

# TANET 2025

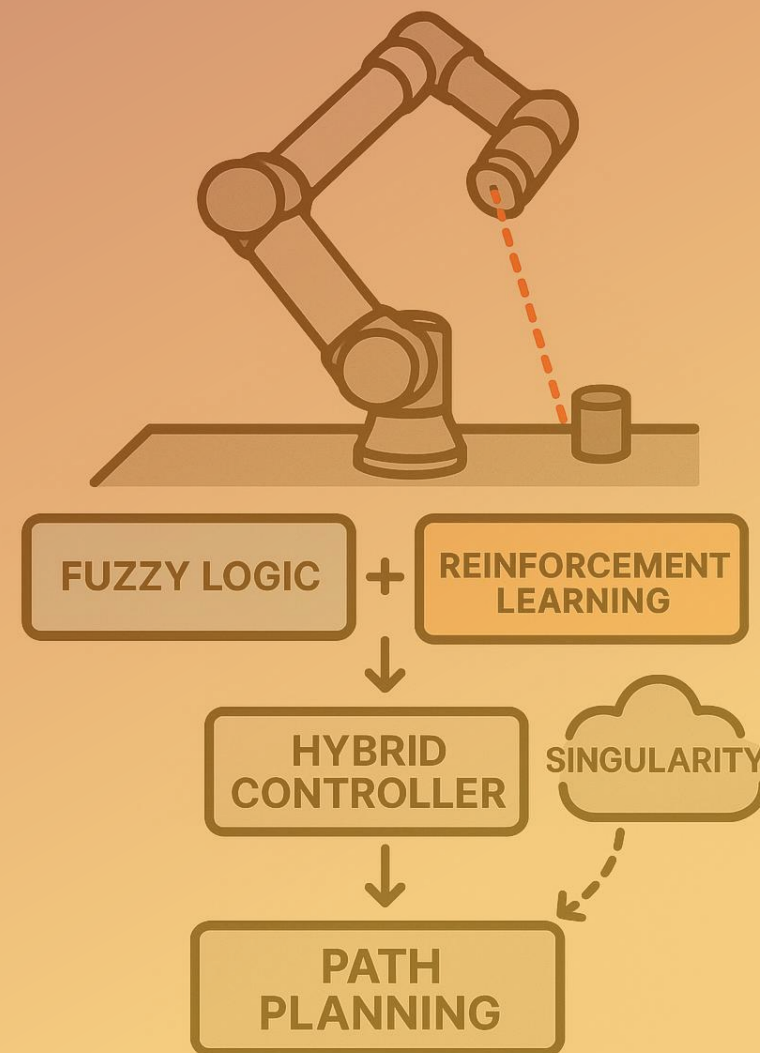
Intelligent Singularity Avoidance in UR10 Robotic Arm Path Planning  
Using Hybrid Fuzzy Logic and Reinforcement Learning

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## INTELLIGENT SINGULARITY AVOIDANCE IN UR10 ROBOTIC ARM PATH PLANNING USING HYBRID FUZZY LOGIC AND REINFORCEMENT LEARNING





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# Background and Motivation

Robotics arms applications are much but still face many problems when moving.

## Research Background

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- **Inverse kinematic and deep learning**

The deep learning model is trained via inverse kinematic so that after the user gives the end point, it can move to the specified fixed point.

- **Human-computer interaction**

By recognizing the direction of a person's face, the arm can be moved in the same direction as the face. Pressure detection can also be performed on the arm to determine the weight of an object.

## Pain Point Analysis

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- **Singularity rotation barrier**

If the robotic arm reaches the singularity point, it will be unable to rotate further and will get stuck in front of the singularity point.

- **Applicability issues**

Robotic arms are divided into four-axis and six-axis arms, and each manufacturer has different designs and rules.

## Goals

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- **Build a virtual environment**

Establish a virtual environment to simulate feasibility first.

- **Move automatically**

The arm can plan its own path and move.

