Proportional Integral Derivative Controller Emulation Using Long Short-Term Memory for Temperature Control

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***Abstract*—Driven by the shortcomings of traditional Proportional Integral Derivative (PID) controllers, particularly their limited responsiveness to changes in system parameters, suboptimal performance in nonlinear systems, and challenges in managing disturbances and noise, this study explores an alternative approach. Long Short-Term Memory (LSTM) controllers, designed to mimic PID controller behavior, are anticipated to effectively learn and predict nonlinear system dynamics, exhibit robustness against disturbances and noise, and automatically adapt their parameters. This paper proposes emulating a PID controller using an LSTM network, with the Internet-Based Temperature Control Lab (iTCLab) Kit as the test platform. The results demonstrate successful modeling and emulation of an adaptive PID controller using LSTM on the iTCLab, evidenced by satisfactory control performance, characterized by a relatively slow rise time, minimal overshoot, and low steady-state error.**

***Index Terms*— controller, emulation, Kit, temperature, Lab.**

I. Introduction

THE most well-known control system in the industry is the Proportional Integral Derivative (PID) [1]-[4]. A PID controller integrates three types of control actions: proportional, integral, and derivative. Each action offers distinct benefits: proportional control ensures a quick rise time, integral control minimizes errors, and derivative control helps reduce errors or overshoot. The combination of these three actions aims to achieve output with minimal error and a rapid settling time [5].

So far, the most recent studies on PID control systems have focused on tuning the PID control action parameters consisting of gain K_P, K_I, and K_D. The parameters K_P, K_I, and K_D can also be expressed in terms of controller gain K_C, integral reset time τ_I, and derived time constant τ_D [6]. Tuning these parameters conventionally usually uses the Ziegler–Nichols method [7]-[9], Linear Quadratic Regulator (LQR) [10]-[12], Robust control [13]-[15]. While the latest methods utilize artificial intelligence or Machine Learning (ML) methods. ML methods that are widely used for the process of tuning these PID parameters include Deep Learning [16], Fuzzy Self-Tuning PSO [17], Artificial Bee Colony algorithm [18], iterative learning control [19], beetle antennae search algorithm [20], Genetic Algorithm (GA) [21], reactive nature-inspired algorithms [22], memorizable-smoothed functional algorithm [23], Archimedes optimization algorithm [24], Nonlinear Sine Cosine Algorithm [25], and others.

PID Controller itself has been successfully applied in various fields, including: combined with fuzzy logic for electric motor optimization [26], combined with robust Integral-Backstepping H^∞ for Hydroelectric Power Generation System [27] and Automated People Mover System [14], optimized using PSO, SFS, and FPA to control the Gantry Crane [12], based on LQR with a level of stability determined through GA, PSO, and SA for optimal control of the Gantry Crane [12] uses H^∞ Integral-Backstepping that is robust under uncertainties in payload mass and string length to control optimal RTGC [28], based on DDPG to control the position and angle of RTGC sway [29], and others.

The other challenge of research on PID controllers is to emulate this controller using an intelligent system. In other words, how to make a PID emulator using an intelligent system. This has not been done much. If anything, most of them still use plant simulations. Among them can be mentioned the use of intelligent system methods Recurrent Neural Network (RNN) [30], Long Short-Term Memory Network (LSTM) [31], and Convolutional Neural Network - Long Short-Term Memory Network (CNN-LSTM) [32]. This study proposes modeling and emulating adaptive PID controllers using Long Short-Term Memory Network (LSTM). The plant used is not a simulated plant but a real

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plant, namely the Internet-Based Temperature Control Lab (iTCLab) Kit [5].

The rest of the article is structured as follows. Section II explains the methodology used in the paper. This section is divided into two subchapters that explain the PID controller and the implemented LSTM emulation. Section III presents the results and discussion of the system based on the results of tests carried out on temperature control. Section IV draws conclusions about our research.

