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Inverse kinematics using neural networks of a 3RRR planar robot

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***Abstract*—This study presents the development, modeling, and validation of a type 3-RRR planar parallel manipulator, with the primary objective of solving the direct kinematics problem using artificial neural networks. The robot's design was carried out in SolidWorks, where circular trajectories were simulated to collect training data. Later, a feedforward neural network was trained in a Python development environment (Spyder), using joint coordinates as inputs and Cartesian positions as outputs. The network was validated with error metrics that demonstrate high accuracy in predicting the position of the end effector. The results confirm that this artificial intelligence-based approach offers an efficient, precise, and computationally inexpensive alternative for the kinematic modeling of parallel robots, being applicable to real-time systems and industrial environments that require high repeatability.**

***Index Terms*—Keywords: Planar Robot, SolidWorks, 3RRR, Robotics, Deep Learning**

I. Introduction

In recent years, parallel manipulators have emerged as a viable and compelling alternative to traditional serial robots. Parallel manipulators have shown an advantage over their serial counterparts in applications requiring higher stiffness and rigidity, with superior accuracy and a high load-to-weight ratio [1]. However, parallel manipulators present disadvantages, such as reduced workspace, complex kinematics [2], and the existence of singularities within its workspace [3].

A 3RRR parallel planar manipulator is a mechanism consisting of 9 revolute joints and 8 links [4]., leading to a mechanism with three degrees of freedom, which requires three different actuators [5].

The study of the 3-RRR planar manipulator's control and kinematics is of interest due to the need for robots capable of highly precise positioning in industrial micro- and nano-applications [6]. Robot kinematic models exist to comprehend the robot's motion and analyze the operational performance [7]. These models facilitate a deeper understanding of the robot's mechanical behavior and allows for the design of more reliable control strategies.

Unlike in a serial configuration, when analyzing the kinematics of a parallel manipulator, such as the 3-RRR robot, a degree of freedom cannot be directly attributed to an independent actuator [8].

This mayor difference leads to the proper understanding of the 3-RRR planar robot's kinematics being a necessity for its design and accurate control.

The inverse kinematics problem of the 3-RRR planar robot has an analytical solution. The forward kinematic problem, on the other hand, does not have an analytical solution and lacks a closed-form solution, making it difficult to analyze the manipulator's forward kinematics [9].

Recently, the use of neural networks has emerged as an alternative for the study of forward kinematics problems [10]. The traditional method for the calculation of the trajectory of planar robots consists in the use of numerical methods, which are computationally expensive and are not guaranteed to obtain every solution, with the possibility of missing critical solutions [11]. This has led to neural networks being adopted as a practical and less computationally expensive alternative, predicting the robot's positioning in situations where the traditional method may fail.

II. Methodology

The main objective of the study is to use a data-driven approach to solve the forward kinematic problem of the 3-RRR planar robot by using training a neural network capable of accurately predicting the X and Y coordinates for the center of the 3-RRR planar robot's central triangular link, using the three motor's. angular coordinates as an input.

Along with the neural model's construction, a cross-validation procedure was used to make sure the training was resistant against potential overfitting. By altering the number of hidden layers and the activation functions, several network configurations were assessed at this phase, and metrics like mean squared error (MSE) and mean absolute error (MAE) were compared. In order to guarantee a fair distribution of the data and prevent biases, several sizes of training and test subsets were also examined. By identifying the best architecture and adjusting the model's hyperparameters, this methodological approach ensured dependable performance in forecasting the 3-RRR robot's direct kinematics in simulated situations.

17 Figure 1 illustrates the iterative methodology employed to solve the forwards kinematic problem of a 3-RRR planar parallel manipulator using a combination of SolidWorks Motion simulation and a neural network implemented in TensorFlow using a Spyder environment in the Anaconda Python distribu-
9 tion. The process begins with the mechanical modeling of the 3-RRR manipulator, where the motor actuators are position at the vertices of the outer triangle. A predefined circular trajectory is then simulated in a motion analysis to extract the end-effector's X and Y positions along with the corresponding
3 actuator q1, q2 and q3 angles. The data is plotted and exported to CSV files for its use in the neural network. Multiple iterations are used when the size of the dataset is deemed insufficient, or the number of neurons and layers doesn't
3 provide proper results. This methodology enables an efficient approach for approximating forward kinematics with lower computational time requirement.

