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Implementation of Level Controller using Machine Learning Algorithm of a Spherical Tank

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***Abstract*—This project explores a novel approach for level control in non-linear spherical tanks by integrating machine learning with mathematical modelling. Spherical tanks exhibit complex non-linear behaviour due to their geometry, which complicates traditional control methods. We begin by developing a detailed open loop model of the spherical tank, capturing the intricate relationship between the liquid height and the tank's volume, as well as the dynamics of fluid inflow and outflow. This model forms the basis for understanding how variations in flow rates affect the liquid level within the tank. To address the non-linearity and enhance control performance, we incorporate machine learning techniques. By training a machine learning model on historical data, including inflow rates, outflow rates, and observed liquid levels, we develop a predictive tool that accurately reflects the system's behaviour. This model is integrated into a Q- learning framework, which uses it to forecast future states and optimize control actions accordingly. Simulation results show that this Q-learning based control strategy significantly improves the accuracy and stability of the liquid level control compared to traditional methods, demonstrating its effectiveness in managing the complexities of non- linear spherical tanks.**

***Keywords*—non-linear; spherical tank; Q-learning; open loop; machine learning**

I. INTRODUCTION

Level control in non-linear systems, such as spherical tanks, presents a unique set of challenges due to the complex interplay between fluid dynamics and tank geometry. Unlike cylindrical tanks, where the relationship between liquid height and volume is linear, spherical tanks exhibit a non-linear relationship that complicates traditional control strategies. As such, maintaining a desired liquid level in these systems requires advanced methods that can accommodate their inherent non-linearity. we propose a novel approach to tackle this challenge by integrating the system with machine learning techniques. To solve this a Multi -model design is created so that the spherical tank is split up into 3 parts and the controller action is done. Initially conventional controller is used to determine the dimension and volume of the spherical tank. Performance measure is done by time domain specifications (ISE, IAE, ITAE) to determine the performance and efficiency of conventional controllers. Then the Q-learning algorithm is incorporated to train the system with the disturbances and uncertainties and to obtain the level of the spherical tank. Through the rewards of the learning model the error can be reduced.

II. MATERIALS

A. MATLAB

This study makes considerable use of MATLAB, a proprietary programming environment created by MathWorks. A whole range of tools for numerical computing, developing algorithms, analysing data, and visualising it are provided by MATLAB. Because of its adaptability, it is ideal for a variety of scientific and engineering uses, including as machine learning, signal processing, and control system design. The development, simulation, and analysis of algorithms pertaining to the design and implementation of a control system for a nonlinear spherical tank were carried out in this study using MATLAB. The study process was made more productive and efficient using MATLAB, which allowed for quick prototyping and iterative control algorithm improvement.

B. DAQ

An ATmega2560 microcontroller-based Data Acquisition (DAQ) system was incorporated into the experimental configuration to facilitate communication with tangible sensors and actuators. The ATmega2560, when used in conjunction with MATLAB, enabled real-time data acquisition and control activities. It was equipped with several Analog-to-Digital converter (ADC) channels, digital I/O ports, and communication interfaces like UART and I2C. The DAQ system made it possible to collect sensor data from the actual system, which was then used as input for MATLAB's control algorithms and to actuate the actuators in the system using control signals. Validation and optimisation of control techniques for the nonlinear spherical tank system were made easier by the smooth transition from simulation to real-world

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experimentation made possible by the integration of MATLAB with the DAQ system contained with the ATmega2560 microcontroller.

C. DPT (Level Transmitter)

This study's differential pressure transmitter is an Allen Bradley precision instrument made especially for process control and monitoring applications. With a 24 V DC input voltage, this type can be used with conventional industrial power sources and control systems. The transmitter output provides a linear signal in relation to the observed pressure differential across its input ports and is arranged in the industry-standard 4-20 mA current loop format. Strong, noise-resistant transmission of measurement data over extended distances is made possible by the 4–20 mA signal range, which makes it ideal for the harsh conditions frequently found in industrial applications. Modern sensor technology is used into the design of this transmitter to provide high differential pressure measuring accuracy, stability, and repeatability

D. CONTROL VALVE

The control valve we describe in our study has an input current range of 4–20 mA and is designed for precise flow regulation. The electrical signal is modulated by this input signal, which then transforms it into a pneumatic output actuation with a pressure range of 3 to 15 psi. With this conversion, a wide range of industrial applications can benefit from precise control over fluid or gas flow rates via the valve. Maintaining ideal process conditions depends critically on how well the device responds to electrical commands and converts them into mechanical movement.

