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Study of Various Neural Network Architecture for Nonlinear System Identification

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ABSTRACT:-

Neural networks have good potential for system identification and modeling due to their abilities to approximate nonlinear functions and learn system characteristics through nonlinear mapping. In this contribution, the theoretical foundations of the theory of identification and adaptation of systems will be discussed. In the experimental work, the structure and learning algorithms of the neural network and the RNN, which is used for the identification of nonlinear systems, were also presented. Finally, the obtained results and conclusions of the experimental work are discussed.

Introduction:-

A system whose response output relies upon the past or future inputs further to the existing enter is referred to as the dynamic system. The dynamic system also are recognised as reminiscence system. Any continuous-time dynamic system may be defined with the aid of using a differential equation or any discrete-time dynamic system with the aid of using a distinction equation as every layer of an synthetic neural network can process data, models can build an abstract understanding of the data.

Neural-network modeling equipment permit the engineer to have a look at and examine the complicated interactions among cloth and manner inputs with the purpose of predicting very last thing properties

A system whose reaction or output is because of gift enter by myself is recognise as static system. The static system is likewise referred to as the memoryless system. For a static or memoryless system, the output of the system at any on the spontaneous of time (t for continuous-time system or n for discrete-time system) relies upon simplest at the enter carried out on the on the spontaneous of time(t own), however now no longer at the beyond or destiny values of the enter. That's why we're the usage of dynamic system in place of static system.

Dynamic neural networks can be considered an improvement on static neural networks by adding additional decision-making algorithms that make the neural networks learn dynamically from the input and generate better results.

Linear Neural networks predict the output as a linear function of the inputs. Like the perceptron, it can only solve linearly separable problems. This allows the outputs to take arbitrary values, while the perceptron output is limited to 0 or 1.

Nonlinear, as the name suggests, breaks linearity with a bunch of activation functions. A network that has action functions like reliance, sigmoid, or reservoir in any of it's layers or even in more than one layer is called a nonlinear neural network.

Different methods can be used to create mathematical models for nonlinear dynamics:

-White box modeling, which is the definition of the model structure and their parameters on a purely physical basis; White box modeling refers to the definition of the model structure and its parameters on a strictly physical basis.

-Grey box modeling refers to the construction of models whose mathematical structure is known from physical insights or conceptualisation (such as a phenomenological model), but whose parameters must be determined by data.

-Black box modeling refers to the purely data-driven derivation of models representing observed physical phenomena.

Soft computing is the usage of approximate calculations to offer vague however usable answers to complicated computational troubles. Soft Computing is liberal of imprecision, indeterminacy, partial truth and approximation benefits of soft computing which is linguistic, understandable and fast with effective solution of real world problems.

The concept of soft computing is based on learning from experimental data. This means that soft computing does not require any mathematical model to solve the problem.

Soft computing helps users solve real-world problems by providing approximate results that conventional and analytical models cannot solve.

It is classified based on fuzzy logic, genetic algorithms, machine learning, ANN and expert systems.

Fuzzy logic is basically designed to arrive at the best possible solution to complex problems from all available information and input data. Fuzzy logic is considered the best solution.

An Artificial Neural Network (ANN) emulates the network of neurons that make up the human brain (meaning a machine that can think like a human mind). So a computer or machine can learn things to make decisions like a human brain.

Artificial Neural Networks (ANNs) are interconnected with brain cells and created using common computational programming. It is like the human nervous system.

Genetic Algorithm is almost based on nature and takes all inspiration from it. There is no genetic algorithm that is based on search-based algorithms that are rooted in natural selection and the concept of genetics. They improve computational methods on the fly.

Neural networks can learn on their own and produce output that is not limited to the input they are given.

Input is stored in its networks instead of a database, so data loss does not affect its operation.

These networks can learn from examples and apply them when a similar event occurs, allowing them to work with events in real time.

Even if the Neuron is not responding or some information is missing, the network can detect a fault and still produce an output.

They can perform multiple tasks in parallel while not poignant system performance.

