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A Comparative Study of Data-Driven Control Tuning: VRFT and FRIT for DC Motor Speed Regulation

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ABSTRACT

This study compares two data-driven control tuning methods Virtual Reference Feedback Tuning (VRFT), and Fictitious Reference Iterative Tuning (FRIT) applied to a DC motor speed control system. Both methods aim to achieve a predefined closed-loop behaviour without explicit plant modelling, relying instead on measured input–output data. For the VRFT method, single-shot open-loop data were collected using a PRBS signal to excite the DC motor, while FRIT used a single-shot closed-loop experiment under an initial PI controller. Each method used the same reference model, a first-order system with a 2 second time constant, to guide the tuning process. The VRFT approach produced a 6-DOF controller through least-squares optimization, whereas the FRIT method refined the parameters of a PI controller by minimizing a defined cost function. Simulations conducted at target speeds of 60 and 100 RPM demonstrated that both controllers delivered comparable tracking performance, despite having different structural designs. These findings confirm that both VRFT and FRIT can generate effective control strategies from limited data, providing design flexibility while still achieving the desired closed-loop behaviour.

1. Introduction

In the design of DC motor speed control systems, an accurate mathematical model of the plant plays a critical role in achieving desired performance, stability, and robustness. Traditional control design approaches, such as PID tuning [1][2], optimal control [3], or state feedback [4][5], generally rely on having an explicit model that captures the system's dynamics. However, in many real-world applications, deriving such a model can be difficult due to system complexity, nonlinearity, unmodeled dynamics, or measurement noise. This modelling often limits the applicability of advanced control strategies in practical scenarios.

Several empirical and analytical tuning methods have been developed to overcome the need for exact models. The Ziegler-Nichols method, for instance, uses step-response or critical-gain experiments to obtain PID parameters based on observed time-domain behaviour [6][7]. In the frequency domain, bode plot analysis provides a graphical technique for controller design by shaping the loop gain to meet phase and gain margin specifications [8]. While these techniques have been widely adopted due to their simplicity, they still require some degree of modelling effort estimating time constants or frequency response and often involve trial-and-error.

To address these limitations, data-driven control has appear as a promising alternative, where controllers are directly tuned from input-output data without explicit system identification. Methods like Virtual Reference Feedback Tuning (VRFT) [9] and Fictitious Reference Iterative Tuning (FRIT) [10] those two methods offering practical solutions when plant models are unavailable or unreliable. These techniques aim to approximate a desired closed-loop behaviour by processing collected data in either open loop or closed loop structure. By eliminating the model-building step, data-driven control not only simplifies the design workflow but also enables fast adaptation and better scalability for complex or poorly understood systems.

In this paper, we aim to explore data-driven control by simulating the speed regulation of a DC motor using both VRFT and FRIT methods. The system is constructed and tested using Proteus simulation software alongside a microcontroller, which emulates a real-time embedded environment. To ensure a fair and consistent comparison, both control strategies will be evaluated using the same reference model, representing the desired closed-loop behaviour. For the VRFT method, we adopt a 6-degree-of-freedom (6-DOF) controller structure that allows flexibility in shaping the closed-loop dynamics through higher-order error feedback terms. Meanwhile, the FRIT method is implemented using a simple and common PI controller, which is more typical in real-time. The phenomenon under observation includes the procedure of both algorithm and implement control strategies in embedded system. By simulating both approaches under the same plant reference model, this research highlights the trade-offs between model flexibility in VRFT and FRIT, offering insights into their practical deployment in embedded control systems.