II. Proposed Methodology

This research aims to tune the Proportional-Integral-Derivative (PID) controller to obtain the desired iTCLab temperature, and the controller will adjust the heater until it reaches the desired point. Then, we want to see if this behaviour can be emulated by the Long Short-Term Memory Network (LSTM) network. The success of this prototype will open up opportunities not only for Controller Emulation, but also in predictive maintenance, anomaly detection, and intelligent automation across various industrial and environmental monitoring applications. By demonstrating that LSTM can effectively replicate controller behaviour, we establish a foundation for data-driven models that can adapt to dynamic conditions, reduce reliance on hardcoded rules, and enhance decision-making processes in real-time systems.

A. PID Controller

The use of Proportional-Integral-Derivative (PID) controllers has become the standard in temperature regulation due to their proven ability to maintain stability and fast response. With a careful combination of proportional settings to adjust output according to temperature differences, integration to deal with errors that accumulate over time, and derivatives to predict future changes, PID controllers can handle temperature variations efficiently and accurately. Its wide use in various industries, from manufacturing to chemical processes, confirms its reliability in maintaining temperatures at desired values, making it the top choice for effective and efficient temperature control [33]-[36].

PID controller stands for proportional, integral, and derivative controller combined. Because each of the three types of controllers has pros and cons of their own, the outcomes obtained when using them separately are not favourable. It is anticipated that combining these three types of controllers into one control system will enhance their benefits. Proportional control is a linear amplifier whose gain can be adjusted. The relationship between the controller output $m(t)$ and the error signal $e(t)$ is described in the below equation. Which K_p is the constant variable that stands for proportional gain.

$$m(t) = K_p e(t) \tag{1}$$

Next is the integral controller which is the change of the integral output $m(t)$ related to changes of time to the error signal $e(t)$. The relationship between two variables is conducted in the equation below.

$$m(t) = K_p e(t) + \frac{K_p}{\tau_i} \sum_{i=1}^{n_t} e_i\,(t) \Delta t \tag{2}$$

The integral time τ_i regulates the integral control action, while K_p enhances both the proportional and integral components of the control action. The reciprocal of the integral time $(\frac{1}{\tau_i})$ is known as the reset rate, indicating how frequently the integral action reiterates or "resets" the proportional action's contribution per second. Last, derivative control is defined by

$$m(t) = K_p e(t) + K_p T_d \frac{PV_{n_t} - PV_{n_{t-1}}}{\Delta t} \tag{3}$$

Derivative control, also known as rate control, generates an output that corresponds to the speed at which the error signal changes. The derivative time, T_d, represents the duration over which the proportional control response is amplified due to the rate of change. Then, we can summarize the PID equation given as follows

$$m(t) = K_p e(t) + \frac{K_p}{\tau_i} \sum_{i=1}^{n_t} e_i\,(t) \Delta t - K_p T_d \frac{PV_{n_t} - PV_{n_{t-1}}}{\Delta t} \tag{4}$$

B. LSTM Emulation

To realize the emulation of PID controller behaviour with LSTM, it is designed according to the research stages shown in Fig. 1.

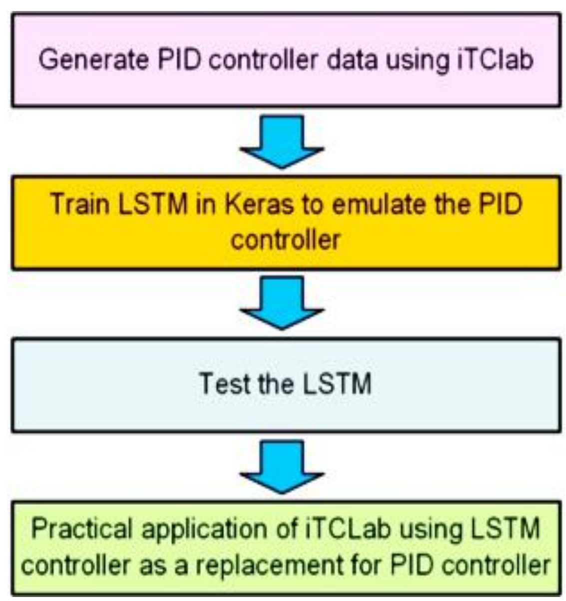

Fig. 1. Steps of the proposed method.

