International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Research Article)

Prophecies using Physics Involved Neural Networks (PINNs) for achieving the accuracy using AI Models in discrete Kinematics

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International Journal of Science and Research Archive, 2025, 16(01), 444-453

Publication history: Received on 27 May 2025; revised on 05 July 2025; accepted on 07 July 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.16.1.2043

Abstract

Artificial Nonmonotonic Neural schema or Networks (ANNNs), a kind of hybrid learning systems that are capable of nonmonotonic reasoning. Nonmonotonic reasoning plays an important role in the development of artificial intelligent systems that try to mimic common sense reasoning, as exhibited by humans in slow and steady but the error is minimized unlike in monotonic where the decision is fast but with more errors. on the other hand, a hybrid learning system provides an explanation capability to trained Neural Networks through acquiring symbolic knowledge of a domain, refining it using a set of classified examples along with Connectionist learning techniques and, finally, extracting comprehensible symbolic information.

Keywords: PINNs; ANNNs; BDA; KNN; SVM

1. Introduction

Training a neural network involves iterating over the training data multiple times, which are called epochs. Increasing the number of epochs can improve the accuracy of a neural network, as it allows the neural network to learn more from the data[1-10].

Neural networks can help computers make intelligent decisions with limited human assistance. This is because they can learn and model the relationships between input and output data that are nonlinear and complex. Accuracy is a metric that measures how often a machine learning model correctly predicts the outcome. You can calculate accuracy by dividing the number of correct predictions by the total number of predictions [11-19]. The main objective of this work is to provide accuracy in predictions in the capacities for robotic systems used to perform typical operations in a semi-constrained environment. In order to maintain system performance in the presence of a PINNs, the corresponding policies must be shown to be sufficiently robust in order to overcome the fault with only minimal effects on the overall system performance[20-24]. Finally, the last objective of the work included is to implement the proposed policy on a real system AI Model in order to demonstrate the increased performance complementary information about the state of the system [25]. The use of the knowledge extracted from this data provides non-dedicated active patterns to train and learn in the redundancy that can be used to increase the overall performance of the prediction. When the data points are identified, recognized and analyzed for patterns, the same pattern in generated but the accuracy in prediction is quite unachievable, so harmonic oscillatior in physics is used as PINNs as the physics involved neural network where multiple layers of neural networks filters and the recognized data patterns well align with actual data patterns, so that the prediction is accurate thereby the data points get mapped.

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1.1. Problem Definition

The actual data points will always be not mapping with the prediction outcome, In this context the actual data points are made overlapped with the Neural network after training so that the training steps will get increased to achieve accuracy in prediction