2. Methods

2.1. Virtual Reference Feedback Tuning (VRFT)

The goal of this method is to tune a controller $C(z,\rho)$ directly from data so that the resulting closed-loop system mimics a desired reference model $T_d(z)$ using only one batch of open-loop data. Choose a stable reference model such as (1) describes the target closed-loop response. This defines the desired closed-loop transfer function denoted in discrete time as model represents the target behaviour. Apply a persistently exciting input $u(k)$ to the real plant and record the output $y(k)$ producing a dataset (2). This is done in open loop.

$$T_d(z) = \frac{Y_d(z)}{R(z)} \tag{1}$$

$$D_N = \{u(k), y(k)\}_{k=1}^{N} \tag{2}$$

Define a parametric controller $C(z,p)$ where $\varphi_i(z)$ are basis functions, and $\rho = [\rho_0, \rho_1, \dots, \rho_n]^T$ is the parameter vector to be tuned. Using the desired model and the plant output, define the virtual reference. This equation simulates the reference signal that would produce $y(k)$ if the plant followed T_d. The filter (3) is introduced in VRFT. Applying the filter is equivalent to reformulating the cost function so that the bias introduced by using real data instead of ideal data is minimized.

$$L(z) = T_d(z).(1 - T_d(z)) \tag{3}$$

$$u_L(k) = L(z).u(k) \tag{4}$$

From the (3), we can compute the virtual error and apply the parametric controller (4) to this virtual error (5). This is the control action that should have produced $y(k)$ if the closed loop behaved like T_d.

$$e_L(k) = L(z).(T_d^{-1}(z) - 1).y(k) \tag{5}$$

$$u_v(k,\rho) = C(z,\rho).e_v(k) \tag{6}$$

Compare the actual input $u(k)$ and the virtual one using (6). This cost measures how well the chosen controller structure matches the ideal closed-loop response in (7). Solve for ρ that minimizes the cost. And implement the optimized controller $C(z,\rho^*)$ by (8) in the real-time control loop.

$$J_N(\rho) = \sum_{k=1}^{N} \|u(k) - u_v(k,\rho)\|^2 \tag{7}$$

$$\rho^* = \arg\min_{\rho} J_N(\rho) \tag{8}$$

2.2. Fictitious Reference Iterative Tuning (FRIT)

The aim of this method is to tune a controller in a closed-loop setting using only one-shot experiment data and perform offline optimization with a fictitious reference signal. Tune a controller like PI in closed loop using only one-shot data from a test experiment, via iterative optimization based on a fictitious reference.

Define a controller structure or equivalently in the time domain such as (9). Typically use a PI let $\rho = [\rho_1, \rho_2]^T$.

$$C(z,\rho) = \rho_1 + \rho_2 . \frac{1}{1 - z^{-1}} \tag{9}$$

$$u(k) = u(k-1) - \rho_1 . e(k) + \rho_2 . e(k-1) \tag{10}$$

Apply $C(z, \rho_0)$ as an initial stabilizing controller to the plant and collect (11). This is closed-loop data from one test.

$$D_N = \{r(k), u(k), y(k)\}_{k=1}^{N} \tag{11}$$

Define a specify reference model $T_d(z)$ that defines desired output dynamics. Compute fictitious reference signal (11) by using the actual input and output to simulates what reference would cause the observed control action under controller ρ.

$$\bar{r}(k,\rho) = C(z,\rho)^{-1} . u(k) + y(k) \tag{11}$$

Calculate the output mismatch between actual output and desired model output using (12).

$$\bar{e}(k,\rho) = y(k) - T_d(z) . \bar{r}(k,\rho) \tag{12}$$

Define a performance index to minimizes this objective function (13). Update controller parameters iteratively using Gauss-Newton Iteration, repeat until convergence using (14). this optimum parameter corresponds to the optimum one in the real closed loop system in figure 1.

$$J_e(\rho) = \sum_{k=1}^{N} \|\bar{e}(k,\rho)\|^2 \tag{13}$$

$$\rho^* = \arg\min_{\rho} J_e(\rho) \tag{14}$$

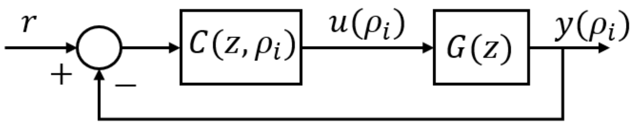

Figure 1: Diagram block of closed loop system

2.3. Experimental Setup

Both the VRFT and FRIT algorithms were implemented on a DC motor speed control system simulated using Proteus software, as illustrated in Figure 2. The system consists of a DC motor equipped with a rotary encoder, providing 48 pulses per revolution (PPR) to measure angular velocity. For the VRFT-based controller design, the required data were collected in an open-loop configuration. Specifically, a pseudo-random binary sequence (PRBS) signal was applied to the motor through a PWM signal, and the corresponding motor speed (RPM) was recorded as the system output. This open-loop input–output dataset forms the basis for identifying the controller parameters without explicitly modelling the plant.