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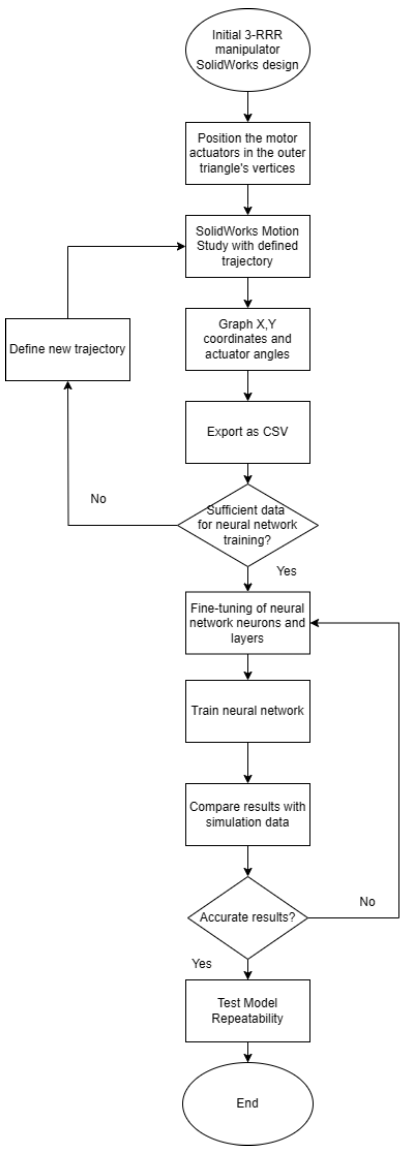

Fig. 1: Neural Network Training Methodology

A. *Kinematic simulation and dataset collection*

A 3-RRR planar manipulator was constructed in SolidWorks using precise dimensions specified in the Design section of the paper. To generate the dataset for the neural network training, the SolidWorks Motion add-on was used to simulate the robot's movement along seventeen predefined circular trajectories, as the 3-RRR planar manipulator shows its advantages of high dexterity and good energy transfer when working in a circular trajectory [12]. For each simulated trajectory, the following data was recorded in 201 different points of the trajectory:

- Joint angles of the three actuated revolute joints (q, q, q) [in degrees].
- Cartesian coordinates of the end effector (X, Y) in centimeters.

Figure 2 illustrates the angles q1, q2, and q3, corresponding to the angular displacement of the motor actuators located on each end of the outer triangle. Sampling was done every 0.04 seconds, with the full 360 degree trajectory taking a time of 8 seconds, resulting in a total of 201 samples per simulated trajectory.

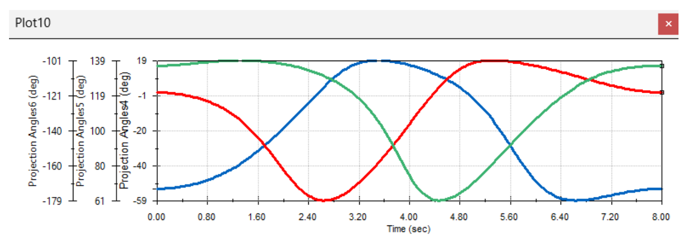

Fig. 2: q1, q2 and q3 graph

Figure 3 illustrates a X and Y position graph, with the same sampling frequency as the previous angle graph, resulting in the corresponding X and Y coordinates for the 201 angle samples taken from the trajectory. Figure 3 illustrates the results for a simulated trajectory with a diameter of 1000 millimeters.

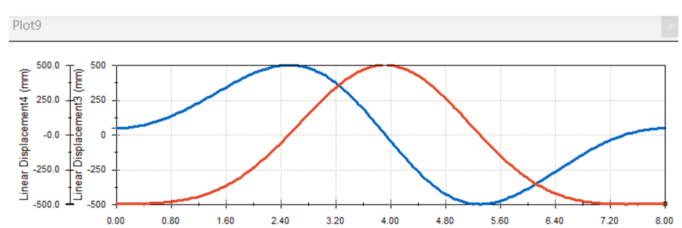

Fig. 3: X and Y coordinate graph

Each circular trajectory was sampled at regular angular intervals to ensure a diverse dataset covering a representative portion of the workspace. Each dataset was exported in .csv format for further processing. The final dataset was compiled with a total of 3418 data points.

B. *Neural network model development*

The obtained dataset was used for the training of a feedforward neural network using TensorFlow within the Anaconda Python distribution. The model development was conducted in a Spyder environment.

The following architecture was utilized for the neural network's layers

- **Input layer**: 3 neurons (q, q, q),
- **Hidden layers**: 3 layers with 64, 32 and 16 neurons each, using the Swish activation function.
- **Output layer**: 2 neurons (X, Y).

The model was trained over 100 epochs, using a test split with a 50% test size. Finally, the predicted X,Y positions were compared with the original dataset to validate the model's accuracy in predicting the forward kinematic behavior of the 3-RRR planar manipulator.

