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Turbojet Engine Control of Unmanned Aerial Vehicle Using Artificial Intelligence Algorithm

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ABSTRACT

Recently, as the field of unmanned aerial vehicles (UAV) is rapidly developing, the scope of required missions is expanding and upgrading. As high-level manoeuvres are required according to the performance mission, related research and development are continuously underway. In particular, engine control of UAV requires various maneuver characteristics depending on the mission, and engine controller design to achieve stability and goals is essential. The control system of a small turbojet engine for UAV shall maintain safe and fast transient response characteristics even if the operating state changes within the normal range of the engine and shall be protected from exceeding the allowable operating range of the engine to meet these design requirements. In this paper, we propose an artificial neural network engine control algorithm for the optimal operation of turbojet engines, which are mainly used in small UAV for high-speed and long-distance use. The artificial neural network was learned by applying the backpropagation algorithm, which is a structure of multi-layer perception (MLP) and was designed to reduce errors by measuring the difference between the desired value and the actual value. In order to reflect the nonlinear characteristics of the turbojet engine in the controller design, the dynamic analysis code of the engine was written, and the limitations of linear analysis were verified from the linear model using the code to prove the utility of the design. The simulation was designed through MATLAB and compared the performance with the existing PID controller, and the proposed controller algorithm ensured operation within a safe range, such as compressor surge, combustion stop area, and turbine temperature limitation, and proved its usefulness. The results of this study are expected to be used in large UAVs and UAM fields in the future.

Keywords: *Deep learning, artificial intelligence, turbojet engines, small unmanned aerial vehicles, surge control.*

1. INTRODUCTION

Unmanned Aerial Vehicles(UAM) refer to an autonomous flying aircraft that recognizes and determines obstacles and routes around the aircraft according to pre-populated programs using sensors and computers mounted without pilots [1]. The engines used in unmanned aerial vehicles are classified as turbojet engines, turbopen engines, and turboprop engines, and future unmanned aerial vehicles are selected as engines for unmanned aerial vehicles to be controlled in this study because they require rapid deployment, short take-off and landing, and high-speed flights to enemy areas. The engine control system for controlling the small turbojet engine for unmanned aerial vehicles shall maintain safe and rapid transient response characteristic performance even if the operating state changes within the normal state range of the engine. To meet these design requirements, the engine shall be protected from outside the allowable operating range, and the controller shall be designed to ensure operational reliability within the range of expected operating conditions [2]. Among the control elements of the turbojet engine, the most important control elements are the fuel flow rate and the exhaust nozzle area, as well as the air inlet, the guide collar of the nozzle, and the air bleed valve. When controlling the fuel flow rate, a rapid increase in the fuel flow rate may cause the engine to deviate from operating limits such as compressor surge or flame loss. In particular, the surge phenomenon is a factor that causes the compressor to stall due to the increase in back pressure in the air flow, which can increase the turbine inlet temperature excessively due to the decrease in the air flow in the engine. Therefore, the main point of the jet engine controller design is to accurately detect rotor rotational speed, temperature, and pressure, which are thermodynamic and mechanical state variables of the turbojet engine, and apply them quickly within a thermal stability range to effectively control the fuel flow input to have high- In the case of small turbojet engine control for unmanned aerial vehicles, as the model characteristics of the engine system are identified, intelligent control such as neural network and genetic algorithms such as engine control unit [3] and neural network [4] and fuel flow controller [5][6] are being actively studied to calculate fuel flow.

If a speed sensor is used to measure the rotational speed information of a compressor rotor to control the fuel flow, the rotational speed can be continuously detected, but the precise speed information can have limitations depending on the operating speed. As a solution to this problem, when using a high-resolution sensor, precise speed measurement is possible at low speeds, but the higher the resolution, the more expensive the sensor is, and it is difficult to obtain accurate speed information at high speeds. In addition, the use environment is limited because it is greatly influenced by the surrounding environment such as vibration and humidity [8]. In the case of a small turbojet engine, speed detection using a sensor is not suitable because it is greatly affected by the surrounding environment. Therefore, using a method of estimating speed by designing an observer without detecting speed using a speed sensor, it is not affected by the surrounding environment and does not need information on the system's dynamic characteristics and internal parameters, and is easy to implement.