In contrast, the FRIT-based controller design relies on data obtained from a closed-loop experiment. In this configuration, the motor operates under an initial stabilizing PI controller, and the following signals are recorded: (1) the reference input (desired speed), (2) the control signal (PWM), and (3) the measured output (actual motor speed). This single batch of closed-loop data is used to construct a fictitious reference signal, from which the controller parameters are iteratively refined offline.

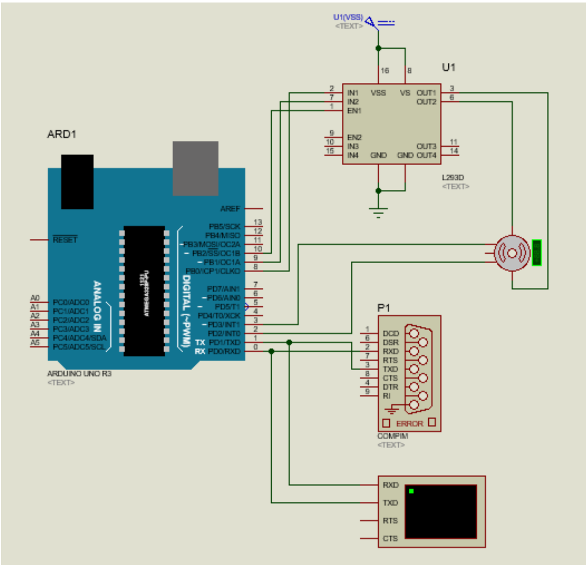

Figure 2: Wiring diagram of motor control system.

3. Results and Discussion

3.1. Results

In the implementation of the Virtual Reference Feedback Tuning (VRFT) method, the DC motor system was excited using a Pseudo-Random Binary Sequence (PRBS) input in an open-loop configuration. The PRBS signal served as the control input (PWM), and the corresponding motor speed output (measured in RPM) was recorded. The experiment was conducted with a sampling time of 0.1 seconds, and a total of 128 data samples were collected, ensuring a sufficiently rich excitation to capture the system dynamics. Here the figure 3 and figure 4 show the data of initial output and input for VRFT purposes.

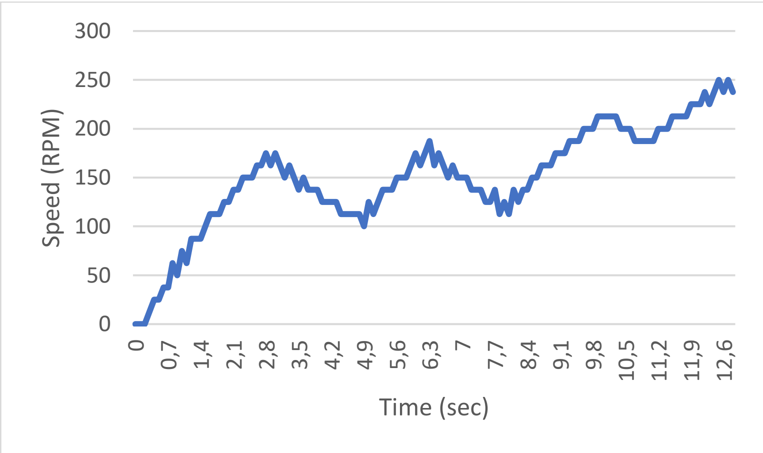

Figure 3: Initial output data for VRFT methods.

