

Neural Networks for Modelling Nonlinear Oscillations in Mechanical Systems

Haran S S¹, Harish S S², Shanthi Chinnasamy³

¹Student, Department of Artificial Intelligence and Data Science, RVS College of Engineering and Technology, Coimbatore, Tamil Nadu, India

²Former Student, Department of Physics, Bharathiar University, Coimbatore, Tamil Nadu, India

³Independent Author, Coimbatore, Tamil Nadu, India

ABSTRACT

Nonlinear oscillations are intrinsic to a wide range of mechanical systems. Modelling the system behaviour is crucial for stability, error identification and optimization of the system parameters. Applying traditional analytical and mathematical expressions to the system often finds difficult due to the nonlinear oscillations. Thus, the advancement of Artificial Intelligence in mechanical systems have transformed this traditional approach into neural network architectures including feedforward, recurrent, convolutional, and physics-informed networks in capturing nonlinear behaviours in mechanical oscillators. It discusses the IoT embedded systems and data acquisition for real-time monitoring of nonlinear oscillations. It also highlights the data processing and feature extraction methods to improve the system's performance. Furthermore, Evaluation and validation of errors in a model is also discussed by statistical approaches. Finally, this review explores emerging trends in neural networks such as hybrid AI-physics model and their integration within the industry and smart manufacturing ecosystem.

Key Words: Artificial Neural Network, Nonlinear Oscillations, Mechanical Systems, IoT systems, Data Processing, Engineering Models, Model Validation

1. INTRODUCTION

Nonlinear oscillations are fundamental phenomena that creates the foundation of many fields in technical sciences from micro-scale resonators and vibration absorbers to large-scale applications. The main goal is to investigate the level of vibration in the mechanical systems. Unlike linear system, nonlinear systems exhibit complex behaviour such as amplitude-dependent frequencies, bifurcations, chaos, and energy transfer between modes. Traditional methods like analytical and mathematical methods like Perturbation, phase-plane, bifurcation, averaging, runge-kutta methods often face limitations while dealing with nonlinear dynamics. This issue can be tackled by modelling a nonlinear response that is crucial for the system's stability and behaviour. This review paper provides a comprehensive overview of recent trends in applying neural networks for a nonlinear oscillation in mechanical system. Advanced architectures like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Physics-Informed Neural Networks (PINNs) are used to optimize the system behaviour. By bridging a gap between Nonlinear dynamics and Artificial Intelligence, this paper aims to provide insights into how neural networks can predict and control the nonlinear oscillations in mechanical systems.

2. OVERVIEW OF NONLINEAR OSCILLATIONS IN MECHANICAL SYSTEM

Oscillations are the periodic variation of some measure around an equilibrium point between two or more different states. In linear oscillations, the restoring force is proportional to displacement. Hence, the behaviour of the system is clearly expressed by linear differential equations.

$$F = -kx$$

But in actual occurrences, the mechanical system doesn't stick to such linearity. The oscillatory motion is said to be nonlinear when the restoring force is not directly proportional to the displacement. Nonlinear oscillations are essential to study the dynamics of mechanical systems as their behaviour is much complex than the linear ones. This nonlinearity arises due to nonlinear damping, large amplitude motions or complex part interactions. It means that system's output is not directly proportional to its input. Using the nonlinear differential equations, can predict the multiple stable states,

amplitude-dependent frequencies and parameter deviations in the system's behaviour. However, it is difficult to solve such problems as it requires possible approach [1]. An example of nonlinear differential equation for a simple pendulum:

$$L\ddot{\theta} + g \sin\theta = 0$$

There are numerous methods to analyse nonlinear oscillations in a mechanical system. Using Classical approaches like Perturbation, Phase-plane, bifurcation, averaging, runge-kutta, it is difficult to apply on complex mechanical system as it often need simplifications. To overcome these problems, Modern AI tools like Neural Network is used to analyse the nonlinear oscillation in the mechanical system. Notably, Physics-Informed Neural Network (PINNs) and Data Driven Neural Network (DNNs) is used when the system's behaviour is highly nonlinear. It also uses big data inputs like measure of vibrations and oscillations, system parameters and other data to model, predict or analyse the dynamics of the mechanical system.