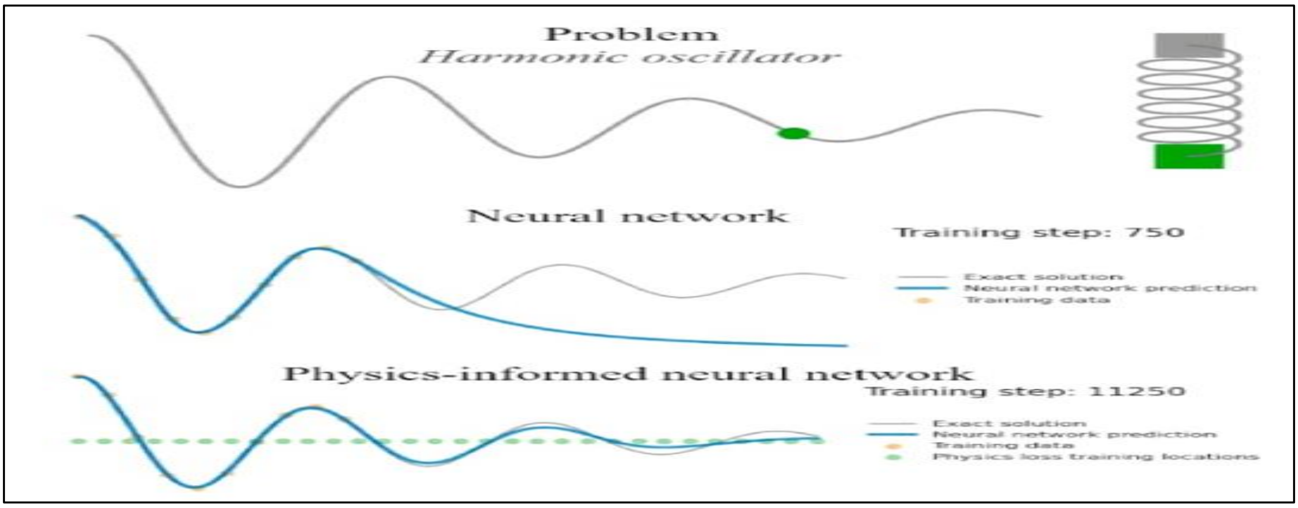

Figure 1 PINNs actual data points overlap when training is maximum

2. Methodologies

- Bringing the Actual location well closer and aligning with the neural network involved predictions
- Data points are fed inside the AI model and subjected to training to recognize patterns
- Outcome

The decisions in predicition are accurate

During the training of data, in deep learning to enhance making prediction faster, I have to use distributing computing where I can bring data analysis (which I used in ANN) and data processing (which I used in deep learning) closer to the source of data, so that I can reduce latency (delay in time) and still improve decision making so that it can operate independently.Benefits

- Reduced latency(10-100x faster)
- Improved real time decision making
- Enhanced security (less data transmitted)
- Better Data Analysis (BDA)
- Cost effective (reduced bandwidth and storage needs)

3. Strategic Analysis of AI using Machine Learning models

Neural weights" are numerical values associated with connections between neurons, determining the strength of those connections.As Neural schema increases Neural weight decreases, so error was minimized. As Neural weight decreases the memory of the long term memory dependencies is improved and the gradient vanishing problem was rectified.

Thus additional one memory cell was incorporated when LSTM short term memory was overcome with respect to RNN which is a traditional network model.

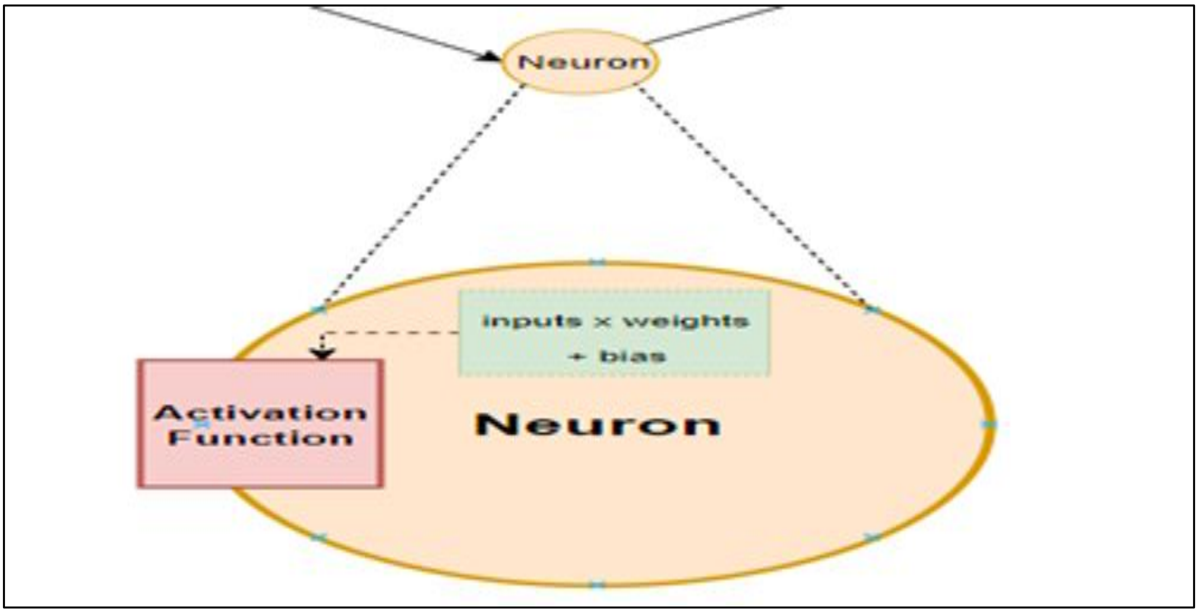

Figure 2 The actual neuron when neural weight decreases can enhance prediction in AI model.