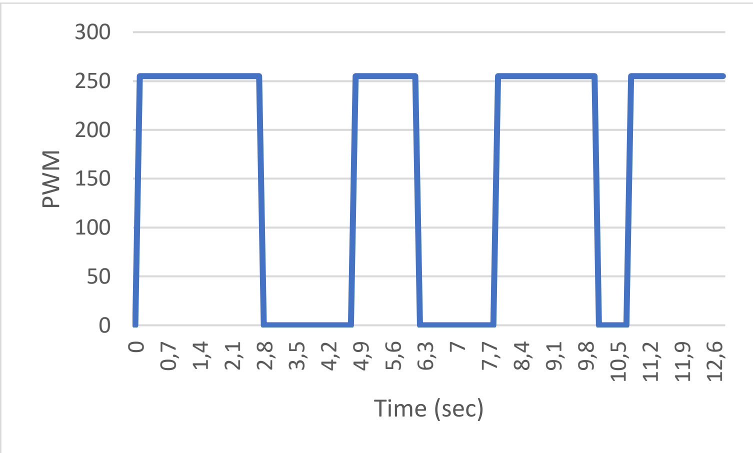

Figure 4: Initial input data for VRFT methods.

This dataset was then processed using the VRFT framework. The desired closed-loop behaviour was defined by a first-order reference model $T_d(z)$ with a time constant of 2 seconds. By using the optimal VRFT filter both the input and output signals were prefiltered to match the virtual feedback structure. A six-parameter controller structure based on integral basis functions was selected. Applying the least-squares fitting procedure to the filtered data yielded the following estimated controller parameters

$$\rho = \{0.850405 \quad 0.000344 \quad -0.541885 \quad -0.508115 \quad -0.066495 \quad 0.300311\}$$

$$C(\rho, z) = \sum_{i=0}^{5} \rho_i \cdot \frac{z^{-1}}{1 - z^{-1}} \tag{15}$$

To evaluate the performance of the identified controller, a step reference input was applied to the closed-loop system in simulation. The resulting output response was compared to the ideal reference model response defined by $T_d(z)$. The comparison demonstrated in figure 5-6 that the controller was able to closely reproduce the desired dynamics, with a stable rise toward the setpoint and smooth convergence. While slight deviations from the ideal model were observed due to unmodeled dynamics and noise in the data, the general behaviour of the system under control remained consistent with the target model.

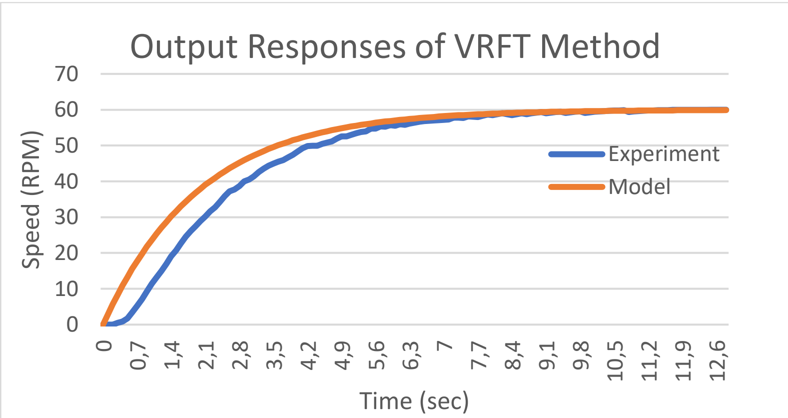

Figure 5: Comparison result of experiment using VRFT method.

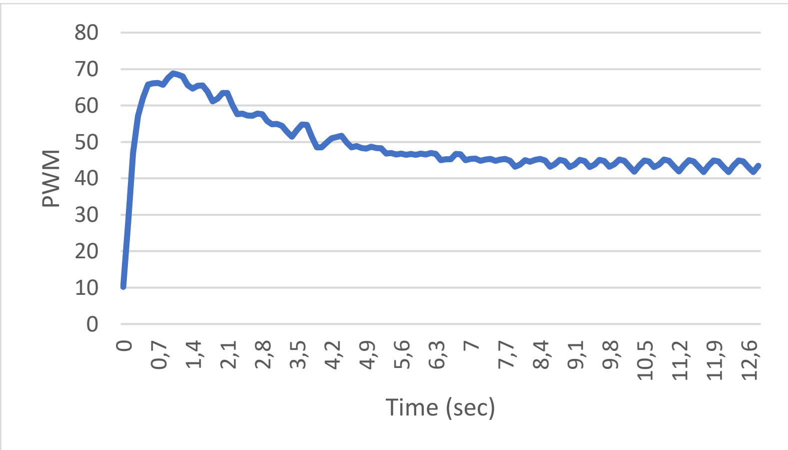

Figure 6: Control signal of VRFT method.