This paper aims to prevent surge and flame loss that can occur during acceleration and deceleration by controlling fuel flow through a controller designed with neural network PID control technique by designing a high gain observer to estimate engine rotation speed and feedback the estimated speed.Simulations using MATLAB were conducted to confirm the performance of the designed controller.

2. TURBOJET ENGINE

2.1 Turbojet Engine Model

The structure of a typical turbojet engine consists of a diffuser, a compressor, a combustion chamber, a turbine and an exhaust nozzle, as shown in Figure 1. The diffuser sends air to the compressor and further compresses the air from the compressor and sends it to the combustion chamber. In the combustion chamber, the fuel nozzle continuously discharges fuel, causing continuous combustion under almost static pressure. The high-temperature, high-pressure gas then enters the turbine, and in the turbine, the gas absorbs all power generated to give the power to drive the turbine into the compressor and auxiliary equipment. After passing through the turbine, the gas may obtain thrust through a process of ejecting at a higher speed from the injection nozzle. If transient characteristics such as temperature and pressure at the beginning of the response violate the thermodynamic stability of the jet engine, the controller design target model can cause damage to parts such as turbines due to operation or thermal shock[10]. Therefore, the controller shall be designed to note out for surge operating points without the surge and flame-out phenomena, and the points are shown in Figure 2.

To design a controller to obtain high-performance, high-motion thrust characteristics that determine the stable and rapid response characteristics of the engine to fuel flow input, modeling to simulate the dynamic characteristics of the engine in an electronic control method must be preceded, and the algorithm is based on a linear model. In this case, it is difficult to accurately derive a dynamic analysis model for each model. Therefore, the controller design target model used a model with three state variables and one control input as a linear model of the turbojet engine that conducted existing research.