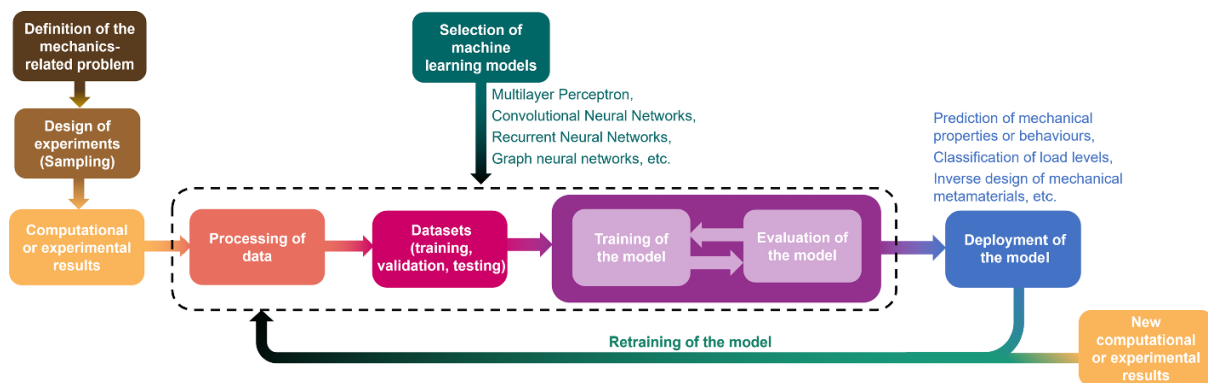


Figure 1. Typical schematic representation for learning mechanics-related tasks.

3. NEURAL NETWORKS IN ENGINEERING MODELLING

3.1 Types of Neural Networks used in Dynamic system modelling.

In the modelling of neural network, few models are used to validate the nonlinear oscillations in the dynamic system. Feedforward Neural Networks (FNNs) are foundational models used for immovable nonlinear mappings. Recurrent Neural Networks (RNNs) including LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) alternatives, are designed to control time-series data, making them ideal for creating dynamic systems with memory effects.

Convolutional Neural Networks (CNNs) though traditionally used in image processing, have been fitting to extract dimensional-temporal features from vibration and sensor data in mechanical systems. In Nonlinear oscillatory system, a trained FNN was successfully used to predict the nature of a five-degree-of-freedom Duffing oscillator, professed the power of data-driven fitting in capturing nonlinear dynamics [2].

3.2 Key Studies on Neural Networks in Mechanical System

In error identification and rectification in mechanical systems has been improved during the past decades. Error identification in a system begins with collection of data which are related to error. This error identification can be by statistical analysis and by model-based predictions [3, 4]. By using the neural networks, the user can identify the system's behaviour, compares the constant conditions, examines signalling and to measure the system parameters without the prior knowledge or training and evaluating the methodology of complete Artificial Neural Network (ANN) [5].

The self-learning ability of ANN, mapping of nonlinear oscillations in system, parallel computing and deviation of error are used to construct an advanced error identification system. The complexity of system's behaviour is due to static and dynamic properties that are considered as the optimization parameter which is integrated in the mechanical system. Using mathematical model is insufficient to overcome these problems in optimization. Henceforth, to calculate and adjust the parameters for optimization process, ANN is used as a methodology to tackle problems such as 2D and 3D structures, composite structures and vibrating systems [6].

