DESIGN OF LEVEL CONTROLLER FOR A NON-LINEAR SYSTEM USING MACHINE LEARNING

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Abstract - This study explores machine learning-based control for nonlinear spherical tank level management, addressing challenges in traditional methods. Leveraging simulated annealing, known for global optimization and robustness in noisy environments, PI controller parameters are optimized for enhanced accuracy and stability. The research aims to fill the gap in applying simulated annealing with linear regression machine learning model to this domain, providing a more effective and accurate solution for industrial processes. Implemented in MATLAB, simulated annealing demonstrates its superiority by globally optimizing PI parameters while offering simplicity in implementation. This research underscores the significance of leveraging simulated annealing for fine-tuning PI parameters with machine learning, offering promising avenues for efficient and reliable level control strategies.

Key Words: Nonlinear spherical tank, PI, Global optimization, MATLAB, annealing, linear regression.

1. INTRODUCTION

For industrial processes to be efficient and safe, liquid levels must be controlled, particularly in spherical tanks. Conventional techniques have difficulty with the changing conditions and the intrinsic nonlinear dynamics. There is potential for increased control accuracy using machine learning.

To close this gap, this study incorporates simulated annealing—a technique that allows one to explore the whole solution space—with machine learning into a machine learning-based nonlinear tank level control controller. By comparing test data with trained data, it seeks to offer an industrial process solution that is more effective.

2. MATERIALS AND METHODS

2.1 MATERIAL DESCRIPTION

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.

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

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.

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.

Components	Specification
Differential pressure transmitter (DPT200)	input-24v and output (4-20mA)
Digital ammeter (SMP35SRS)	measuring range (4 – 20mA) DC
Data Acquisition card (DAQ)	operating voltage(5v)
Control Valve	Input current (4-20mA) and output pressure (3-15 PSI)

2.2 DESIGN PROCESS

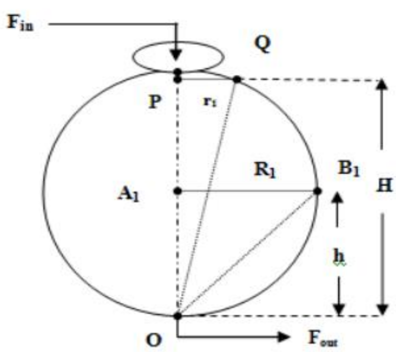

Figure -1: Cross Sectional Diagram Of The Spherical Tank

MATHEMATICAL MODELLING

By conservation of energy,

$$\frac{dV}{dt} = A\frac{dh}{dt} = F_{in} - F_{out}$$

Where V – Volume of spherical tank.

A- Area of spherical tank.

Fin & Fout- Inflow and Outflow respectively.

$$F_{in} - c\sqrt{h} = A\frac{dh}{dt} \quad \text{Where, } F_{out} = c\sqrt{h}$$

By taking Laplace Transformation of above equation

A spherical tank model with process dead-time (td) is given by

$$\frac{H(s)}{F_{in}(s)} = \frac{Kp}{1+\tau s} e^{-t_d s}$$

Where, $F_h = b\sqrt{h}$, $Kp = \frac{2h}{F_h}$, $\tau = \frac{2hA}{F_h}$, $c = \frac{b}{2}$

c = constant of proportionality, b = outflow valve coefficient. h = 175mm, R = 205mm, r = 40.2 mm, H = 350 mm b= 5, kp = 5.2918, $\tau = 26852.5$

Let the td = 1 sec.