From Fig. 1, the stages begin with the preparation of the dataset. As discussed previously, this research uses the iTCLab plant. Therefore, the first stage is to prepare a dataset obtained from running the PID controller on the iTCLab. Several arrays are prepared to store data over time, and the controller is run to ensure that a lot of data is obtained. The temperature setpoint is changed periodically so that a good mix of steady-state and transient behaviour is obtained. The method of changing the set-point as a powerful method to improve the transient performance has been developed and proved to be practical in references [37]-[39]. The method works with the help of the hybrid system approach [40]-[42].

Next, in the second stage, after having some data to work with, we want to see if LSTM can emulate the behaviour of the PID controller. LSTM has become a popular approach for all kinds of machine learning models due to its versatility. What distinguishes it from standard recurrent neural networks is the presence of its cell memory units, which help to overcome the vanishing gradient problem. The vanishing gradient issue arises during the training of recurrent neural networks using gradient-based learning techniques and backpropagation.

In the context of emulating the PID controller, a window of data is input, such as temperature, setpoint, error, or heater value, and the next heater value is predicted to reach the desired setpoint. This prediction emulates the output that would be given by the PID controller with certain tuning constants. If the tuning constants change, then the type of controller behaviour changes. This is an interesting idea to explore.

In this stage, we look at what features are useful to include in the model. Intuitively, the PID controller takes the error between the sensor temperature and the setpoint as input, so it is likely that the LSTM will need it. In addition, there are many hyperparameters that can be used to optimize the fidelity of the LSTM to the PID controller. The appropriate ones are selected. Next, the LSTM model is created and trained with the prepared dataset.

Next is the third stage, which is testing the LSTM. Before using the LSTM to control the iTCLab, we want to make sure its behaviour is close to what the PID controller will do. This is not only important for sanity checks, but it is also an important safety issue. One can imagine using a temperature controller on a reactor that is not sure if it will work properly. If it does not work properly and an unintended reaction occurs, it can cause a lot of chaos.

Fortunately, we already have some prepared data samples, all in the correct format that the LSTM expects to be input. Later, we need to see that, considering the input, the LSTM's heater output prediction is in line with what the PID controller will do. Make sure no data scaling is used so that the actual values are obtained.

And the last stage, if we already have a well-functioning LSTM model, then the last step is to encode it as a controller. Then, direct testing is carried out to control the iTCLab plant using the LSTM controller as a replacement for the PID controller. Next, all that remains is to check and analyse the results of the LSTM performance replacing the PID Controller in controlling the iTCLab plant. Therefore, the design of the PID controller emulation architecture with LSTM is as shown in Fig. 2.

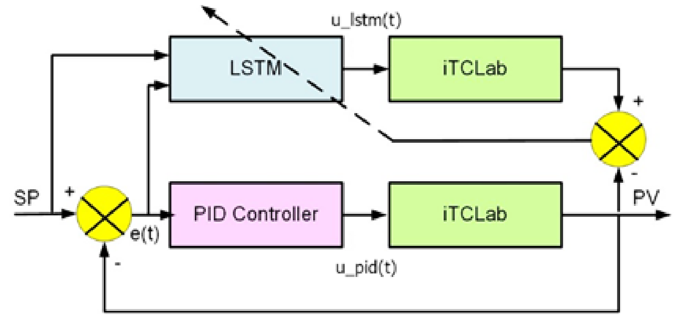

Fig. 2. Proportional Integral Derivative Controller (PID) Modeling and Emulation Architecture with Long Short-Term Memory Network (LSTM).

C. *iTCLab*

This project implements a PID control system with the iTCLab Kit, a purpose-built platform for remote temperature experiments. The kit's design centers on an ESP32 microcontroller, which facilitates Internet of Things (IoT) connectivity for monitoring and control. Key components are two TMP36GT9Z sensors for accurate temperature sensing and two TIP120 transistors that act as heaters. The heaters are positioned close together to produce complex, second-order system dynamics ideal for advanced control studies. For precision, the ESP32 uses its 12-bit Analog-to-Digital Converter to process sensor data and Pulse Width Modulation (PWM) to manage the heaters and an LED. Figures 3 and 4 provide visual references of the kit and its circuit layout.