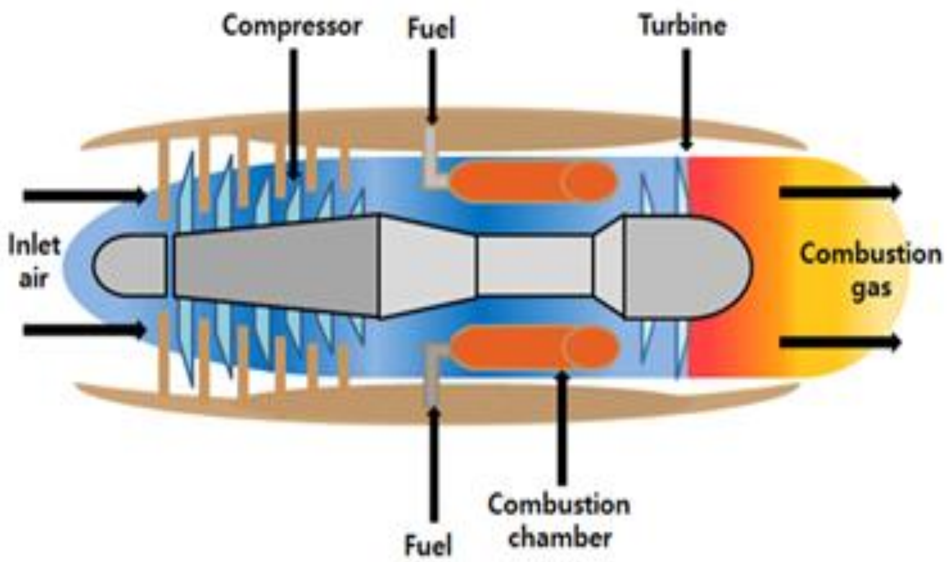

Fig. 1 Structure of Turbojet Engine

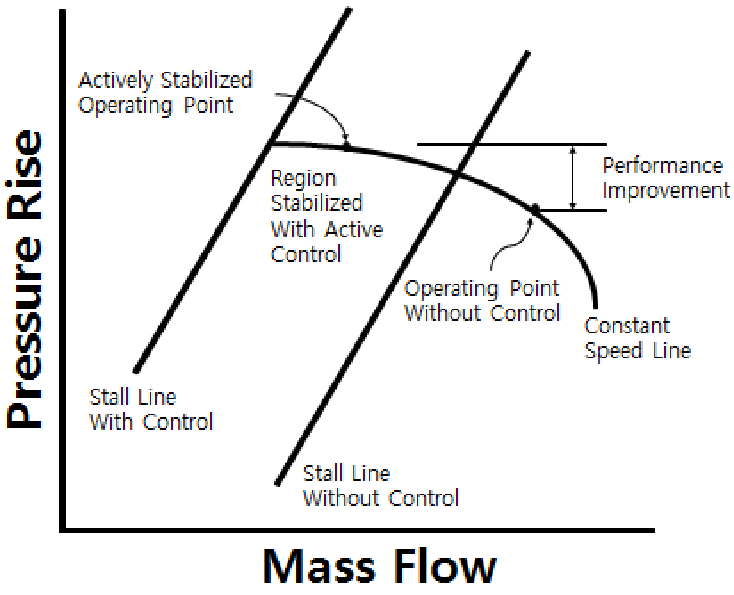

Fig. 2 Surge Operation Point

2.2 Linear Model of Engine

The dynamic control equation of the jet engine model can be obtained from the equilibrium equation such as power, energy, and flow for each component (compression, combustion, turbine, etc.), and the combined nonlinear equation is a combined component matching program solution from the reference operating point[2]. The state equation of the engine may be expressed as Equation (1).

$$\dot{x} = f(x,u) \tag{1}$$

In Equation (1), x is the state vector of the engine, and u is the control input vector of the engine. If x and u are vector (scalar) quantities with a single element, $\dot{x} = 0$ at any normal operating point (Steady-State) (x_0, u_0)Considering this, as a result of ignoring the higher-order differential term in the Taylor series development, a linear relational expression as in Equation (2) can be obtained.

$$\Delta\dot{x} = \frac{\partial \dot{x}}{\partial x}|_0 \Delta x + \frac{\partial \dot{x}}{\partial x}|_0 \Delta u \tag{2}$$

In Equation (2), $\Delta x = x - x_0,\quad \Delta u = u - u_0$. Since the actual system includes several state variables and input variables, the form of vector matrices, such as Equation (3), is generally established near one operating point.

$$\Delta\dot{x} = A\Delta x + B\Delta u \tag{3}$$

If there are n state variables and m control input variables, i is a subscript representing a row and j is a column, each matrix can be expressed as Equation (4).

$$[A] = \left[\frac{\partial \dot{x}_\iota}{\partial x_j}\right]_0 \quad where \begin{pmatrix} i = 1, n \\ j = 1, n \end{pmatrix}$$

$$[B] = \left[\frac{\partial \dot{x}_\iota}{\partial x_j}\right]_0 \quad where \begin{pmatrix} i = 1, n \\ j = 1, m \end{pmatrix} \tag{4}$$

$$\dot{x_p}(t) = A_p x_p(t) + B_p u_p(t) \tag{5}$$

In Equation (5), $x_p = \left[x_{p1} x_{p2} x_{p3}\right]^T$: state variable vector, and each variable is as follows.

x_{p1} : Compressor rotor rotation speed

x_{p2} : Turbine inlet temperature

x_{p3} : Compressor outlet pressure

u_p : fuel flow rate

In this paper, compressor rotation speed (Δx_1), turbine inlet temperature (Δx_2), compressor outlet pressure (Δx_3), and fuel flow rate (u) were used as state variable vectors.