Prediction is accurate. *The fundamental formula for a single neuron in a neural network is*

Z = Bias + W1X1 + W2X2 + ... + WnXn.

This equation represents a linear combination of inputs (X1, X2...Xn) with their corresponding weights (W1, W2...Wn), plus a bias term. The output of this neuron (Z) is then passed through an activation function

3.1. Experimental Parameters

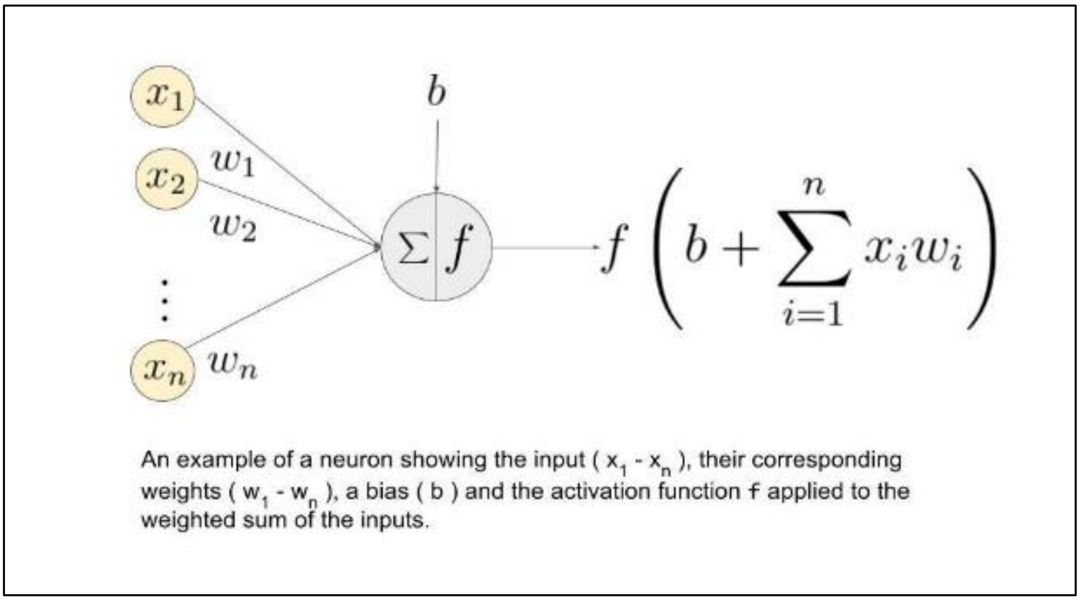

Figure 3 The neuron activation function in response to the AI predictions

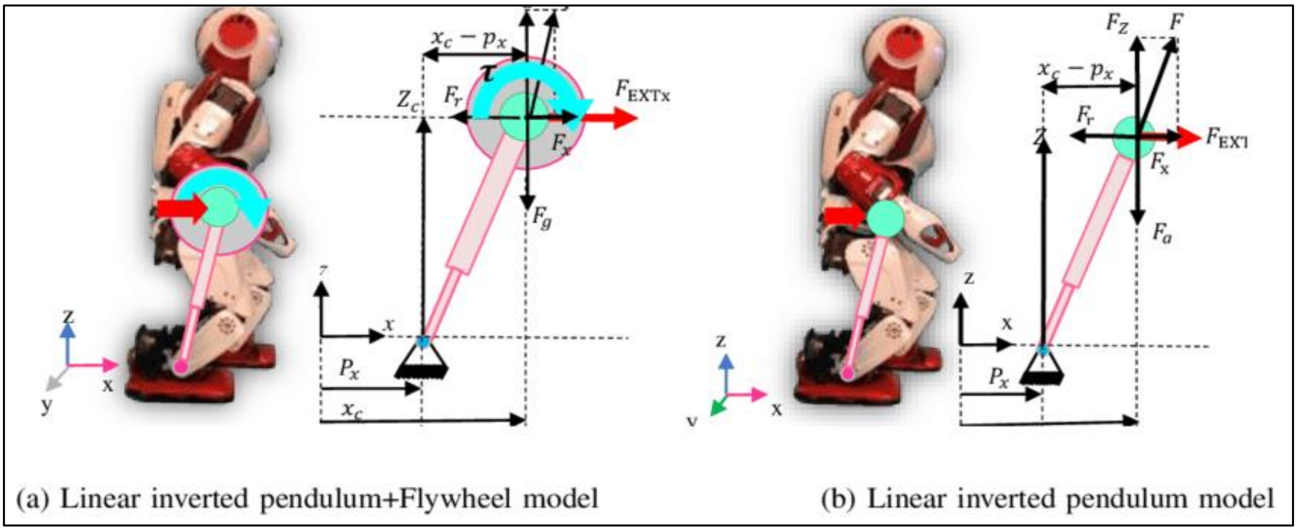

Figure 4 The actual prediction in a robot pendulum model when AI prediction incorporated

Figure 5 Developed Prediction can be used over the wide range of applications

4. Calculating the Dissimilarity Measure

We measure dissimilarity by calculating the ratio of the cross-dissimilarity between *V B* and *V A* to the self-dissimi-larity of *V B* . *N (Vi, k)* denotes the *k*th nearest neighbor of *Vi* in *VB* . Let *E* denote the number of dissimilarity evalua-tions. *CD(V)* measures the cross-dissimilarity between *V B* and *V A* in the following equation: *CD(V)*