This confirms the effectiveness of VRFT in producing a high-performance controller using only a single batch of open-loop data and without requiring an explicit plant model. The identified controller not only tracked the desired reference but also preserved stability and robustness, making it suitable for embedded real-time applications such as the simulated DC motor system.

In the implementation of the Fictitious Reference Iterative Tuning (FRIT) method, a closed-loop experiment was conducted on the DC motor speed control system. The motor was initially controlled using a basic Proportional–Integral (PI) controller with manually set gains $K_p = 1$ and $K_i = 1$. Under this initial control law, the system was subjected to a predefined reference input (speed setpoint), and three key signals were recorded there are (1) the reference input $r(k)$, (2) the control signal $u(k)$, and (3) The measured output $y(k)$ as shown in figure 7-8

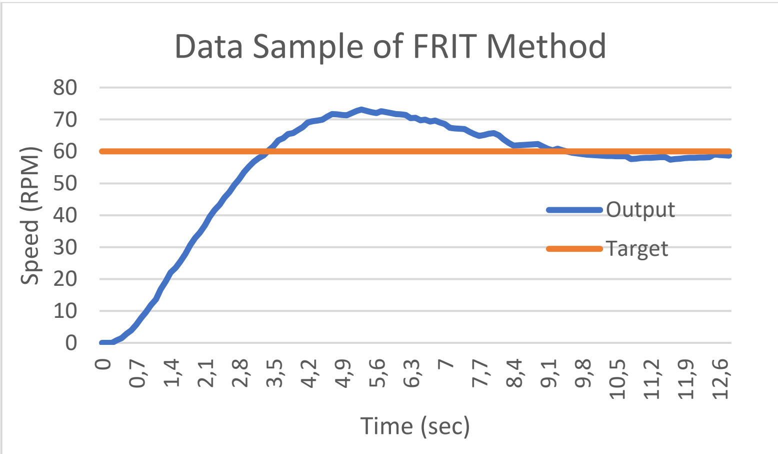

Figure 7: Initial output and reference data for FRIT method.

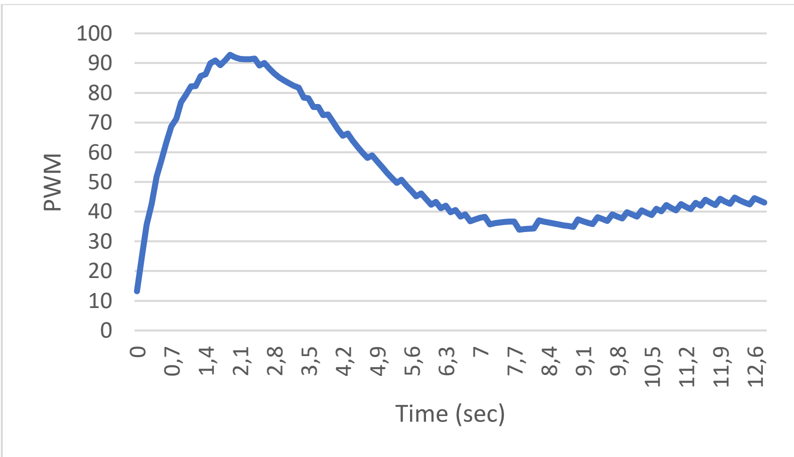

Figure 8: Initial output data for FRIT method.

