iTCLab PID Control Tuning Using Deep Learning

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***Abstract*— This paper presents a novel approach for tuning Proportional-Integral-Derivative (PID) controllers using deep learning techniques, specifically applied to the iTCLab, an advanced industrial control laboratory system. PID controllers are widely used in industrial processes for their simplicity and effectiveness. However, their performance heavily relies on proper tuning, which can be a complex and time-consuming task. In this study, we leverage the capabilities of deep learning to automate and optimize the PID tuning process for the iTCLab setup. We propose a data-driven methodology that combines system identification, Deep Learning networks, and optimization algorithms to achieve superior PID controller tuning.**

Keywords—iTCLab, PID, Tuning, Parameter, Deep Learning

I. INTRODUCTION

A Proportional-Integral-Derivative (PID) controller is a feedback mechanism extensively employed in industrial control systems and other scenarios that demand ongoing finely-tuned regulation. It functions as a control system that constantly tweaks the output of a process or system based on feedback to align with a target value.

PID controllers find broad utility in diverse fields such as temperature regulation, flow management, and motor operation. This is owed to their capability to deliver steady and precise regulation while being relatively straightforward to implement. An illustration of this can be observed in the Arduino-based Temperature Control Lab (TCLab) [1]–[6] and internet-Based Temperature Control Lab (iTCLab) [7]–[9].

Proportional-Integral-Derivative (PID) controllers are fundamental in control systems due to their simplicity and effectiveness. The performance of a PID controller heavily relies on its tuning parameters, which determine how quickly and accurately the controller responds to changes in the system. Various methods exist for tuning these parameters. One common approach is manual tuning, where engineers adjust the parameters iteratively based on their understanding of the system's dynamics. Alternatively, heuristic methods like the Ziegler-Nichols method involve step tests to determine critical gains and oscillation periods, from which proportional, integral, and derivative gains are derived [10]. Model-based techniques utilize system models to optimize parameters, often through techniques like the Internal Model Control (IMC) or the Tyreus-Luyben method [11]. Advanced methods, such as optimization algorithms like genetic algorithms or particle swarm optimization, use computer-based iterations to find optimal parameters by minimizing a performance criterion [12]–[14]. Additionally, adaptive tuning methods continuously adjust parameters based on real-time system behavior [15]. Each method has its advantages and disadvantages, and the choice depends on factors like system complexity, desired performance, and available resources.

Deep Learning techniques have found innovative applications in PID parameter tuning, offering a modern and data-driven approach to optimizing control system performance. By leveraging large volumes of process data, Deep Learning algorithms can learn complex relationships between system inputs, outputs, and control actions. This enables them to automatically identify optimal or near-optimal PID parameters that lead to improved system behavior. In industries such as manufacturing, where systems can exhibit intricate dynamics, Deep Learning can rapidly adapt to changes and non-linearities. This approach is especially advantageous for systems with uncertain or time-varying characteristics, as the algorithms can continuously refine PID parameters based on real-time observations. Furthermore, Deep Learning-based PID tuning can optimize control under various operating conditions, leading to enhanced stability, responsiveness, and reduced overshoot. Through its ability to extract patterns and insights from vast datasets, Deep Learning contributes to more efficient and effective PID control across a wide array of applications, from industrial processes to robotics and beyond. In this study, a novel approach involving PID tuning parameters using Deep Learning is applied to the iTCLab Kit.

II. Proposed Methodology

A. Research Design

The research design is illustrated in Fig. 1. The application of the PID parameter adjustment method utilizing Deep Learning for the iTCLab Kit is founded upon the temperature control outputs obtained from the iTCLab Kit. The objective is to attain a minimal steady-state error. Certain checks are necessary. Should the control outcomes achieved with the default parameters lead to temperature control within the iTCLab with a minor steady-state error, then these parameters can be retained. However, in cases where such control fails to achieve temperature regulation with a small steady-state error, parameters generated via Deep Learning are employed. The aspiration is that the parameters produced by Deep Learning will yield temperature control within the iTCLab with a minor steady-state error.