$$\frac{H(s)}{F_{in}(s)} = \frac{5.2918}{1+26852.5s} e\text{^-s}$$

2.3 BLOCK DIAGRAM

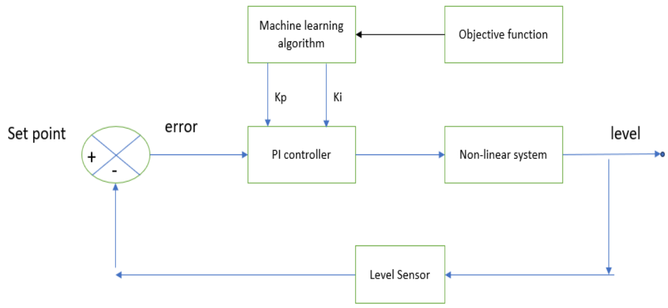

Figure -2: Block Diagram

2.4 HARDWARE DESIGN

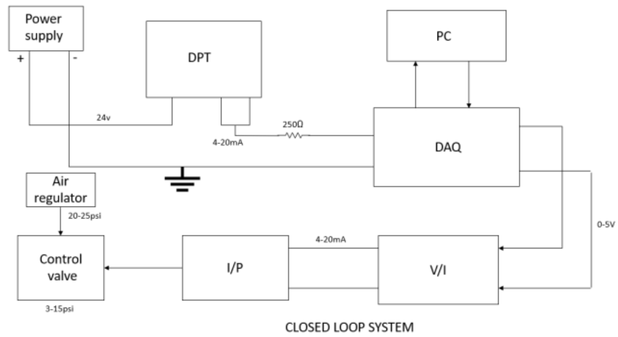

Figure -3: Hardware Model

2.5 SOFTWARE DESIGN

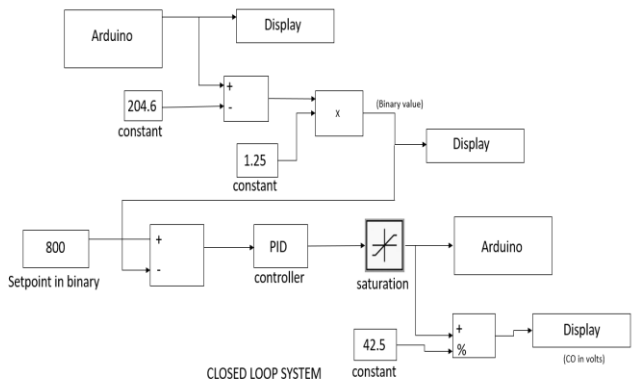

Figure -4: Software Model

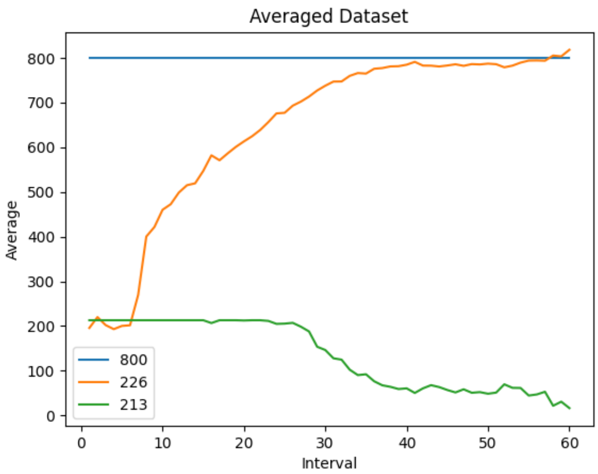

Figure -5: Closed Loop Output Graph

The above graph shows the average output of a closed loop system.

2.6 Simulated Annealing Algorithm:

Through iterative adjustments, Simulated Annealing (SA) optimises the parameters of PI controllers in order to minimize a cost function, which commonly represents the performance of the system. By probabilistically accepting inferior solutions to escape local optima, the technique theoretically simulates the annealing process.

Every time an iteration occurs, SA uses a probabilistic distribution to disturb the existing solution in order to produce a new candidate solution. This new solution is accepted or rejected based on a mathematical criterion that takes the temperature parameter and the variation in the cost function into account. Early in the optimisation process, the temperature parameter regulates the probability of accepting subpar answers; it subsequently decreases to favour the exploitation of superior solutions.

