

# Generative AI-Assisted PID Tuning from Control Performance Requirements toward Instructional Use

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**Abstract:** PID parameter tuning has traditionally relied on the expertise of the tuner, requiring an understanding of the effects of proportional, integral, and derivative actions. However, in practice, users often possess control performance requirements without having such specialized knowledge. On the other hand, generative AI, exemplified by ChatGPT, has made remarkable progress and can emulate human trial-and-error behavior depending on prompt design. It can also acquire PID tuning know-how from the vast amount of information available on the web. In this study, we propose a method for obtaining PID parameters that meet control performance requirements using generative AI, even in the absence of expert knowledge. Furthermore, we discuss the potential application of this method to interactive educational simulators, where learners can experience control tuning through dialogue with AI. This research provides a foundation for bridging control engineering education and AI-driven instructional tools.

**Keywords:** PID control, Generative AI, Control Performance

## 1. INTRODUCTION

Various tuning methods for PID control have been proposed. However, in practice, trial and error is often required at the field level. This tuning process heavily relies on the know-how of the person performing the adjustment, including an understanding of the effects of proportional, integral, and derivative actions. While field users may have required specifications, they often lack such knowledge.

On the other hand, generative AI, exemplified by ChatGPT[1], has made remarkable progress. In the field of control engineering, there have been reports of using AI for model and/or controller design[2]. With appropriate prompt settings, generative AI can potentially substitute human trial and error even in PID parameter tuning. In this paper, we explore a method for tuning PID parameters using generative AI technology[3], [4]. We verify whether it is possible to derive parameters that meet required specifications through interaction with generative AI, even without expert knowledge.

## 2. PROBLEM SETTING

When tuning PID parameters, if a mathematical model reproducing the plant characteristics is available, repeated simulations can be conducted to reach optimal parameters. However, field adjustments are typically required in cases where the control performance degrades due to changes in the plant's behavior. This study assumes a scenario where the system is already stable but aims to improve control performance.

We assume the following conditions:

The control law follows a discrete-time PID control law:

$$\Delta u(t) = K_p \Delta e(t) + K_I e(t) + K_D \Delta^2 e(t) \quad \dots (1)$$

where,  $K_p$ ,  $K_I$  and  $K_D$  are PID parameter. The initial response based on the initial PID parameter set is given,

and parameter tuning is performed to improve this response. The controlled system is given as:

$$G(s) = \frac{0.7}{30s+1} e^{-s} \quad \dots (2)$$

The initial response obtained using the following PID parameters

$$K_p = 0.5, K_i = 0.5, K_d = 0.5$$

the control system described in equation (2) is shown in Fig. 1. This result was given as text of time series data.

Under this condition, the following prompt is given to ChatGPT-4o, one of the generative AIs:

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You are a skilled professional control engineer. This is not a step response. A PID controller was implemented with a sampling period of 1 second and a target value of 25, using parameters  $K_p = 0.5$ ,  $K_i = 0.5$ , and  $K_d = 0.5$ . The PID control law is given as:  
 $u[t] = u[t-1] + K_p*(e[t] - e[t-1]) + K_i*e[t] + K_d*((e[t] - e[t-1]) - (e[t-1] - e[t-2]))$

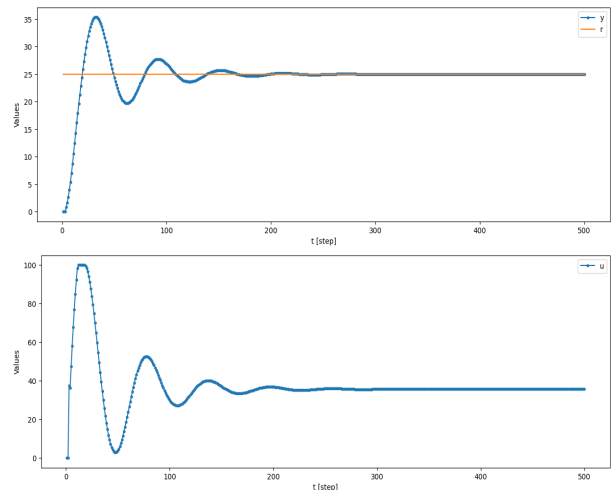


Fig. 1: Initial control result.

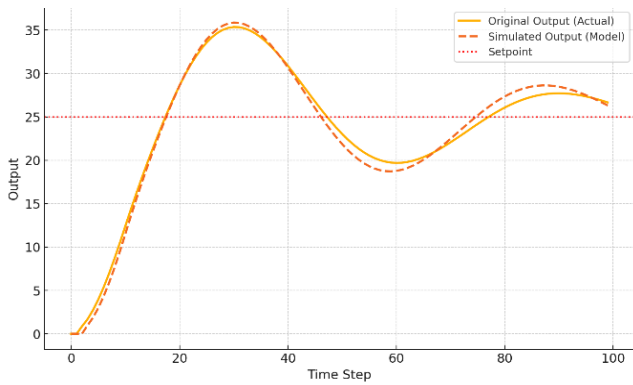


Fig. 2: Comparison Between the Initial Response and the Model Output by AI.