E. SYSTEM DESCRIPTION

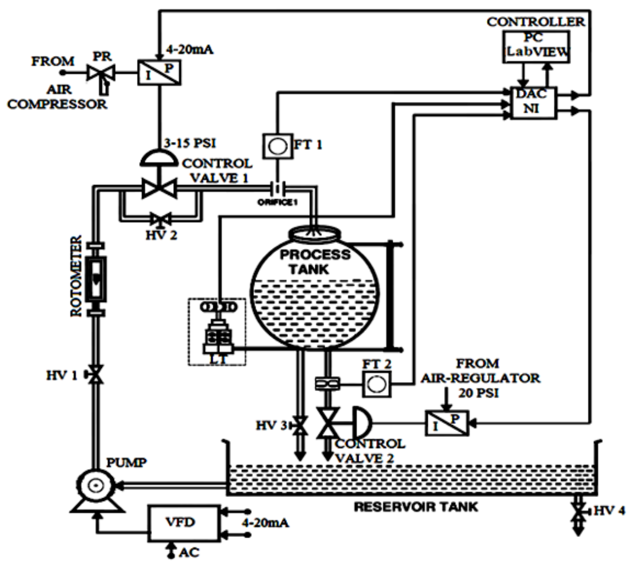

Fig. 1. P&I diagram of spherical tank water level process

S. No.	*Parts/Field instruments*	*Specifications/Description*
1	Spherical Tank	Material: Stainless Steel, Diameter: 43 cm, (LRV= 436 mmH2O, URV=866, mmH2O, Volume: 42 liters
2	Pump and VFD	VFD: ABB-ACS350, 3Φ 4- 20 mA to 0 to 50 Hz. Pump: Grundfos-JP5 centrifugal pump, 3 Phase.
3	DPT for level measurement (LT)	6200T Series, Range: 0 to 6500 mmH2O, Output: 4 to 20mA+HART
4	DPT for Flow measurement (FT)	6200T Series, Range: 0 to 6500 mmH2O, Output: 4 to 20mA+HART
5	Control valves	Linear, Air to open, Body: 1", Trim1/2"
6	Rotameter	150 to 1500 LPH
7	I/P converter	Input: 4 - 20 mA, 20 psi Output: 3 to 15 psi

[a] *Component specifications of spherical tank process*

III. METHODS

A. BLOCK DIAGRAM

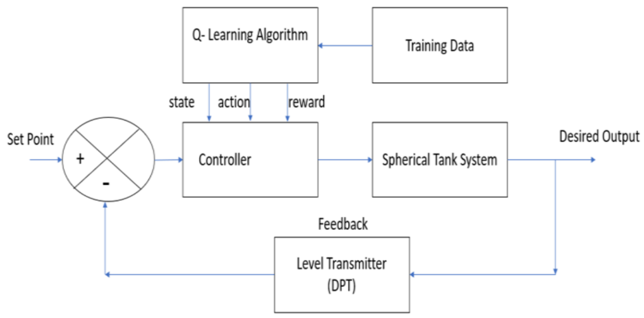

Fig. 2. Block diagram of the system

Taking into consideration elements like the nonlinear relationship between liquid level and volume and the curvature of the tank walls, the non-linear system depicts the dynamic behaviour of the spherical tank. The Proportional-Integral-Derivative controller is selected because it can control the dynamics of the system by modifying the controller's output in response to the accumulation of past errors as well as current errors. While Ki provides steady-state control by integrating prior errors over time, the Kp reacts to the current error and Kd reacts to reduce the current error. Machine learning method is essential to optimize the performance of the PID controller. It uses iterative optimization techniques, like Q-learning algorithms to continuously modify the values of Kp, Kd and Ki. The algorithm aims to optimize the objective function by iteratively fine-tuning these parameters in response to system feedback, guiding the controller towards optimal performance. The objective function is a statistic used

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to assess how well the PID controller is performing. It measures the difference between the level that the level sensor actually measures and the desired level setpoint. By optimization oscillations and overshoot, this function can be optimized to ensure that the controller maintains the required level as efficiently as possible.

B. Q-LEARNING

This section includes the introductory part of Q-learning which could be implemented in the future to obtain optimal and robust control for level in the spherical tank. Q-learning algorithm includes the 5 key components they are given as follows: State includes the liquid level, rate of change, and inflow rate. Action includes controlling the inflow to maintain inlet flow. Reward function could be designed to minimize the large deviations from the set point and long settling times. Q-values are the combinations of states and actions (e.g., Q (s, a)). Q-table is the combination of Q-values. Q-table is a matrix where row represents states and column represents actions. Each cell in the table holds the Q-value for particular state action pair. 'Bellman equation' is used for updating the Q-values in the Q-table.

$$Q(s, a) \leftarrow Q(s, a)+\alpha[r+\gamma \max Q(s', a)-Q(s, a)] \qquad (1)$$

- α: Learning rate (how much new information overrides old).
- r: Immediate reward after taking action a.
- γ: Discount factor (how much future rewards are taken into consideration).
- s′: The next state after taking action a.