It's a type of machine learning process called deep learning that uses interconnected nodes or neurons in a layered structure that resembles the human brain. It creates an adaptive system by which computers learn from their mistakes and constantly improve. Artificial neural networks thus attempt to solve complicated problems, such as document summarisation or face recognition, with greater accuracy. Deep neural networks or deep learning networks have several hidden layers with millions of artificial neurons connected together. A number, called a weight, represents the connection between one node and another. The weight is a positive number if one node excites another, or a negative number if one node suppresses the other. Nodes with higher weight values have more influence on other nodes. Dynamic Neural Networks can be considered as an enhancement of Static Neural Networks in which by adding additional decision algorithms we can make the Neural Networks learn dynamically from the input and generate higher quality results.

These networks do not operate in a fixed direction; they have the ability to learn from the environment and inputs. After learning, they can change the direction of their work, which can provide a healthy output without having to perform higher calculations and incur higher calculation costs.

Because they have these abilities, we can say that they are adaptive to situations, and the adaptation to the situation is dynamic, as each neuron takes into account a set of input values. Each of these associated with a weight. Which is a numerical value that can be derived using supervised or unsupervised training, such as data clustering, and a value called "bias". The network selects from the response produced by the neuron based on its weight and bias.

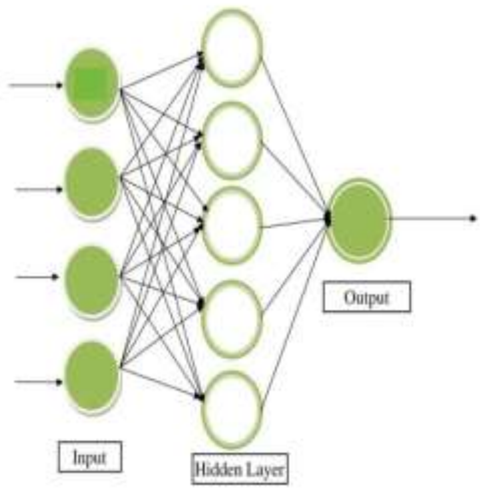

Fig 1: Neural Network

The importance of neural networks is also perfectly suited to help people solve challenging problems in practical settings. They have the ability to learn and model nonlinear, complex relationships between inputs and outputs, draw generalisations and conclusions, and uncover hidden relationships, patterns, and predictions. They can also model highly volatile data (such as financial time series data) and the variance needed to predict sporadic events (such as fraud detection). Neural networks can thus improve decision-making in areas such as:

A class of feed forward artificial neural network is called multilayer perceptron (MLP) (ANN). The most basic deep neural network, which consists of a series of fully connected layers, is the MLP model. Modern deep learning architectures need a lot of computing resources, but MLP machine learning techniques can get around that.

It is not known how much the dependent variable affects each independent variable.Calculations take a great deal of your time and energy.

The effectiveness of the training affects how well the model works.6

The MLP is fully connected, so it has an excessive number of parameters. Every node is connected to every other node, creating an extremely dense network that is redundant and inefficient.

Recurrent Neural Networks (RNNs) are so named because they consistently complete the same task for each element in a sequence, with the results dependent on earlier computations.

Another type of artificial neural network that uses sequential data feed is the recurrent neural network (RNN). In order to solve the time series problem of sequential input data, RNNs have been developed. The current input and the previous samples form the input of the RNN. A directed graph is created as a result of connections between nodes along a time sequence. Additionally, each RNN neuron has an internal memory that stores computation information from previous samples.

The types of RNNs are Elman, Jordan recurrent neural network and long short term memory (LSTM).

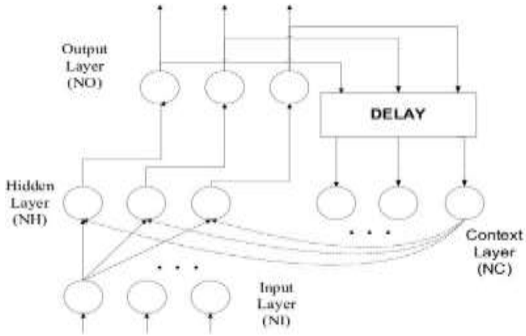

Fig 2: Jordan RNN architecture

Resembles a feedforward network with one hidden layer, the difference is the addition of a context layer.