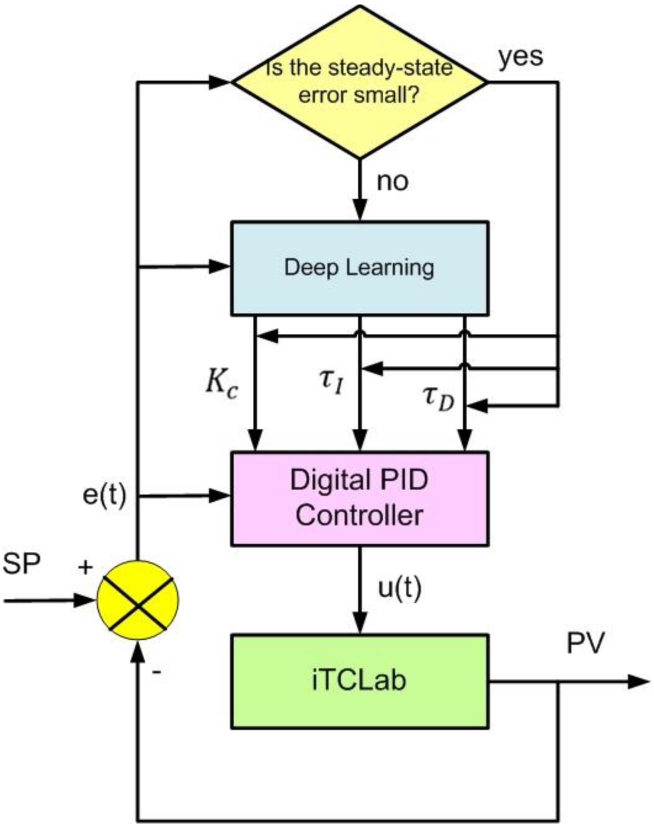

Fig. 1. Deep Learning for PID Parameter Tuning on iTCLab

B. Deep Learning Architecture

With an overview of the system as shown in Fig. 1, the training data is prepared according to these requirements. The input-output data pairs consist of errors, delta errors, and three PID parameters, respectively. The suitable Deep Learning architecture for this requirement is depicted in Fig. 2. The optimal data pair was acquired from multiple experiments, resulting in several ideal training data pairs that yield the highest PID control performance. Subsequently, utilizing this optimal training data pair, the Deep Learning training process is executed to derive the most effective weights. These training weights are then employed for an auto-tuning procedure by Deep Learning, aiming to enhance the performance of the PID parameters utilized in iTCLab control for optimal results.

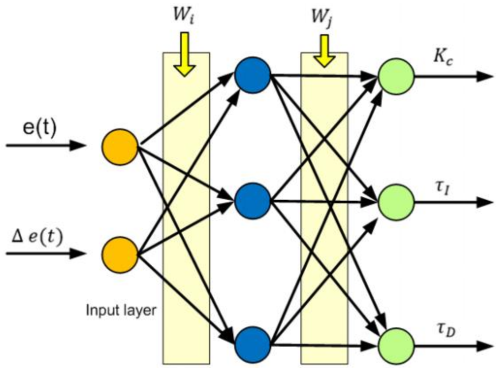

Fig. 2. Deep Learning architecture for PID auto tuning

C. Control Design

After obtaining the best training data using the architecture in Fig. 2 and training until the best weights are obtained, Deep Learning will then work using these weights to generate the three PID parameters (K_c, τ_I, τ_D). With this system, the auto-tuning process operates. Subsequently, the control signal generated by the PID controller is input into the iTCLab plant to obtain an output that matches the desired SetPoint. This control process continues until it is stopped. Afterward, an analysis of the control results is conducted. An overview of the iTCLab control system using Deep Learning-PID, as shown in Fig. 3.