- **Prevent arm from unable rotating**

Keep arm away from points where they cannot turn.

# Methodology

Showing full system architecture.

## Model Training

- **Virtual Environment via Digital Twin**

Use PyBullet to collect data, train models, and verify the dataset, such as whether route A will encounter singular points, etc.

- **Reinforcement Learning**

Maintaining the use of reinforcement learning for model training enables the model to be more adaptive to various situations.

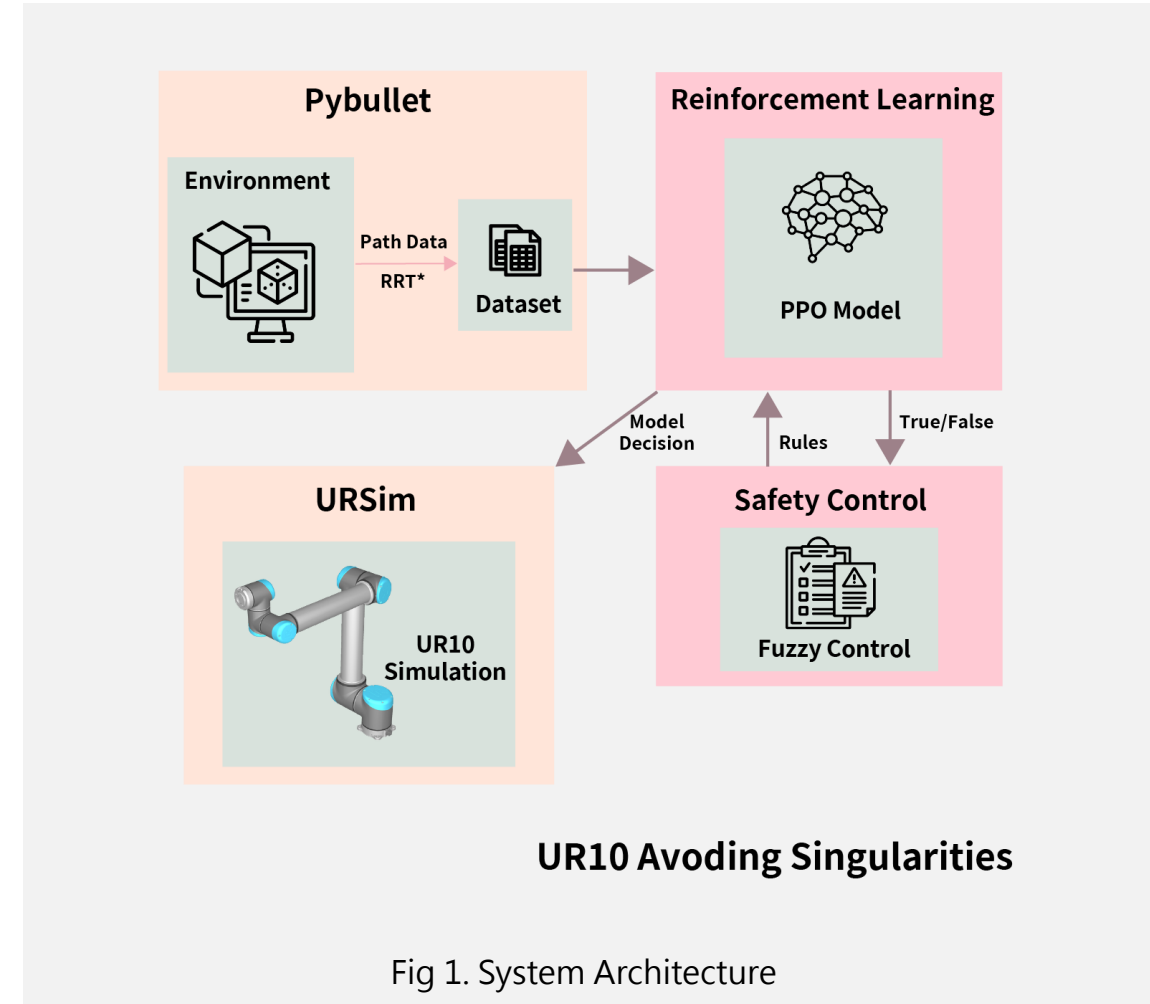
## Safety Control

- **Fuzzy Control**

By setting various fuzzy control conditions, controllability, singularity points and optimal distances are determined.