C. OPEN LOOP RESPONSE

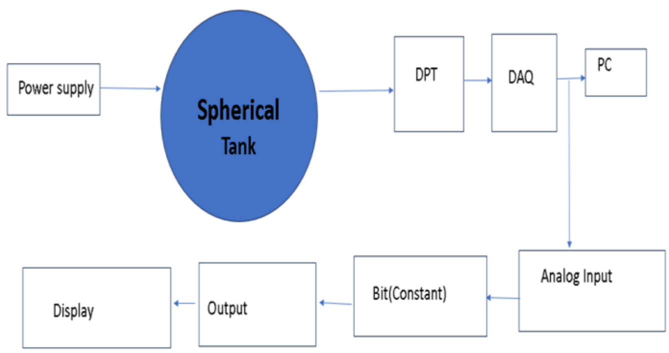

Fig. 3. Block representation of open loop system

A 24-volt power supply is provided to the system, serving as the primary source of electrical energy for the components. Differential Pressure Transmitter converts the supplied power into a 4-20 milliampere (mA) signal, which is proportional to the measured pressure difference across the tank. The 4-20 mA signal is transmitted to a data acquisition card (AT Mega 2560), which interfaces with a computer for data processing and analysis purposes. The data acquisition card is connected to a computer running MATLAB Simulink, facilitating real-time monitoring and control of the system's performance. The Simulink model receives signal from DAQ (AT Mega 2560).The conversion involves translating the voltage values from a binary representation (0-1023 bits), where each volt corresponds to approximately 204.6 bits. With the bit representation the value of level is determined and with the help of digital output block the output bit is represented. The Simulink model includes a display component that visualizes the system's performance through graphs or other visual representations. This allows users to monitor and analyze the system's behavior in real-time.

Time (in sec)	*Setpoint(bit)*	*Output(bit)*	*Level (in cm)*
0	800	226	8.82
10	800	225	8.00
20	800	427	16.67
50	800	604	23.19
70	800	725	28.32
80	800	751	29.33
90	800	828	32.39

$\alpha + \beta = \chi.$ (1) b. *Open loop response of the spherical tank*

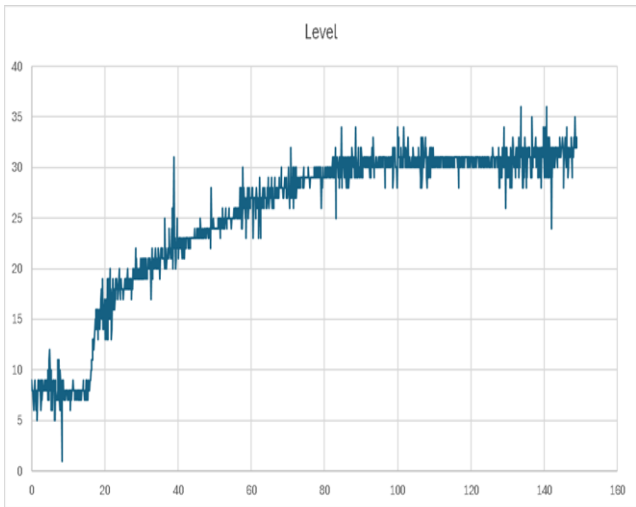

Fig. 4. Graphical representation of open loop response

IV. RESULT AND CONCLUSION

A. RESULT

By using Arduino input and output tools in MATLAB, the open loop response in a nonlinear spherical tank system was obtained, successfully achieving the desired outcome. This study showcased the simplicity and efficiency of the method, demonstrating its usefulness in industrial applications. The study confirmed that machine learning may improve control accuracy and stability by using advanced optimization techniques such as Q-learning. Taken as a whole, these results demonstrate the influence of sophisticated optimization techniques on industrial operations, offering increased control performance and productivity.

B. CONCLUSION

In conclusion, the utilization of Arduino input and output tools in MATLAB presents several advantages in finding the open loop response of spherical tank level control. Furthermore, the study of Q-learning algorithm ensures the importance of employing advanced techniques to achieve optimal control strategies. These findings suggest that leveraging Q-learning model can lead to more robust and accurate control systems, ultimately improving overall performance and efficiency in industrial processes.

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