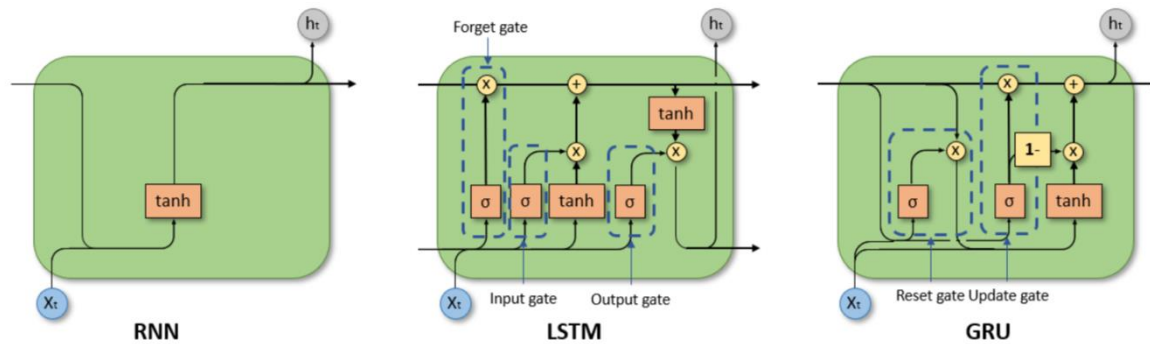


Figure 2. A Comparison of different neural network models.

4. DATA ACQUISITION AND IOT INTEGRATION

ANNs play a vital role in IoT-based mechanical system to analyse vibration and oscillation data through pattern recognition and anomaly detection. The sensors detect vibrations and oscillation in the mechanical system and transmits the data via IoT network for data processing. ANNs analyse these data to identify the errors or deviations found in the mechanical system. For instance, Convolutional Neural Networks (CNNs) represents the acoustic data that enables high accuracy error identification without the need of any traditional analytical methods. The progression of mechanical wear and failure is predicted by obtaining temporal dependencies within the sequential sensor data by using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks [7].

Sensor technologies and edge computing are remodel IoT-based data acquisition by permissive faster, smarter, and well-planned systems. Like MEMS (Micro-Electro-Mechanical Systems), optical, and piezoelectric sensors overture high sensitivity and miniaturization. These are contemporary sensor technologies making them ideal for embedded IoT systems. Edge computing processes this data narrowly-at or adjoining the sensor that shrinking latency and bandwidth usage correlated to cloud-only architectures. Energy-efficient microcontrollers and AI accelerators at the fringe allow for lightweight machine learning assumption directly on sensor nodes. By integrating AI with edge computing enhances responsiveness and reduces cloud dependency in smart manufacturing systems [8].

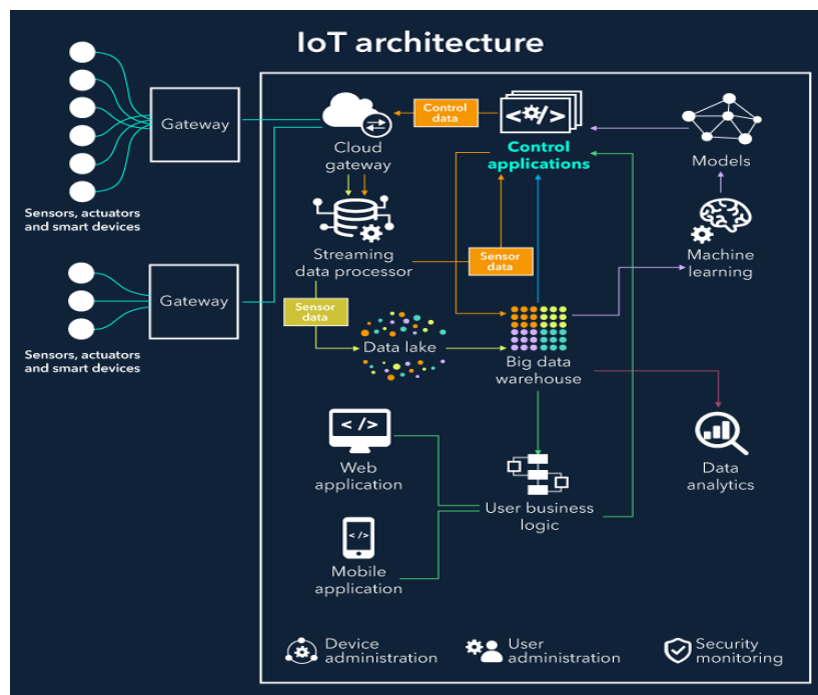


Figure 3. The structure of the Internet of Things (IoT) sensing system.