Using the FRIT methodology, this data was used offline to compute a fictitious reference signal that represents the ideal behaviour the system would have exhibited under a desired reference model. The desired behaviour was modelled using a first-order transfer function with a time constant of 10 seconds same as the transfer function used for VRFT method.

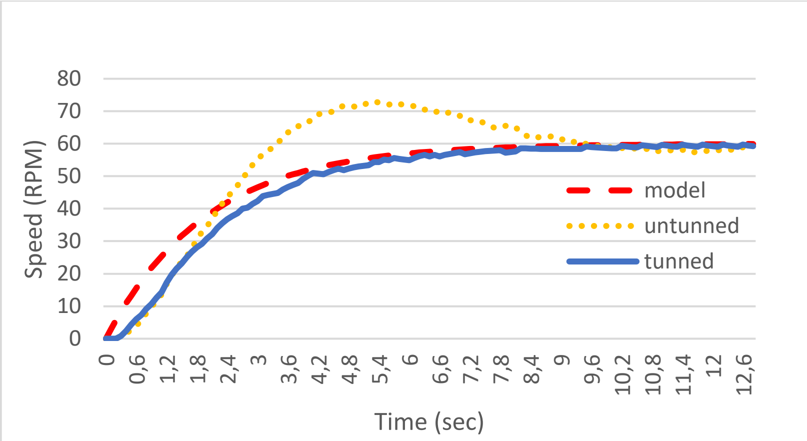

Figure 9: Comparison result of experiment using FRIT method

With this reference model, an optimization problem was formulated to minimize the error between the actual system output and the output that would have resulted had the system followed the model with the fictitious reference. This process involved iteratively updating the controller parameters using a numerical optimization technique. After 12 iterations, the algorithm converged to the following optimal PI controller parameters $K_p = 1.471769$ and $K_i = 0.336420$

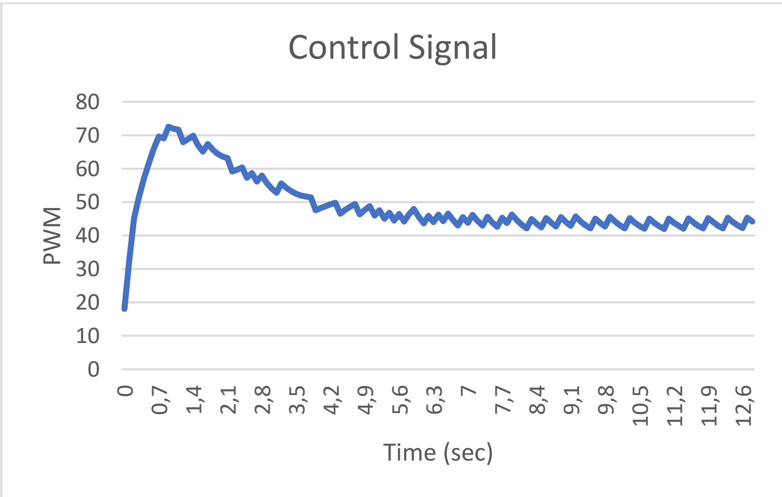

Figure 1: Control signal of FRIT method

These gains significantly improved the tracking performance of the closed-loop system, reducing the output mismatch with the reference model. The FRIT method successfully tuned the controller using only one set of closed-loop data, avoiding the need for plant modelling or repeated experiments.

1.1. *Discussion*

To evaluate the effectiveness of both control strategies, the VRFT and FRIT methods were each implemented in a DC motor speed control simulation using a target setpoint of 100 RPM in figure 11 and the control signal in figure 12. Despite differences in controller structure and tuning methodology, both approaches were designed to track the same desired closed-loop behaviour, as defined by a shared reference model with a first-order response and a 2 second time constant.