Table 1 Training Behavior in patterns

Data Points Training	Actual	Predicted
Harmonic	23	12
ANN	540	750
PINNs	600	1120

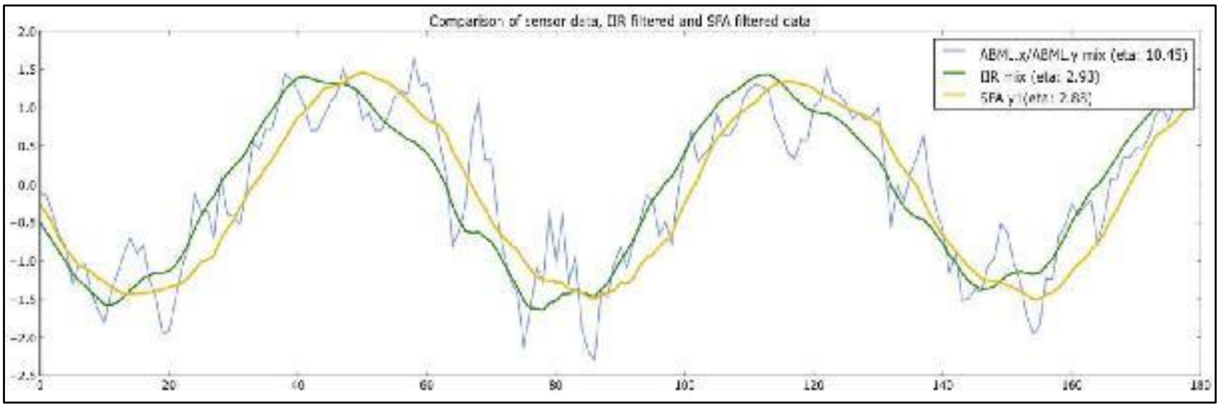

Figure 6 AI model prediction analysis

5. Results and Discussions

DS(V) is the dissimilarity score *S* for a given *V*

VB ={ ntïtÎWB} = {nl+1, nl+2,….., nl+P}

VA = {ntïtÎWA} = {nm+1, nm+2,….., nm+Q}

Let V = VB È VA, so |V | = (P + Q). Let Vi denote the *i*th element of V. The distance matrix DMX of a cue X is calculated by measuring the pairwise distance between cue elements in V ; DMX (*i, j*) describes the distance between cue vectors Vi and Vj using a predefined distance metric for the cue X. We will describe distance metrics for visual cues, motion & body pose Pitsch K, Kuzuoka H, Suzuki Y, Sussenbach L, Luff P, Heath C et al [2], In [3], we learned a threshold value on the dissimilarity score from the training data and used that to classify the score as being contingent or not. This simple evaluation method can-not be used in our probabilistic model for multi-cue integration because it does not have the confidence on the decision made, and because it does not take into account how informative a used cue is. Triesch J, Teuscher et al [15].We propose a new evaluation method that resolves the two problems described above. To determine that an ob-served change (i.e. a dissimilarity score) actually resulted from a human response and not from changes that occur naturally in the human's background behavior, we should evaluate the change not only under the contingency condi-tion, but also under the non-contingency condition. To this end, we model two conditional probability distributions: a probability distribution of the Time is shown as.

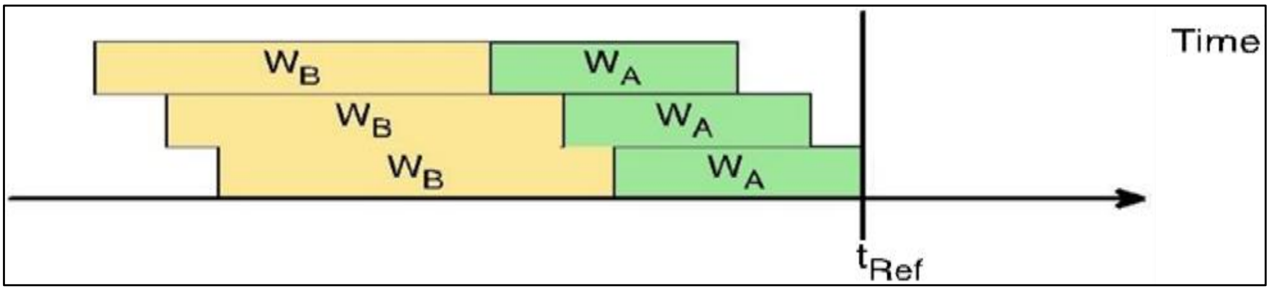

Figure 7 A method for building null hypothesis. Dissimilarity score sam-ples are obtained by evaluating data in windows over time

5.1. Outcome of Research

The AI model was accurate in the predicted decision. In this case of data paths aligned well with the actual poings, the path itself had a substantial impact on the result thus making the AI Model to predict and come out with a decision to turn back after recognizing the obstacles in patterns