Mathematically, the probability of accepting a worse solution is calculated using the Metropolis criterion:

$$P(E) = \exp(-\Delta E / T),$$

Where:

- ΔE is the change in the cost function between the current and candidate solutions.
- T is the current temperature parameter.

As the algorithm progresses, the temperature parameter decreases according to a cooling schedule, leading to a higher probability of accepting only better solutions. This process allows SA to explore the solution space effectively and converge towards an optimal set of PI controller parameters.

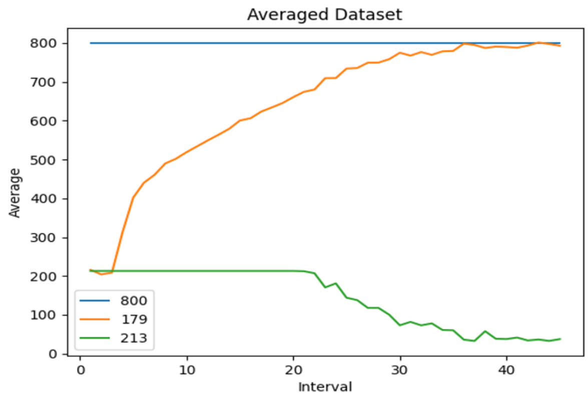

Figure -6: Simulated Annealing Output Graph

The above graph shows the output of a closed loop system with optimized controller parameter using simulated annealing.

2.7 Linear Regression

When optimizing PI controller parameters, linear regression makes use of a dataset made up of input-output pairs, where the outputs are related system performance measures (such as error and stability) and the inputs are different combinations of controller parameters. To assess the model's performance, the dataset is usually split into a test set (20%) and a training set (80%).

By fitting a linear equation to the training set of data, linear regression determines the link between controller parameters and system performance. By using this equation as a predictive model, system performance can be estimated for novel combinations of controller settings.

The predicted accuracy of the model is tested using the test data after it has been trained. Metrics like root mean square error (RMSE),which calculates the average divergence between expected and actual system performance values, are used to quantify the model's performance. An improved match between the model's predictions and the observed data is indicated by a reduced RMSE.

The model offers insights into how changes in parameters affect system performance, allowing for educated modifications to accomplish desired control objectives while minimising mistakes. By utilizing linear regression, PI controller settings can be optimize systematically.

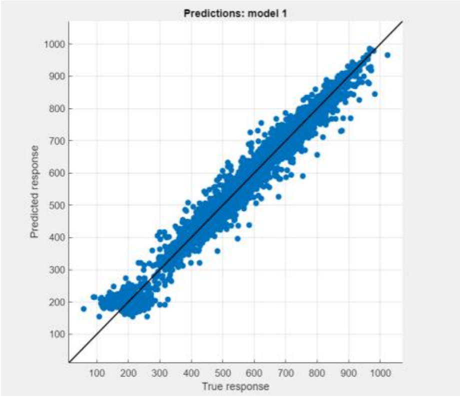

Figure-7: Linear Regression Output Graph

3. Result and discussion

The utilisation of simulated annealing in MATLAB resulted in the global optimal solution for reaching the target level by efficiently optimising the PI controller parameters for a nonlinear spherical tank system. The study illustrated the algorithm's usefulness in industrial applications by showcasing its simplicity and efficiency. Through the use of sophisticated optimisation methods such as simulated annealing, the study confirmed that machine learning may improve control stability and precision.

All things considered, the successful use of linear regression validation and simulated annealing highlights the potential of these methods in improving control systems and enhancing productivity in industrial processes.

4. Conclusion

In conclusion, there are several advantages to using simulated annealing to optimise the settings of the PI controller in non-linear spherical tank level control. Its promise for optimizing PI parameters is highlighted by its ability to optimise globally, robustness in noisy conditions, ease of implementation, and improvement of control accuracy and stability. This study emphasises how important it is to take advantage of simulated annealing's advantages in order to maximise control system performance. Furthermore, the use of a linear regression model offers valuable insights into the test model's accuracy, hence augmenting trust in the optimised control measures.

5. References

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