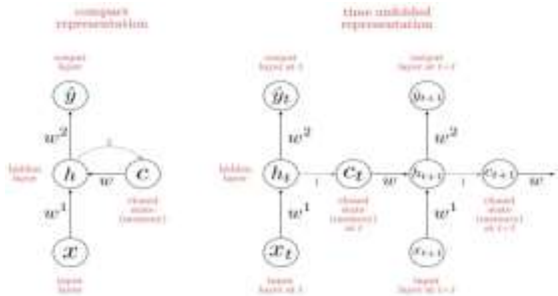

Fig 3: Elman RNN Architecture

Elman architecture is a feedforward networks(feedforwardnet) with recurrent layer connections and tap delays are Elman

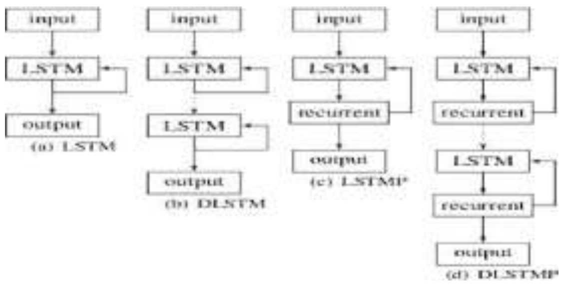

Fig 4: LSTM RNN architecture

Many recurrent neural networks (RNNs) are capable of learning long-term dependencies, especially in tasks involving sequence prediction.

Partially Recurrent Neural Networks In a fully recurrent neural network, each neuron is connected to every other neuron. Both the current neutron output and the previous outputs of its predecessors have an effect on the neutron. These networks are particularly suitable for real-time applications due to the complex dynamic behaviour of the RNN neuron and nonlinear activation functions. RNNs with the same structure would dynamically evolve in a different way if trained with a different algorithm. As a result, the architecture of the RNN and the training strategy together completely define it.

Literature Survey:-

Savran, A., 2007.

The multi-feed-back layer neural network, a novel recurrent neural network (RNN), is the subject of the study in this paper, which focuses on its architecture and training process (MFLNN). The proposed network's key distinction from existing RNNs is that it uses neurons grouped in three feedback layers rather than simple feedback elements to establish temporal links, enhancing the recurrent networks' capacity for representation. The feedback layers use nonlinear processing components to produce local and global recurrences. A novel RNN termed MFLNN's architecture and training process have been described. Three feedback layers with nonlinear processing units have been used to introduce recurrences into the network structure.These feedback layers apply feedforward neurons with weighted sums of the delayed outputs of the hidden and output layers after passing them through specific activation functions. The LM algorithm produces the MLFNN weights' quick convergence. In order to demonstrate the structural capabilities of the network and the efficacy of the training process, the performance of the MFLNN is compared with different feedforward and recurrent networks.

Savran, A., 2007. Multi-feedback-layer neural network. IEEE Transactions on Neural Networks, 18(2), pp.373-384

Deng, J., 2013.

The dynamic neural networks (DNNs) that are the focus of this paper's work have significant qualities that make it easy to combine them with nonlinear control methods based on state space models and differential geometry, such as feedback linearization. This study has proven this DNN limitation with an example. Despite minimal structural changes, the new constructed DNN in this paper has a significantly better mapping capabilities.

Deng, J., 2013. hybrid dynamic neural networks for nonlinear system identification. pp. 281-292 in Engineering Applications of Artificial Intelligence, 26(1).

Kroll, A.2014.

In this article, a number of benchmark issues for nonlinear control and system identification are collected and presented in a uniform manner. Examples of the problem being used for comparison are added to each problem. The chosen examples, which mostly come from the fields of mechatronics/drives and process systems, span from component to plant level issues. The authors are hoping that by providing this overview, benchmarking will be more widely used in method development, testing, and demonstration.

2014; Kroll, A.; Schulte, H. Benchmark issues for soft computing approaches of nonlinear system identification and control: Need and overview. Applied Soft Computing, Volume 25, Pages 496 to 513.

Behera, S.K. and Rana, D., 2014.