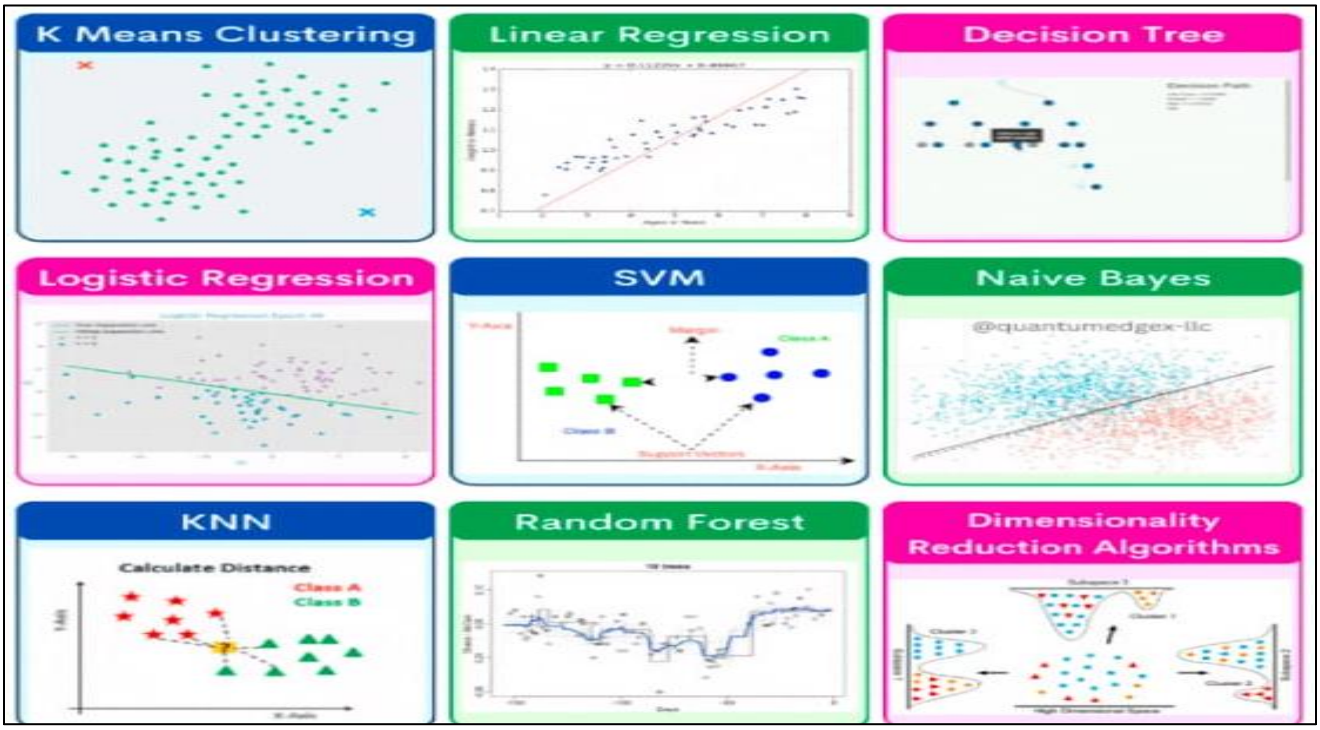

Figure 8 Actual results of various models

5.2. Experiments Parameters

We calculate accuracy by dividing the number of correct predictions (the corresponding diagonal in the