- **Path Planning**

The arm's path is planned using the RRT\* algorithm (singular points are considered obstacles).



# Methodology

Showing the rules of the fuzzy control.



## Input Variables

The three input values determine the results of fuzzy control, which are manipulability level, condition number quality and joint velocity magnitude.



## Safety Rules

There are 45 fuzzy control rules in total.



## Levels

Based on the comprehensive consideration of the degree achieved by each input value, the result can be divided into six situations. These are emergency stop, critical, warning, caution, safe and optimal.

## Input Variables



Manipulability  
Level



Condition  
Number Quality



Joint Velocity  
Magnitude



Optimal

## Safety Rules

There are 45  
fuzzy control  
rules in total.

### Levels

⚠	Emergency Stop
⚠	Critical
⚠	Warning
⚠	Caution
✓	Safe
🎯	Optimal

# Methodology

Showing the details of reinforcement learning.

## Model Training

- **4-stage progressive training**  
Targets within 0.10, 0.15, 0.20m and full workspace.
- **Algorithm**  
Proximal Policy Optimization
- **State Space**  
Includes Joint positions, Target coordinates and Singularity measures.

## Reward Function Components

- Distance-based reward
- Target achievement bonus
- Progress rewards
- Singularity proximity penalty
- Joint velocity penalties

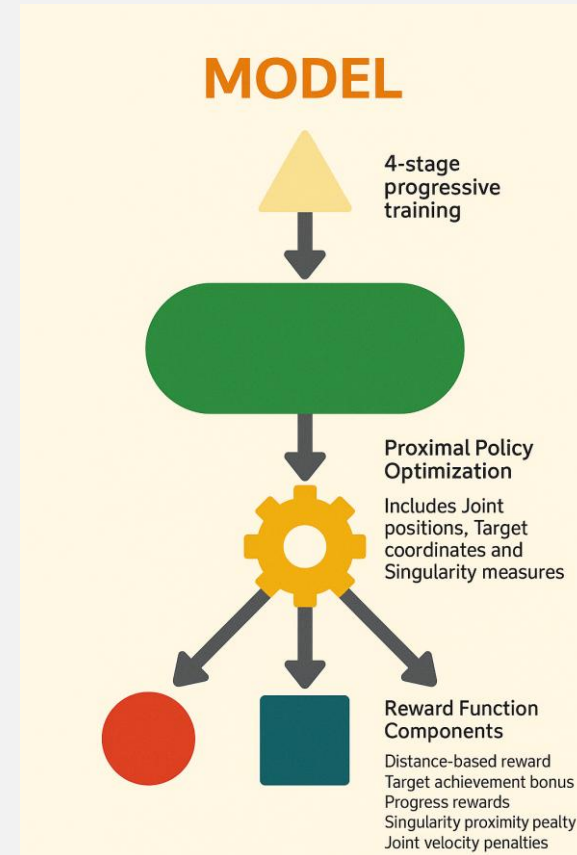


Fig 2. Reinforcement learning diagram

# Results

Showing the results of model training.

## Value Showing

- **Success rate**

It demonstrates learning progression with final performance reaching 90%.

- **Policy loss**

It decreased from 0.525 to 0.001, representing a 99.8% reduction over the training period.

- **Value loss**

It improved from 96.2 to 3.3, achieving a 96.6% reduction.

## Conclusion

These learning curves show stable convergence without divergence issues.