A larger commitment to evaluating and showcasing emerging approaches on benchmark challenges is a fruitful endeavour for both the individual researcher and the community: With minimal effort, well-defined identification and control problems can be solved while allowing for the comparison of one's own findings with those of other subject matter experts. Because of this, a lot of original articles don't offer all the details needed for a benchmark problem to enable validation, reproducibility, and comparability. This corresponds to the same data used for identification, the same reference signals and disturbance signals for control, and a set of generally agreed evaluation standards. Contrarily, it is crucial that benchmark adopters abide by the benchmark's specifics. For instance, a continuous-time system may occasionally be sampled using a different sample-time.

S.K. Behera and D. Rana 2014.Recurrent neural networks are used for system identification. Int. J. Adv. Res. Electr. Electron. Instrument. Eng., 3

Patel, K.K., Patel, 2016.

This paper's major goal is to create a trustworthy model for the nonlinear process. The term "Nonlinear System Identification" refers to this procedure. The most prevalent framework for creating empirical models is artificial neural networks. In this study, the neural black-box identification using a Nonlinear Autoregressive Exogenous Input (NARMAX) model has been adopted to produce this trustworthy model for the process dynamics. To control the nonlinear system, trained data from nonlinear process identification can be used. The usage of multilayer perceptron networks for dynamic modelling has been thoroughly examined in this research. The simulation result shows that the nonlinear model identification is both valid and feasible. To control the nonlinear system, reliable data from nonlinear process identification can be used.

Patel, K.K., S.M., and P. Scholar (2016). IOT definition, attributes, architecture, enabling technologies, applications, and upcoming difficulties. Engineering Science and Computing: An International Journal,

2016 Vancouver

H. Khodabandehlou and MS. Fadali. Neural networks and trajectory-based optimization are used for nonlinear system identification. 2018 April 27. arXiv preprint arXiv:1804.10346.

A recurrent neural network is trained to detect the Bouc-Wen system and the cascaded tanks, two difficult nonlinear models, using two distinct global optimisation techniques. According to the findings of the simulation, both methods successfully identify the model of the Boucwen system and the cascade tanks. The nonlinear dynamical system's trajectories are used in the first method, quotient gradient system (QGS), to locate the local minima of the optimization issue. The second method, a dynamical trajectory-based methodology, finds related elements of the viable region using two separate nonlinear dynamical systems.

Chicago 2017

"Nonlinear system identification in structural dynamics: 10 more years of advancement," by Jean-Philippe Noel and Gatan Kerschen. 83 (2017): 2-35 in Mechanical Systems and Signal Processing.

When nonlinearity is present, the identification of nonlinear systems tries to create mathematical models with high accuracy from input and output data on the real structure.

Finally, by examining the crucial function that experimental models play in the engineering structure design cycle, a broader view on nonlinear systems identification is offered. The topic of this essay is how crucial experimental models are to design cycles.

Harvard 2017

Gu, X., Jiang, S., and Gans, Ogunmolu, O., 2016. detection of nonlinear systems using deep dynamic neural networks. The preprint number is 1610.01439.

Deep neural networks have recently shown to be particularly successful at modelling highly nonlinear real-world systems, as well as pattern recognition, classification, and human-level control tasks.

The efficiency of deep neural networks in modelling dynamical systems with complicated behaviour is examined in this research.

2019 MLA

"Nonlinear System Identification using Neural Networks and Trajectory-Based Optimisation," by Hamid Khodabandehlou and Mohammed Sami Fadali. Preprint A: 1804.10346 (2018).

A recurrent neural network is trained to detect the Bouc-Wen system and the cascaded tanks, two difficult nonlinear models, using two distinct global optimisation techniques. The first method locates the local minima of the optimization problem by using the trajectories of the nonlinear dynamical system. The second method, dynamical trajectory based methodology, finds related elements of the feasible region by combining two different nonlinear systems. The results of the simulations demonstrate that both methods successfully identify the model of the cascade tanks.

APA 2020

Brahmajirao, V., Rajendra, P. (2020). deep learning modelling of dynamical systems. 1311–1320 in Biophysical Reviews, 12(6).

