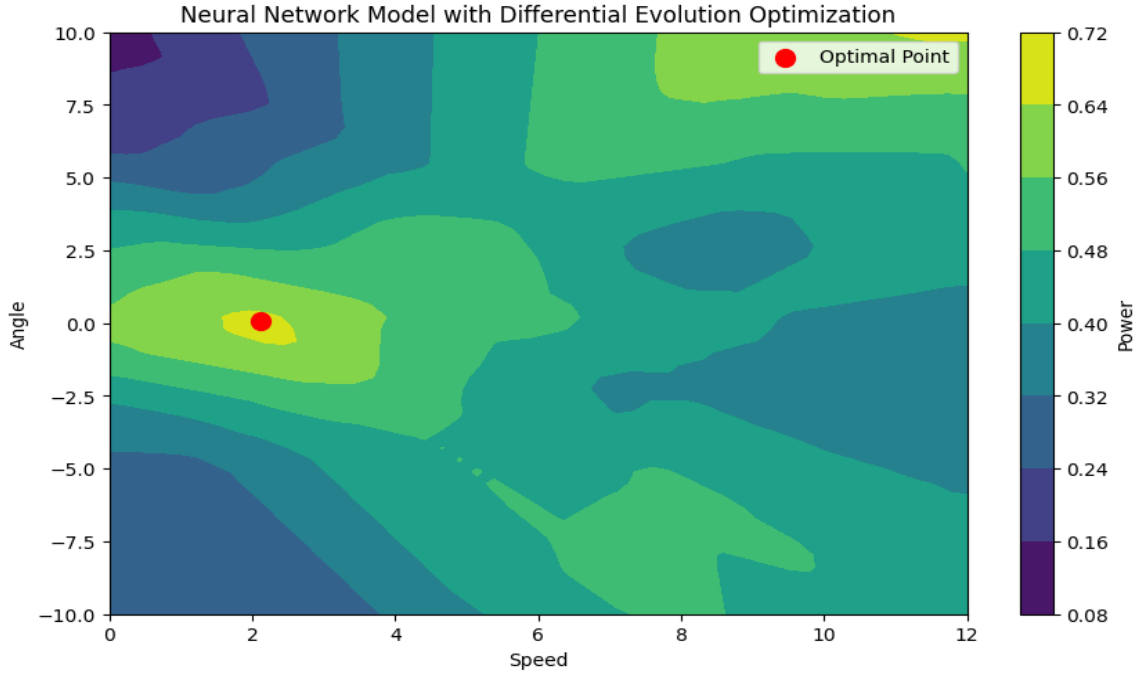

Figure 3: Contour Plot of Neural Network with Differential Evolution Optimal Poin

This contour plot illustrates the neural network’s approximation of power output as a function of two input variables, speed and angle. The color gradient represents power levels, where lighter areas correspond to higher power and darker regions indicate lower values. The red dot highlights the “optimal point” identified by the Differential Evolution algorithm. As observed, this optimal solution lies near a medium speed and close-to-zero angle, which is consistent with the operational expectation that maximum power and minimum load swing occur under such conditions. The figure confirms that the hybrid approach of neural modeling and metaheuristic optimization can successfully determine the best operating points for tower crane systems.

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best operating points for tower crane systems