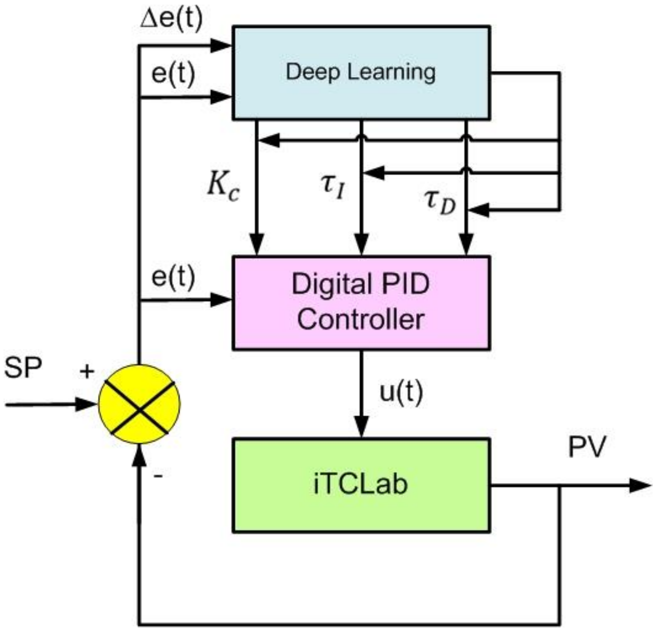

Fig. 3. iTCLab Deep Learning-PID Control Design

D. iTCLab Design

The plant used in this PID control system is the internet-based temperature control lab (iTCLab). The iTCLab is a PCB shield designed to interface with an ESP32 microcontroller. It incorporates a pair of transistors for heating purposes along with two LM35 temperature sensors. The system exhibits second-order dynamics, and the presence of these two neighboring heaters results in a compact multivariate control setup. The ESP32 microcontroller is equipped with a 10-bit analog-to-digital converter (ADC) that measures the voltage from the temperature sensors in 1024 discrete analog levels. Additionally, it employs Pulse Width Modulation (PWM) with 256 levels to control the output to both the heaters and an LED [7]. The complete circuit design of the iTCLab is shown in Fig. 4.

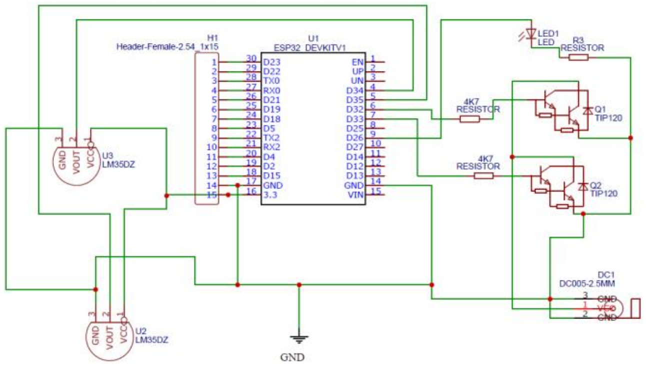

Fig. 4. iTCLab circuit design

III. Results And Discussion

In this section, we present the results and delve into the discussion surrounding the application of Deep Learning for tuning the PID control system in the iTCLab environment. The integration of Deep Learning techniques into the traditional PID control methodology has yielded promising outcomes. Our control design, as illustrated in Fig. 3, is expected to demonstrate the effectiveness of this approach in achieving precise control over complex processes.

The results of training Deep Learning using a pair of input-output training data consisting of error, delta error, and the three PID parameters, using a sequential model, are shown in the following outcomes. The Deep Learning parameters and training results obtained are presented in the following results.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_3 (Dense)             (None, 2)                 6

 dense_4 (Dense)             (None, 3)                 9

 dense_5 (Dense)             (None, 3)                 12

=================================================================
Total params: 27
Trainable params: 27
Non-trainable params: 0
_________________________________________________________________
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Fig. 5. Deep Learning training parameters

The results of the Deep Learning training process are as follows:

- Input: error e(t) and delta eror Δe(t)
- Output: K_c, τ_I, τ_D
- Input Layer (2 Neurons, Activation Function: ReLU)
- Hidden Layer (3 Neurons, Activation Function: ReLU)
- Output Layer (3 Neurons)
- Epoch: 500
- Batch Size: 1
- Optimizer: Adam
- Learning Rate: 0.001
- RMSE: 16.034

The performance of the iTCLab system, equipped with the Deep Learning-PID controller, was assessed across various scenarios. The obtained results reveal substantial improvements in control performance when compared to energy balance and linear First Order Plus Dead Time (FOPDT) model. More detailed discussion regarding the energy balance and linear FOPDT model can be found in the following article [1]. The Deep Learning-PID model successfully adapts and optimizes its parameters, including K_c, τ_I, τ_D, based on real-time data, resulting in enhanced control signal generation.

Furthermore, the system's ability to auto-tune and adapt to changing operating conditions was observed, highlighting its robustness and adaptability. The control signal generated by the Deep Learning-PID controller consistently matched the desired SetPoint, demonstrating its capability to efficiently regulate the iTCLab plant.

The results of testing the iTCLab control system using Deep Learning-PID, as shown in Fig. 6, indicate that the temperature output measurements closely approach the SetPoint. The performance results of the proposed system yield a smaller steady-state error and reduced overshoot compared to the output from the energy balance and linear FOPDT models.