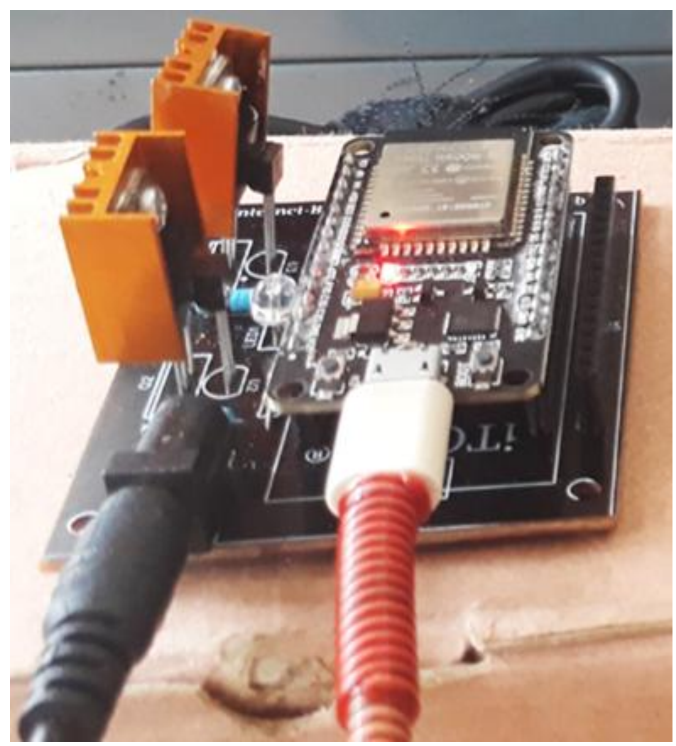

Fig. 3. Internet-Based Temperature Control Lab (iTCLab) kit.

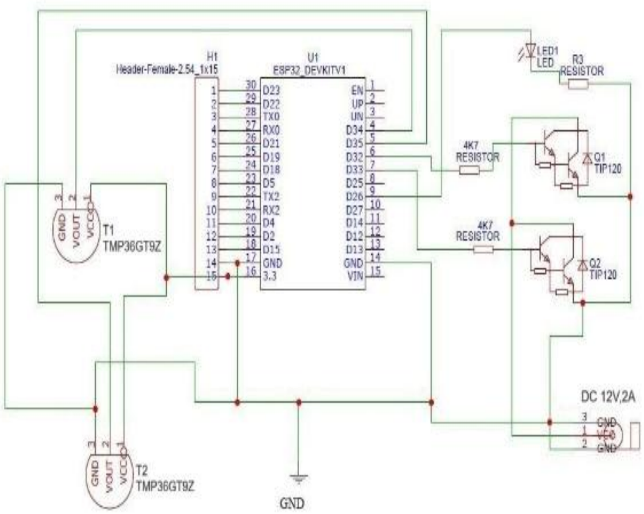

Fig. 4. iTCLab Circuit Layout.

D. LSTM

Long Short-Term Memory (LSTM) is a specialized form of Recurrent Neural Network (RNN) designed to handle long-term dependencies by retaining information over extended periods. In LSTMs, the traditional hidden layer nodes in RNNs are replaced by LSTM cells, which function as storage units for prior knowledge. Each LSTM cell consists of three gates: the input gate, forget gate, and output gate. These gates work together to control how past information is read, stored, and updated within the memory cell, enabling efficient management and utilization of historical data [43]-[45].

For conventional RNNs, the vanishing gradient issue led to the development of the LSTM architecture. The reason for the disappearing gradient is because it never converges or produces better results because the gradient gets less until the last layer, keeping the weight value constant. Nevertheless, the optimization procedure turns divergent, or explodes the gradient, when the increasing gradient drives the weight values in other layers to increase as well. The architecture of LSTM model shown in Fig. 5.