5. DATA PREPROCESSING AND FEATURE ENGINEERING

Through Pattern recognition, ANNs can be able to solve Nonlinear time series though they are not efficient like traditional linear models. Hence, to forecast the nonlinear time series, new models are developed. Hybrid models are the combination of ANNs with a linear model ARIMA (Auto-Regressive Integrated Moving Average) such as bilinear model like Auto-Regressive Conditional Heteroskedasticity (ARCH), Smooth Transition Auto-Regressive (STAR) and Nonlinear Auto-Regressive (NAR) models [9]. To analyse or predict a nonlinear oscillation, the NAR model is found efficient with ANNs. NAR is a discrete model holds an input layer, input delay, hidden layer, output layer and output delay [8]. It is mathematically expressed as

$$x(k) = [x(k), x(k-1), x(k-2) \dots x(k-t), y(k-1), y(k-2) \dots y(k-p)]$$

$$o(k) = f_{N_1}(x(k)w_{N_1} + b_{N_1})$$

$$y(k) = f_{N_2}(x(k)w_{N_2} + b_{N_2})$$

Here, x is the input vector of the P dimension and y is the output vector of the Q dimension. O is the hidden layer node vector of N dimension, t is delay order and p is output delay order, b_{N_1} is a threshold of the input layer, b_{N_2} is a threshold of the hidden layer. Where t as an input delay step, the number of resultant delay step is p then the output of j^{th} hidden nodes. Connection weight between hidden and delay layer is symbolized by w_{N_1} , the transfer function for the hidden nodes is f_{N_1} an activation function for output nodes is f_{N_2} .

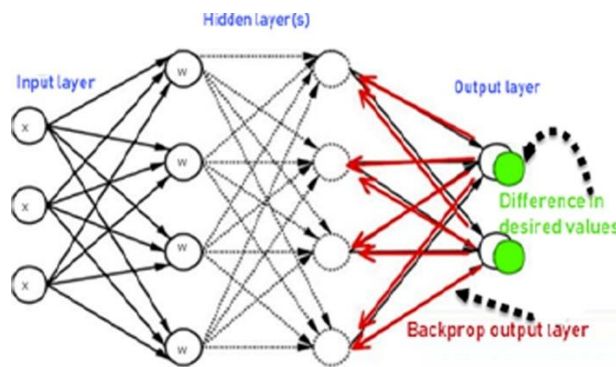


Figure 4. Structure of NAR neural network model.

Signal processing approach like FFT (Fast Fourier Transform) and filtering are crucial for transforming raw sensor data into purposeful features for machine learning and engineering analysis. Filtering techniques like low-pass, high-pass, and band-pass filters that helps to withdraw noise and segregate relevant signal bands, improving signal clarity. Smoothing filters help to sustain signal trends while condensing high-frequency noise. Feature eradication from filtered signals consists of metrics like RMS (Root Mean Square), peak amplitude, spectral entropy, and kurtosis are used in fault detection and classification.

6. EVALUATION METRICS AND MODEL VALIDATION

ANN models are used to predict the nonlinear oscillations in system's behaviour due to their ability to solve the complex problems. The ability of ANN models should be validated to ensure the proper functioning of algorithm. Hence, it is validated by using statistical error metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). These statistical approaches help us to quantify the oscillatory responses and compare with the experimental data.

To evaluate the frequency and phase synchronization of oscillations in a dynamic system, statistical methods like correlation coefficients, spectral error measures and phase error analysis are employed. Using coefficient of determination (R^2) in a nonlinear system is not so effective due to inaccuracy and misleading assessment of ANN models [10]. To develop and assess the accuracy of ANNs, Cross Validation (CV) is performed by providing an input of oscillatory data. The CV error is defined as

$$\frac{1}{k} \sum_{i=1}^k (MSE_{(k)})$$

where $MSE_{(k)}$ is the Mean Square Error for the k^{th} -fold dataset and the smallest CV error suggests the optimal setting of the hyperparameters. When the data points are selected randomly, it causes serious issues in time-series data as it violates the pattern recognition to proceed further studies. To tackle this issue, Block cross validation is introduced. It involves four strategies that includes the fivefold CV, leave-one-out CV, h-block fivefold CV, and out-of-sample evaluation [11].