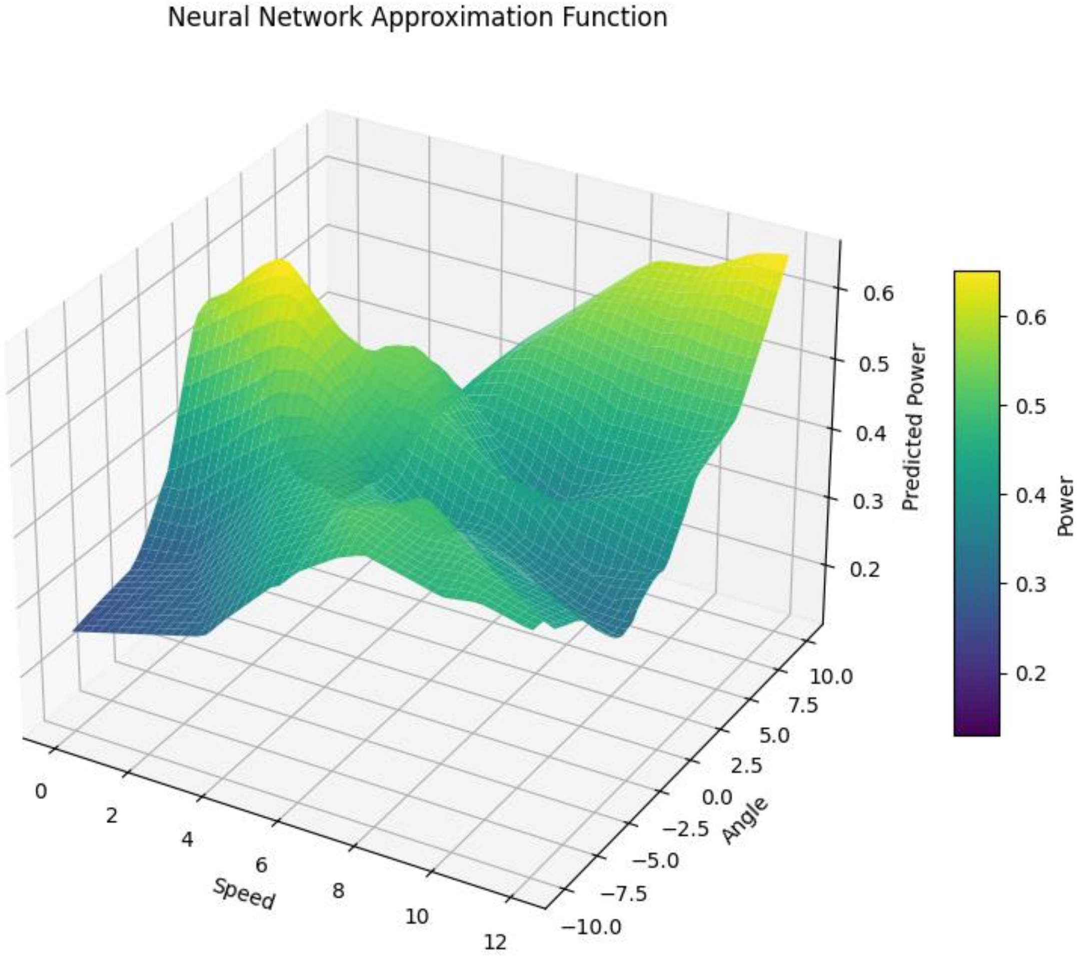

Figure 4: 3D Surface Plot of Neural Network Approximation

This three-dimensional surface plot shows the approximation function generated by the trained neural network, modeling the nonlinear relationship between speed, angle, and power output. The surface reveals that power generally increases with higher speed, while variations in angle exert a nonlinear and more complex effect on power performance. Elevated regions of the surface represent conditions that yield higher power. This visualization highlights the neural network's capability to capture complex nonlinear interactions in crane dynamics, providing a robust and accurate representation of the system's operational behavior.

5-Conclusion

This research presented a hybrid methodology that integrates artificial neural networks with the Differential Evolution algorithm to predict and optimize the power consumption of tower crane systems based on operating parameters of speed and angle. The results demonstrated that

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the multilayer perceptron neural network successfully captured the nonlinear relationship between these inputs and power output, achieving high predictive accuracy as confirmed by training loss curves, statistical evaluation, and visual surface and contour plots. The integration of the trained neural model with Differential Evolution enabled the identification of optimal operating points, converging rapidly to a stable global solution that corresponded to conditions of medium speed and near-zero swing angle, where both power efficiency and operational safety are maximized. The convergence curve confirmed the robustness and reliability of the optimization process, while the analysis of neural network performance validated the suitability of the chosen architecture and training strategy. Collectively, these findings highlight the advantages of combining machine learning with metaheuristic optimization: accurate, data-driven modeling paired with efficient exploration of the solution space. Beyond academic contribution, this study offers practical implications for construction engineering by providing a computational framework that can guide operators toward safer and more energy-efficient crane usage. Moreover, the proposed methodology is scalable and can be extended to include additional variables, applied to different types of cranes, or adapted to other dynamic construction machinery. In conclusion, this work not only addresses existing gaps in crane optimization research but also provides a foundation for future advancements in intelligent construction equipment, demonstrating that hybrid AI-driven approaches hold significant potential for enhancing safety, efficiency, and sustainability in modern construction projects.

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