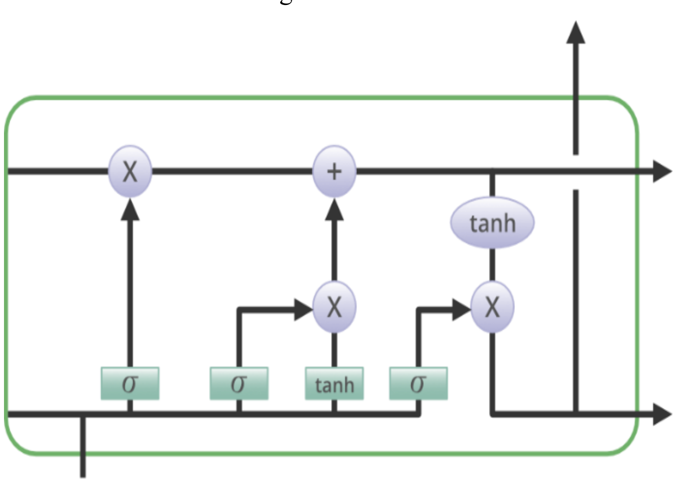

Fig. 5. LSTM Architecture.

LSTM algorithm has several stages in processing, there are Input Gate, Forget Gate, and Output Gate [46]. For the Input Gate equation is conducted below

$$i_s = \sigma(w_i x_s + u_i h_{s-1} + b_i) \tag{5}$$

The input gate, denoted as i_s, is determined by the weight w_i applied to the input value x_s at time s, combined with the weight u_i applied to the output value h_{s-1} from the previous time step s-1, plus the bias b_i at the input gate, with σ representing the sigmoid activation function. The equation for the forget gate is provided below.

$$f_s = \sigma\left(w_f x_s + u_f h_{s-1} + b_f\right) \tag{6}$$

The forget gate, denoted as f_s, is determined by the weight w_f applied to the input value x_s at time s, combined with the weight u_f applied to the previous output h_{s-1} from time s-1, plus the bias term b_i at the forget gate, with the sigmoid function σ as the activation. The output gate is explained subsequently.

$$o_s = \sigma(w_o x_s + u_o h_{s-1} + b_o) \tag{7}$$

The output gate, denoted as o_s, is determined by the weight w_o applied to the input value x_s at time s, the weight u_o applied to the previous output value h_{s-1} from time s-1, the bias term b_o at the output gate, and the sigmoid activation function σ.

III. Results and Discussion

As described in the methodology section, in the second stage, after having some data to work with, we wanted to see if the LSTM could emulate the behaviour of the PID controller. We have included a data window, such as temperature, setpoint, error, or heater value, and predict the next heater value to reach the desired setpoint. This prediction emulates the output that a PID controller would give with certain tuning constants. If the tuning constants change, then the type of controller behaviour changes. Useful features are included in the model. Intuitively, the PID controller takes the error between the sensor temperature and the setpoint as input. In addition, the appropriate hyperparameters are selected. Next, the LSTM model is created and trained with the prepared dataset. From the results of the LSTM training, the following results are obtained:

Parameters:

Input LSTM	:	PV and error
Output	:	Q (PWM) for heater
Layer LSTM	:	
• Layer	:	2
• Dropout	:	2
Optimizer	:	Adam
Batch Size	:	100
Loss	:	MSE (Mean Squared Error), Train 0.002, Val 0.00069

Next, after the LSTM training process, LSTM testing is carried out. Before using LSTM to control iTCLab, we want to make sure its behavior is close to what the PID controller will do. The results of the LSTM test are shown in Fig. 6.

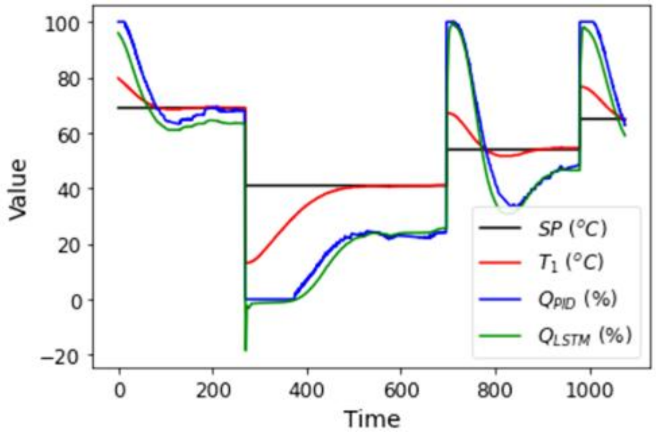

Fig. 6. LSTM test results.