-[] From this response, use the least squares method to identify the parameters of the discrete-time model  $y(t) = a*y(t-1) + b0*u(t-1) + b1*u(t-2)$ , and calculate the time constant and system gain from the identified model. Report the results. Then, perform a control experiment using the initial parameters on the identified model and verify whether the resulting response matches the initial one.

-[] Perform repeated simulations in Python on the identified model and determine PID parameters that yield a control result satisfying the following conditions. Use the initial parameters  $K_p = 0.5$ ,  $K_i = 0.5$ , and  $K_d = 0.5$  as the starting point:

1. No steady-state error
2. Overshoot must not exceed 30 for a setpoint of 25
3. The 5% settling time must be within  $t = 30$

-[] Also present the result of this simulation  
 -[] The setpoint is 25  
 -[] The input  $u$  is constrained between a minimum of 0

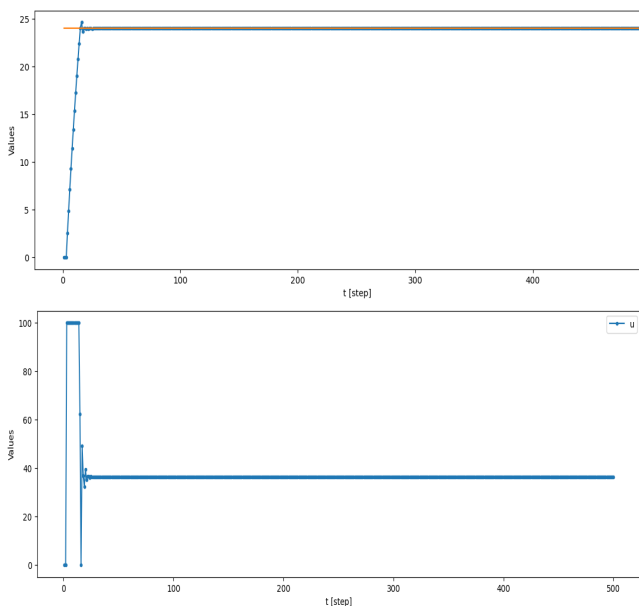


Fig. 3: Tuned control result 1.

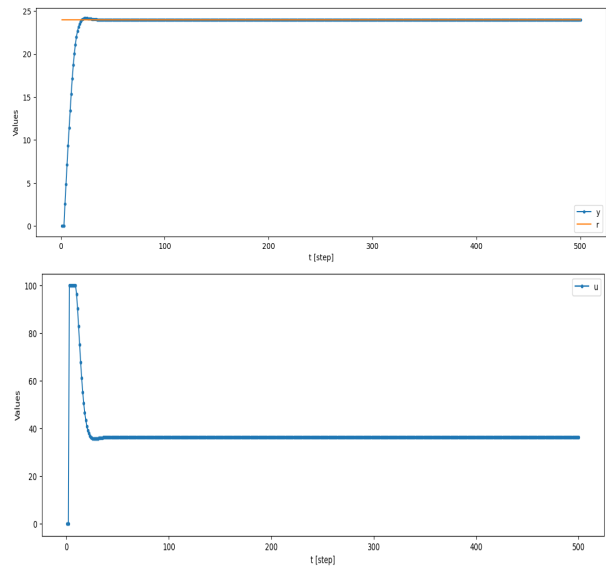


Fig. 4: Tuned control result 2.

and a maximum of 100

-[] All PID parameters must be positive values

The results obtained from the above prompt are shown below. First, a model was constructed based on the initial response, as expressed by the following equation.

$$y(t) = 0.963y(t-1) + 0.0254u(t-1) - 0.00101u(t-2),$$

A comparison between this model and the initial response is shown in Fig.2. Next, the initial PID parameters proposed by the AI were as follows.

$$K_p = 20.18, K_i = 91.27, K_d = 0.01$$

The corresponding results are shown on Fig.3. This response was highly oscillatory due to input saturation. In response, a command was issued: "This is too oscillatory. re-tune for more good result." As a result, the AI proposed the following PID parameters.

$$K_p = 14.51, K_i = 2.85, K_d = 0.55$$

The results of this tuning are shown in Fig. 4.

### 3. CONCLISIONS

In this paper, we examined whether AI can adjust PID parameters in response to control performance requirements specified by the designer (or requester). A mathematical model was created from the input-output data of the initial response, and it was confirmed that the simulation results closely matched the actual response. When the results from the AI-adjusted PID parameters were insufficient, it was found that providing performance-based feedback led to improved control performance.

On the other hand, the method used by AI to tune PID parameters employs an algorithm that closely resembles trial-and-error, and it can be said that there is no need to explicitly apply traditional PID tuning

rules such as those originating from the Ziegler–Nichols method. How to approach education in this field remains an important issue to be addressed in the future.

This research was supported by The Telecommunications Advancement Foundation and JSPS KAKENHI Grant Number 25K00756.

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