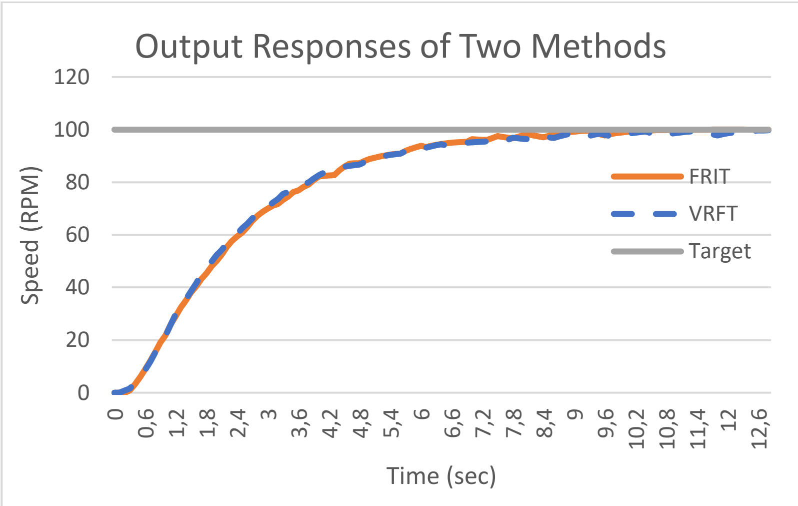

Figure 2: Comparison output responses

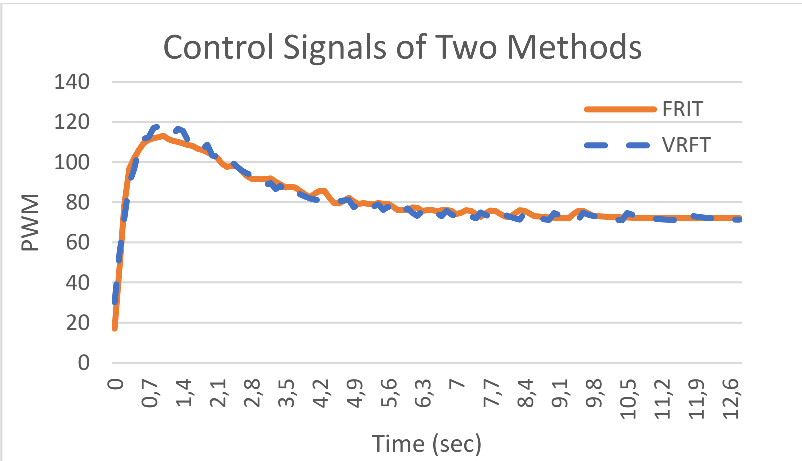

Figure 3: Comparison control signal

The VRFT method utilized a 6-degree-of-freedom (6-DOF) controller, offering a rich and flexible control law derived from open-loop data and optimized using least-squares fitting against a virtual reference signal. On the other hand, the FRIT method employed a classic PI controller structure, whose parameters were optimized iteratively from closed-loop data using fictitious reference signals and cost minimization. Simulation results revealed that both controllers achieved comparable performance, closely following the reference trajectory and effectively reaching the 100 RPM setpoint. This outcome confirms a key theoretical premise: when both methods are aligned with the same target model, the resulting control performance can converge to similar behaviour even if derived using different data-driven strategies and controller forms.

4. Conclusion

The experimental results demonstrate that both VRFT and FRIT methods can deliver effective speed control for a DC motor system, even when using fundamentally different controller structures and data collection schemes. By targeting the same reference model, both controllers exhibited comparable tracking performance to a 60 and 100 RPM setpoint. This confirms that data-driven control strategies can achieve consistent and reliable results without requiring explicit system identification. VRFT offers high flexibility with open-loop data and multi-parameter tuning, while FRIT provides an efficient, model-free solution using closed-loop data and a simpler PI structure. Beyond the 6-DOF controller used in VRFT, other practical controller structures can also be considered. For instance, standard PID controllers, lead-lag compensators, or two-degree-of-freedom (2-DOF) controllers can be structured into the VRFT framework by selecting appropriate basis functions. In FRIT, more advanced forms such as fractional-order PI controllers, gain-scheduled PI, or nonlinear feedback laws can be optimized iteratively, provided the controller remains differentiable or parameterizable. These alternatives may offer improved performance or easier hardware implementation, particularly in systems with specific dynamic constraints or limited computational resources.

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