From Fig. 6, we can see the setpoint and T1 data (from which the error value is obtained), and the actual data from the PID controller with parameters $K_P = 6, K_I = 0.08$, and $K_D = 0$.The green color then shows how the LSTM will behave, with exactly the same input dataset. It seems to follow the behavior of the PID controller with tight accuracy, so it should be tried as a proxy controller, with just one adjustment. From the figure, it can be seen that the LSTM output sometimes exceeds the [0, 100] range that is bound to the heater. This should be limited to the [0, 100] range when we encode it as a controller according to real-world conditions.

Next, in the last stage, if we already have a well-functioning LSTM model, then the last step is to encode it as a controller. Then, direct testing is carried out to control the iTCLab plant using the LSTM controller as a replacement for the PID controller. From the results of testing the control of the iTCLab plant using the LSTM controller, the results are obtained as shown in Fig. 7 and Fig. 8.

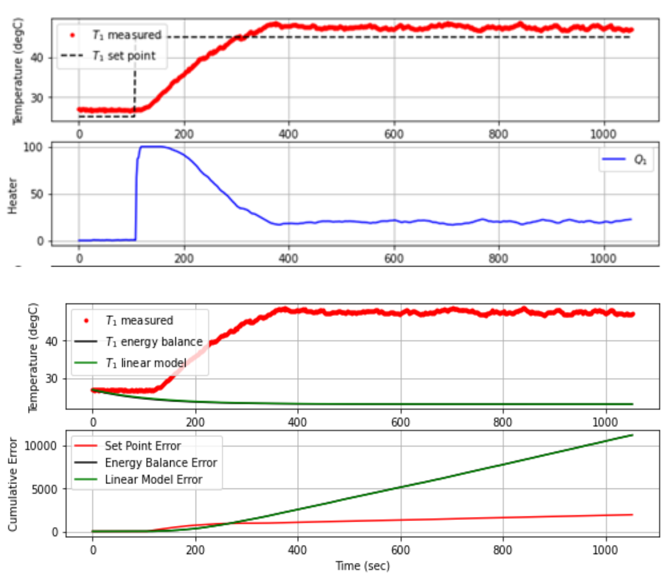

Fig. 7. The results of controlling the PID Emulator with LSTM.

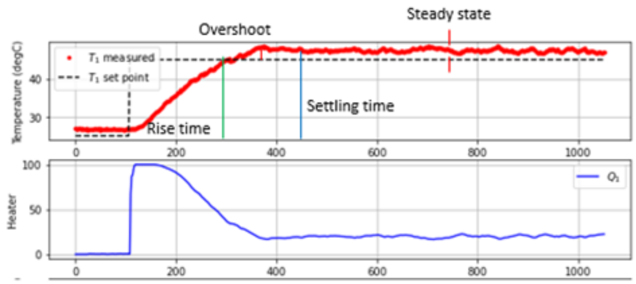

Fig. 8. System Response Time Analysis.

The results of the system response time analysis according to the experimental results in Fig. 8 are as follows:

Rise time	:	180 s
Overshoot	:	(47-45/47)*100% = 4.25%
Settling time	:	450 s
Steady state error	:	reference value-steady value = 45-47 = 2

The system's evaluation confirms the superior performance of the LSTM controller, which achieves a lower steady-state error than both the energy balance and linear FOPDT models. Its response is characterized by a smooth, gradual rise time of about 180 seconds, a minimal 4.25% overshoot, and a settling time of 450 seconds. This profile—marked by a slow but stable ascent, negligible overshoot, and a definitive return to a narrow band around the setpoint—demonstrates a controller that prioritizes stability and precision. The resulting steady-state error is a negligible 2 units, underscoring the LSTM's accuracy for long-term control in industrial applications.

Additional research and refinement could improve specific performance elements and fine-tune system parameters. Nevertheless, this study establishes a strong basis for progressing the development and application of LSTM control in real-world industrial systems.

IV. Conclusion

The emulation of a Proportional Integral Derivative (PID) controller using an intelligent Long Short-Term Memory (LSTM) network to manage the Internet-Based Temperature Control Lab (iTCLab) plant was successfully implemented. This is evidenced by minimal overshoot and a low steady-state error. Despite a relatively slow rise time, the system demonstrates its capability to deliver stable and precise control.

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