Repeating the cross validation with test groups, the errors can be minimized. It is ideal to evaluate each analytical approach equally when benchmarking performance. This might include applying the same data collection and accuracy measurement method. Therefore, using CV to assess the accuracy of both the ANN and linear regression may seem reasonable [12].

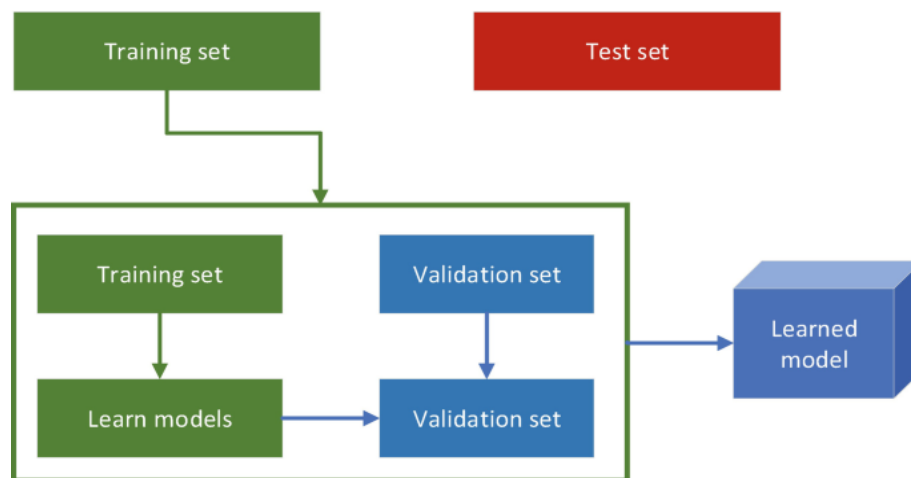


Figure 5. Metrics for Performance Evaluation.

7. EMERGING TRENDS AND FUTURE DIRECTIONS

Cloud computing even up access to high-performance GPUs (Graphics Processing Unit) and TPUs (Tensor Processing Unit), enabling researchers and engineers to train deep models beyond possessing expensive hardware. Unified ML tools like TensorFlow on Google Cloud or SageMaker on AWS simplify pipeline creation and monitoring. Distributed computing splits model training across various nodes, indulgent parallel processing of large datasets and deep architectures. The distributed CNN (Convolutional Neural Network) training significantly accelerates convergence on large datasets [13]. Physics-Informed Neural Networks (PINNs) incorporate physical laws directly into the training process, improving accuracy and generalization for complex mechanical systems. Neural networks embedded in edge devices analyse vibration signals in real time. Neural networks can model chaotic attractors, and which has bifurcation behaviour without explicit equations which mainly enhances the Data-Driven approaches for chaotic and Multi-Degree-of-Freedom Oscillations. Hybrid models blend machine learning with physics-based equations to seizure complex system practice more accurately than either method alone. The Hybrid Modelling that as the next frontier in scientific computing, blending Newtonian and Keplerian paradigms [14]. Explainable AI aims to make black-box models like deep neural networks intelligible to engineers and domain experts. Physics that helps in explaining neural networks for constitutive modelling, improving interpretability in material mechanics [15]. Smart factories leverage cyber-physical systems and IoT to integrate AI for autonomous decision-making and embellished productivity. Machine learning algorithms revise to dynamic production environments, developing quality and reducing waste.