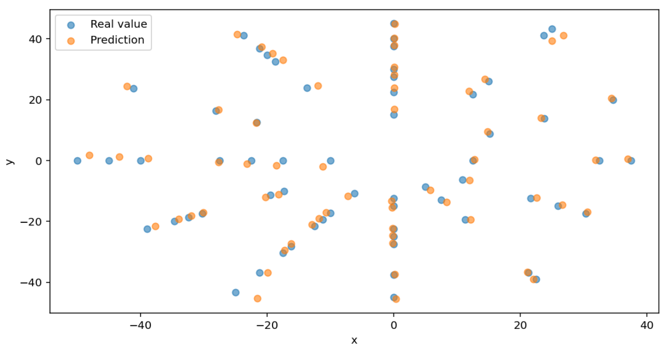

Fig. 4: Initial results of Neural Network Training

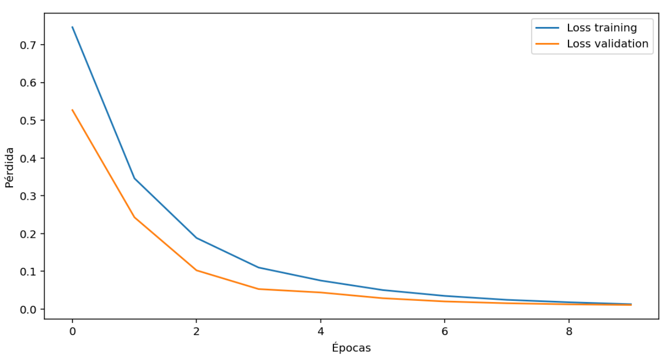

Fig. 5: Initial Graphs of the Neural Network

III. Design

A parallel 3-RRR robot consists of three identical arms, each formed by two links labeled in series (R-R), that converge on a mobile platform with three degrees of freedom in the plane. For the proposed design:

- Link length: each bar measures 0.20m, ensuring a good relationship between stiffness and reach
- Base spacing: The three motors are located at the vertices of an equilateral triangle with a side of 2.00 m, defining the base perimeter.
- Joints: The motors on the base actuate the first link; the second connects via a ball and socket to the mobile plate. Kinematics:
- The three geometric chains are solved to obtain the position (x, y) and orientation theta of the platform.
- Given (x, y, theta), the motor angles are calculated using the law of cosines for each 0.20 m link.
- Aluminum or lightweight steel profiles for links, low-friction ball joints, rigid supports at the base.

For the presented design, key references have been considered that not only support the theoretical foundations of the development of 3-RRR parallel robots but also closely align with the physical configuration and functional objectives of the shown prototype. These previous investigations allow for the construction of a solid foundation that justifies every decision made in the development of the system, from the geometric arrangement to the implemented control approach.

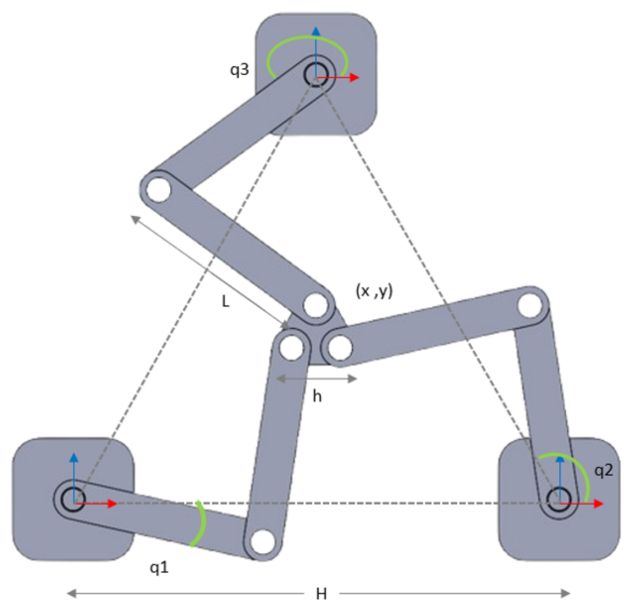

Fig. 6: Diagram of Planar Robot with joints and variables

A. *Design Fundamentals According to the Literature*

Various studies have described configurations similar to the developed model. For example, the use of triangular bases with actuators placed at each vertex has been documented, which allows for a balanced distribution of forces [13]. Previous experimental tests have validated both direct and inverse kinematics, essential elements for verifying the positioning accuracy of the mobile platform.

B. *Kinematic Analysis and Structural Validation*

An efficient design undoubtedly requires precise kinematic modeling. There are works that provide useful mathematical tools to describe the behavior of the 3-RRR manipulator under different configurations [14]. The importance of analyzing singularities to prevent loss of control zones has been emphasized, something crucial when operating the robot reliably in its workspace. Applying these criteria to the design, an effective and safe operational area has been delineated, avoiding problematic regions where the robot could become unstable.