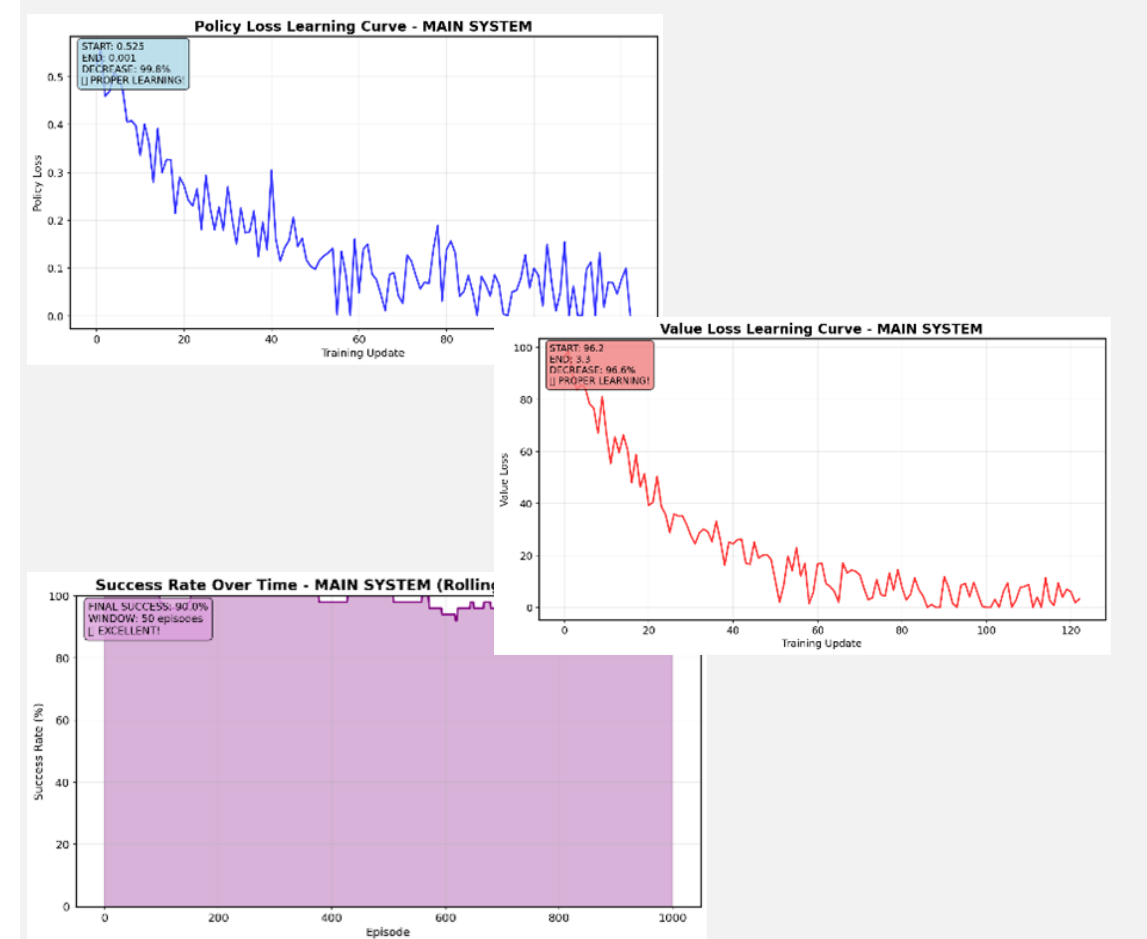
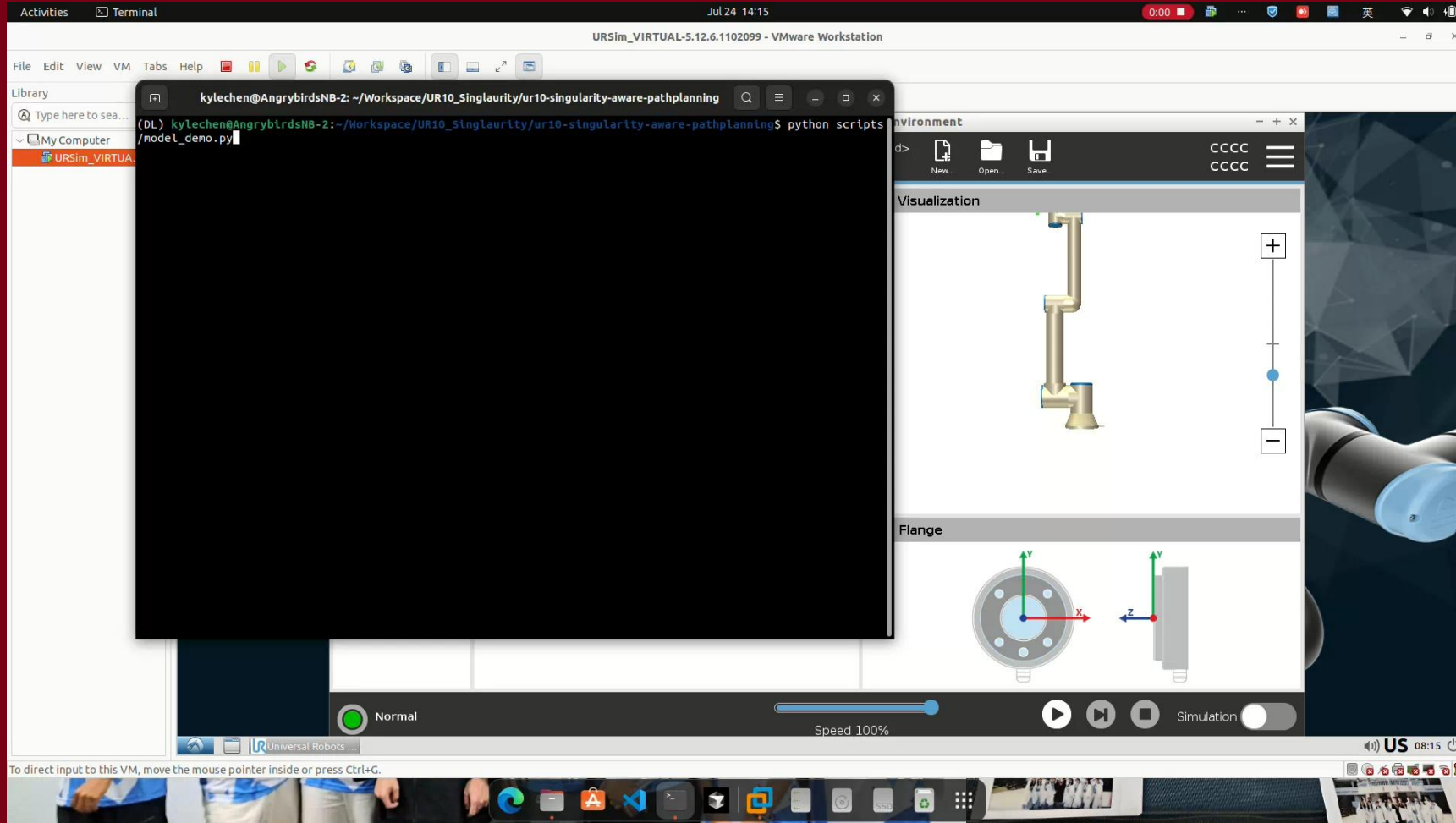


Fig 2. Reinforcement learning diagram



# Results

Showing the system avoiding singularities moving UR10 arm.





# Future Work

Where it can be applied in future projects.



## Physical Arm Application

The model has been tested in the UR official virtual environment and can then be placed on a physical arm for application.



## Universal Arm Applicability

Future research will explore whether this system can be adapted for use with other similar 6DOF arms or even placed on 4DOF arms.

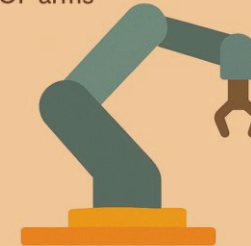
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# Thank You



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