matrix) by the total number of samples. The result tells us that our model achieved a 44% accuracy on this multiclass problem.

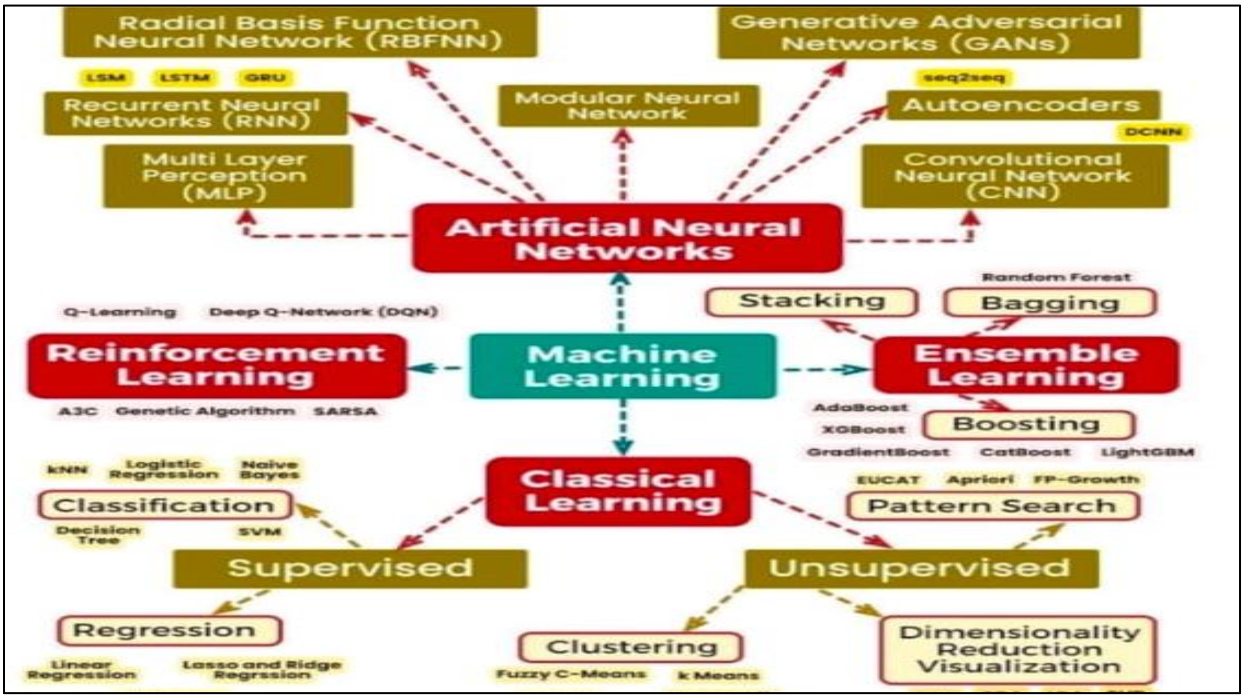

Figure 9 Various Models tested against PINNs concept.