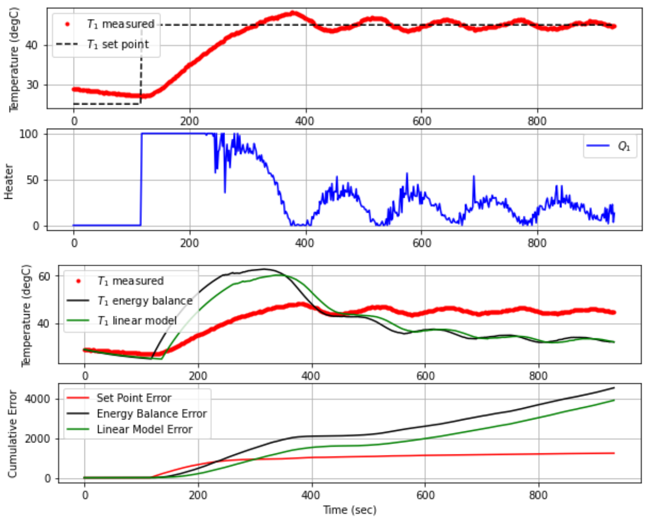

Fig. 6. iTCLab Deep Learning-PID Control Result

Analysis of the system response is as shown in Fig. 7.

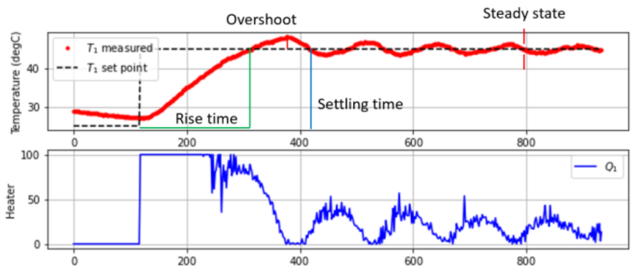

Fig. 7. System response analysis

From the results of iTCLab control testing using Deep Learning-PID, the following results were obtained:

- Rise time: 190s
- Overshoot: (peak-sp)/peak * 100% = (49-45/49)*100% = 8.16%
- Settling time: 360s
- Steady state error: |setpoint value-steady value| = |45-46| = 1

Based on the performance results, the proposed system demonstrated smaller steady-state errors and reduced overshoot compared to the output from the energy balance and linear FOPDT model. The system exhibited a rise time of approximately 190 seconds. This metric indicates the time it takes for the controlled variable to reach its final value from the moment a step change is introduced. The relatively slow rise time suggests that the system responds gradually to changes, which may be advantageous in certain applications requiring stability.

The calculated overshoot was found to be approximately 8.16%. Overshoot represents the maximum percentage by which the controlled variable exceeds the desired setpoint value before stabilizing. The relatively low overshoot suggests that the Deep Learning-PID controller effectively mitigates excessive deviations from the setpoint, contributing to system stability.

The settling time for the iTCLab Deep Learning-PID control system was approximately 360 seconds. Settling time indicates the duration required for the controlled variable to remain within a specified range around the setpoint, typically within a certain percentage of the setpoint value. This metric demonstrates the system's ability to stabilize after a disturbance, and the observed settling time aligns with expectations for controlled systems of this nature.

The steady-state error was calculated as 1 unit, indicating a small deviation between the steady-state value of the controlled variable and the desired setpoint value. A low steady-state error signifies that the Deep Learning-PID controller effectively maintains the controlled variable close to the target value over extended periods, demonstrating its precision.

These results collectively demonstrate the effectiveness of the Deep Learning-PID control approach in the iTCLab system. The relatively slow rise time, low overshoot, and small steady-state error showcase the system's ability to provide stable and accurate control. It is important to note that these findings align with the goals of achieving precise control performance in various industrial applications.

However, it's worth noting that further research and optimization may be necessary to fine-tune the system parameters and potentially improve certain aspects of its performance. Nonetheless, the results obtained in this study lay a solid foundation for the continued exploration and implementation of Deep Learning-PID control in practical industrial systems.

IV. Conclusion

In this paper, we introduce an original method for fine-tuning Proportional-Integral-Derivative (PID) controllers through the utilization of deep learning methods, with a specific focus on its application to the internet-based temperature control lab (iTCLab). The experimental results show that the proposed system exhibits smaller steady-state errors and reduced overshoot compared with the output from the energy balance and linear FOPDT models.

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