On the other hand, recent research has proposed using neural networks as an alternative to solve the direct kinematics of 3-RRR type robots. This approach, as presented in [4],
41 allows obtaining the end effector position (x, y) from the joint angles (q1, q2, q3) without the need to solve complex nonlinear equations. The process includes:

1. Design of the robot using similarity laws:

1
$$h = \frac{1}{10}H \tag{1}$$

$$L = \frac{2}{5}H \tag{2}$$

2. Obtaining data (q1, q2, q3, x, y) through simulations in SolidWorks.

3. Training a deep neural network with different activation functions.

4. Evaluation of the mean squared error (MSE) and the Euclidean distance between the actual value and the one estimated by the network.

The design proposed in Figure 6 is constructed using these fundamental principles.

C. Dynamic modeling and force-moment capabilities

In addition to the kinematic analysis, it is important to
45 consider the dynamic capabilities of the 3-RRR manipulator.
2 [15] Has proposed an approach to evaluate the force-moment capabilities of planar manipulators with additional actuated branches. Applying graphical analysis methods and capacity limits, the mechanical performance of the robot under different loads can be estimated. This analysis is essential to ensure that the design can withstand the stresses it will be subjected to during operation, without compromising structural integrity.

D. Robustness against joint failures

The robot's behavior in the face of partial failures has also been the subject of research. [16] Analyze how to predict the fault-tolerant workspace in 3R manipulators when joint locks occur. Using density mixture networks, the robot's performance can be anticipated even when a joint locks, which allows for improved system reliability in critical scenarios. This opens up the possibility of incorporating prediction algorithms to automatically switch the mode of operation in the event of mechanical failures.

46
E. Recursive Approach for Inverse Dynamics

Finally, [17] developed a recursive model to calculate the
47 inverse kinematics and dynamics of a 3-R manipulator. This approach allows for real-time control optimization by reducing computational load, especially useful for embedded implementations. Adapting this approach to the proposed 3-RRR robot facilitates a better estimation of actuator efforts, essential for tasks that require precise trajectory control.

IV. Results

Figure 7 illustrates the loss training and loss validation curves over the 100 epochs of training. The model converges rapidly, with the loss training dropping sharply at the third epoch and the validation loss stabilizing at a very low value. These curves indicate the neural network model successfully learned the relationship between the inputs (q1, q2, q3) and the outputs (X, Y). With a final MAE of 0.0103, the model was able to predict the end effector position output within a tenth of a centimeter.

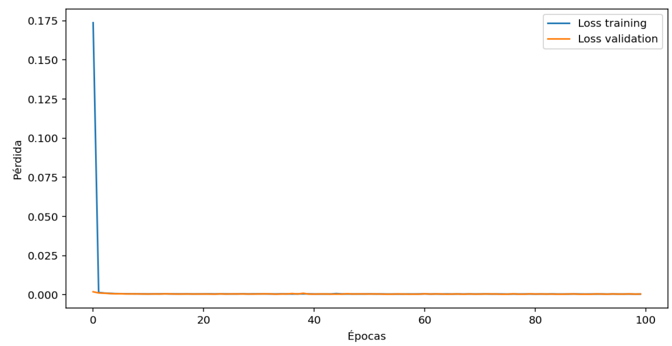

Fig. 7: Loss evolution during training

As shown in figure 8, the predicted points (in orange) closely overlap the ground-truth values (represented in blue), which correspond to the circular trajectories simulated in SolidWorks.

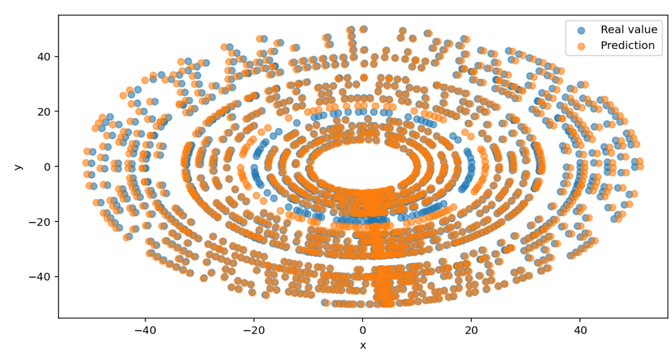

Fig. 8: Comparison of real (blue) and predicted (orange) end-effector positions across various circular trajectories

The plot reveals the neural network's excellent results with close agreement of the predicted and real values of the X and Y coordinates, proving the viability of neural networks as a less computationally expensive alternative to solve the forward kinematic problem for 3-RRR planar manipulators.

V. CONCLUSION

The Swish and ELU function was found to provide the lowest average deviation, with results more consistent than other common functions such as Sigmoid, Tanh, or ReLU. This method can be employed as an alternative when a quick and sufficiently accurate solution is desired for real-time systems. Additionally, data validation was performed in Jupyter Notebook, creating a code that allows capturing the data of angles q1, q2, and q3 to predict the values of X and Y.

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