The kinematics solution of any robot manipulator consists of two sub problems 1) forward and 2) inverse kinematics. kinematics (the hub angle, tip position, and deflection) and dynamics (the control torque input of the link) of the robot arm model.

Forward Kinematics = to get co-ordinate of end effector(OUTPUT) from given angles of all joints (INPUT), Inverse Kinematics = to get all joints angle from given co-ordinate(s), path trajectory plan This model provides an efficient procedure for the computation of the motion in the joints that makes the end- effector motion to trace a given geometrical curve with prescribed linear and angular velocity.

5.3. Implementation & Experimental Testing

In order to fully assess the capacities and limitation of the proposed methodology and policies, more extensive testing is necessary. The *Fault Rejection* policy based on the use of the predictive Polynomial algorithm requires experimental testing. This requires the development of faster vision processing routines in order Table 5.to increase the bandwidth currently available from the, As mentioned earlier in this research, the processing delay is currently the major limiting factor for the high-level feedback. Even if the bandwidth gained through the optimization of the vision processing algorithm is limited (i.e., the maximum bandwidth of the sensor is about 50 Hz), in order to demonstrate the flexibility of the policies, to perform some training based on correction factor.

Table 2 Training Sensor Z-score of AI Model based on the long term dependencies in LSTM over RNN

t_{max}	$time_{end}^{i}$	D_{end}^{i}	$road_{end}^{i}$	$Sensor_{ob}$ (Z-Score)
12	9.6	6.7	9.0	-2.27
3	7	6.29	1.02	8.27
5	-0.5	0.04	0.28	7.67
6	5	8.68	7.21	2.47
7	-0.5	0.04	0.25	-1.96
9	-0.5	4.76	4.17	5.59
8	0	3.79	3.21	6.58
6	-0.5	0.04	0.29	6.42
2	0	8.55	4	5.85
3	-0.5	0.04	0.24	-1.23
4	8.6	4.92	4.19	5.73
6	-0.5	0.04	0.22	8.06
8	-9.8	7.4	3.02	7.2
8	-0.5	0.04	0.26	6.07
1555	-9.3	9	3.16	7.24
0	-0.5	6.4	4.39	6.09
0	-0.5	0.04	0.23	9.24
8	-7.4	9.6	11.5	-0.81
8	-0.5	0.04	0.29	8.86
8	-0.5	0.04	0.25	7.8
8	-0.5	0.04	0.26	0.38
10	0	-0.15	2.59	8.33

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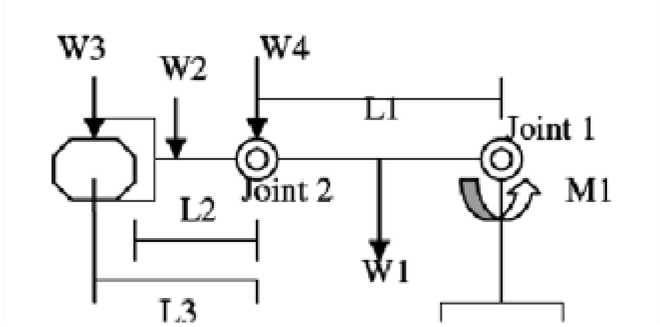
Appendix

Neural weights W1,W2,W3,W4 for joints 1 and 2 at angular rotation in M1 during memory cell append.



Torque about joint 1:

$$M1 = \frac{L1}{2} * W1 + L1 * W4 + (L1 + \frac{L2}{2}) * W2 + (L1 + L3) * W3$$

Torque about joint 2:

$$M2 = \frac{L2}{2} * W2 + L3 * W3$$

Figure 10 Training induction over neural weights in joint angles when AI PINNs are fused.