8. CONCLUSION

Neural network offers a powerful alternative to traditional methods for modelling and controlling nonlinear oscillations in mechanical systems. They enable more accurate predictions and enhanced system stability when AI is integrated with nonlinear dynamics. Nonlinear oscillations in mechanical systems provides complex behaviours that challenge traditional analytical methods. Artificial Neural Networks (ANNs) have proven that it is effective in modelling nonlinear oscillations

and optimizing mechanical systems. Integration with IoT and edge computing enhances real-time data acquisition and processing. Hybrid models which help to improve forecasting accuracy for nonlinear time series. Emerging trends that mainly focus on AI-driven mechanical systems emphasize hybrid modelling and real-time edge analytics. The Synergy between nonlinear dynamics and AI is poised to revolutionize intelligent system design and predictive maintenance in modern engineering.

REFERENCES

- [1]. Nekorkin, V. I. (2015). *Introduction to nonlinear oscillations*.
- [2]. L. Zhang, Y. Sun, A. Wang, and J. Zhang, "Neural network modeling and dynamic behavior prediction of nonlinear dynamic systems," *Nonlinear Dynamics*, vol. 111, no. 12, pp. 11335–11356, Mar. 2023.
- [3]. M. Szczepanik and T. Burczyński, "Swarm optimization of stiffeners locations in 2-D structures," *Bulletin of the Polish Academy of Sciences Technical Sciences*, vol. 60, no. 2, pp. 241–246, Oct. 2012,
- [4]. J. A. Landay and B. A. Myers, "Sketching interfaces: toward more human interface design," *Computer*, vol. 34, no. 3, pp. 56–64, Mar. 2001.
- [5]. P. Meesad and G. G. Yen, "Pattern classification by a neurofuzzy network: application to vibration monitoring," *ISA Transactions*, vol. 39, no. 3, pp. 293–308, Jul. 2000.
- [6]. H. A. Khayyat, "ANN based Intelligent Mechanical Engineering Design: A Review," *Indian Journal of Science and Technology*, vol. 11, no. 27, pp. 1–7, Jul. 2018.
- [7]. Nasir, Waseem and Banaras, Faizan, "Real-Time IoT-Based Monitoring of Mechanical Systems Using Acoustic and Vibration Data," *Research Gate*, Feb. 2025.
- [8]. I. Ficili, M. Giacobbe, G. Tricomi, and A. Puliafito, "From Sensors to Data Intelligence: Leveraging IoT, Cloud, and Edge Computing with AI," *Sensors*, vol. 25, no. 6, p. 1763, Mar. 2025.
- [9]. A. Tealab, H. Hefny, and A. Badr, "Forecasting of nonlinear time series using ANN," *Future Computing and Informatics Journal*, vol. 2, no. 1, pp. 39–47, Jun. 2017.
- [10]. H. Khoshvaght, R. R. Permala, A. Razmjou, and M. Khiadani, "A critical review on selecting performance evaluation metrics for supervised machine learning models in wastewater quality prediction," *Journal of Environmental Chemical Engineering*, vol. 13, no. 6, p. 119675, Oct. 2025.
- [11]. C.-Y. Guo, T.-W. Liu, and Y.-H. Chen, "A novel cross-validation strategy for artificial neural networks using distributed-lag environmental factors," *PLoS ONE*, vol. 16, no. 1, p. e0244094, Jan. 2021.
- [12]. Z. Zakeri, N. Mansfield, C. Sunderland, and A. Omurtag, "Cross-validating models of continuous data from simulation and experiment by using linear regression and artificial neural networks," *Informatics in Medicine Unlocked*, vol. 21, p. 100457, Jan. 2020.
- [13]. P. Chaudhary, S. Vats, and V. Sharma, "Performance insights of convolutional neural networks operating on distributed computing platforms," *SN Computer Science*, vol. 6, no. 4, Apr. 2025.
- [14]. S. Kurz *et al.*, "Hybrid modeling: towards the next level of scientific computing in engineering," *Journal of Mathematics in Industry*, vol. 12, no. 1, Mar. 2022.
- [15]. A. Koeppe, F. Bamer, M. Selzer, B. Nestler, and B. Markert, "Explainable artificial intelligence for mechanics: Physics-Explaining neural networks for constitutive models," *Frontiers in Materials*, vol. 8, Feb. 2022.