The modelling of nonlinear dynamical systems using long short-term memory (LSTM) neural networks has recently received attention. Many contributions are made with the assumption that the system's input is well-known or quantifiable, even though this is frequently not the case. The method for output-only modelling, identification, and prediction of nonlinear systems presented in this thesis is based on LSTM. A numerical investigation of Duffing systems with various cubic nonlinearities is conducted and discussed. The presented and discussed thesis.

Zancato et al.(2021)

The work in this paper focuses on fading memory systems, deep nets, biases, nonlinear system identification, and regularisation.

In this study, a Deep Neural Network (DNN) architecture is utilised to identify nonlinear systems and promote generalisation by limiting the representational power of the DNN. This design enables automatic complexity sections based purely on data that is provided, reducing the number of hyperparameters that the user must select. The strategy is successfully used on massive datasets.

L. Zancato and A. Chiuso, 2021. a fresh Deep Neural Network design for nonlinear system identification. 186–191 in IFAC-PapersOnLine, 54(7).

Gedon D (2021)

The approach presented in this study is based on deep learning, black box modelling, and non linear system identification.

This article explains a deep SSM class and its parameter learning algorithm in an effort to add a deep learning-based method to the repertoire of nonlinear identification techniques.

Due to the adaptability of deep neural networks, using deep SSMs as a black-box identification model can represent a variety of behaviours.

Deep state space models (SSMs), which are closely related to traditional SSMs, are a model class for temporal models created in the deep learning field that is now the subject of active study.

A study from 2021 by Gedon, D., Wahlström, N., Schön, T.B., and Ljung. Deep state space models for identifying nonlinear systems. 481-486 in IFAC-PapersOnLine, 54(7).

Ahmed (2022)

System identification, neural networks, the koopman operator, nonlinear dynamics, and nonlinear control were used in this paper's research.

They suggest a cutting-edge deep learning framework to figure out how to convert a nonlinear dynamical system into an equivalent higher dimensional linear representation, and they show that the resulting learned linear representation accurately captures the dynamics of the original system for a wider range of conditions than standard linearisation. As a result, we demonstrate how the learnt linear model may be successfully applied to regulate the initial system.

Del Rio-Chanona, E.A., M. Mercangöz, and A. Ahmed, 2022. IFAC-PapersOnLine, 55(12), pp. 161–169. Learning Linear Representations of Nonlinear Dynamics Using Deep Learning.

kumar (2019)

This study compares various neural network topologies in order to evaluate their capacity for approximation. It uses three neural networks: the nonlinear autoregressive with exogenous inputs (NARX) neural network, the diagonal recurrent neural network, and the multilayer feedforward neural network (MLFFNN). When the system is subjected to parameter adjustments and disturbance signals, their robustness is also evaluated and compared. The parameters connected to these neural networks are also updated using a dynamic back-propagation process.

S. Srivastava, J.R.P. Gupta, A. Mohindru, and R. Kumar, 2019. a comparison of neural networks for identifying dynamic nonlinear systems pp. 101–114 in Soft Computing, 23(1).

Ljung (2020)

The Model Structure, Bias, Variance Trade Off Model, and LSTM are the foundations for this paper's work.

The study has linkages to the field of system identification that the community of automatic control has established.

In the contribution, these linkages are looked into and used.

It is emphasised that popular deep nets like feedforward and cascade-forward nets are nonlinear ARX (NARX) models, making them suitable for simple integration into system identification and practise.

An illustration of NonLinear State-Space (NLSS) models is the situation of LSTM nets.

2020, Ljung, L., Andersson, C., Tiels, and T.B. Schön Identification of systems using deep learning. 53(2), 1175–1181; IFAC-PapersOnLine.

Ljung, L.,2020.

Deep learning is a topic of great interest at the moment, and that is the major goal of this essay. There are linkages to the topic of System Identification developed in the Automatic Control community because it works with estimating or learning models. In this contribution, these relationships are investigated and used. An illustration of NonLinear State-Space (NLSS) models is the situation of LSTM nets.

2020, Ljung, L., Andersson, C., Tiels, and T.B. Schön Identification of systems using deep learning. 53(2), 1175–1181; IFAC-PapersOnLine.