3. ARTIFICIAL NEURAL NETWORK CONTROL

3.1 Structure of Artificial Neural Network Algorithm

Neural network algorithms are networks constructed by mimicking human brain and neural cell models that produce excellent results for complex problems and are used primarily for pattern recognition, learning, classification, generalization, prediction, control, and signal processing as well as interpretation of incomplete and noisy inputs [7]. The algorithm applied in this paper corrects the error with the Error Back Propagation algorithm, which is a multi-layer perceptron structure, to reduce the difference between the desired response to the input and what is actually obtained. In learning internal representation by error propagation, the input pattern can always be coded if there is a sufficient hidden layer. This process is carried out by repeatedly adjusting the connection strength of the network to reduce the difference between the vector of the real neural network and the desired output [8], and Figure 3 shows the structure of the multilayer perceptron.

U_{ij}refers to the weight from the i input layer to the j hidden layer, and V_{jk} refers to the weight from the j hidden layer to the k output layer. The j node ($1 \le j \le p$) of the hidden layer is defined as Equation (6). In addition, the k node ($1 \le k \le m$) of the output layer is defined as Equation (7). Here, τ uses the sigmoid function as the activation function and is the same as Equation (8).

$$z_s um_j = \sum_{i=1}^{d} x_i \, U_{ij} \qquad z_j = \tau(z\_sum_j) \tag{6}$$

$$o_s um_k = \sum_{i=1}^{d} z_i \, V_{jk} \qquad o_k = \tau\{o\_sum_k) \tag{7}$$

$$F(x) = \frac{1}{1+e^{-x}} \tag{8}$$

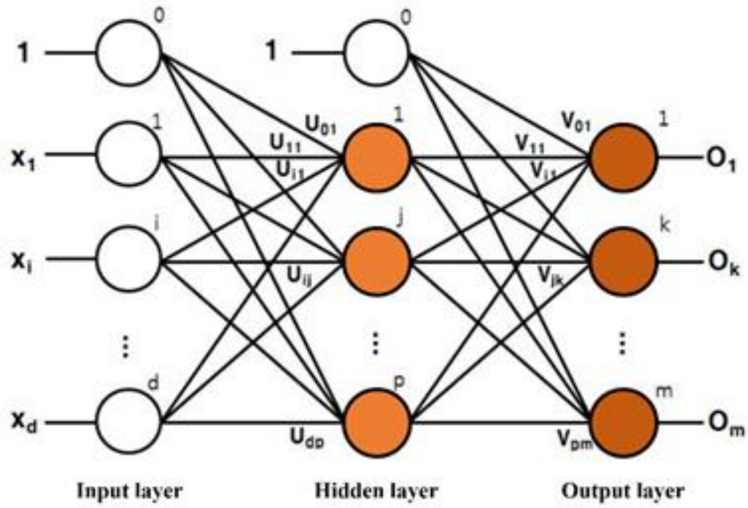

Fig. 3 **Multi-Layer Perceptron**

The method of modifying the connection weights in the direction of minimizing the error value (E_p), defined as the sum of error squares between the desired target value and the output value of the real neural network, for a given input via backpropagation learning rules is defined as Equation (9).

$$E_p = \frac{1}{2}\sum_{k=1}^{m}(t_k - o_k)^2 \tag{6}$$

$p \ = \ pth\ learning\ data$

$E_p = error\ for\ the\ pth\ pattern$

$t_k = Kth\ element\ of\ target\ output\ for\ pth\ pattern$

$o_k = kth\ element\ of\ the\ actual\ neural\ network\ output$

In Equation (9), the weight value should be modified in the direction of minimizing the error value (E_p). The correction method uses the Gradient Decent Method of finding the lowest point by finding the direction in which the slope descends most rapidly from the current position and moving slightly in that direction to hold a new position, and is defined as Equation (10).

$$\theta(h+1) = \theta(h) + \Delta\theta = \theta(h) - \rho\frac{\partial E}{\partial \theta} \tag{10}$$

The ρ value represents the learning rate, and the direction was determined when applying the downhill slope method, but it is difficult to estimate the amount to move, so it is used to determine the amount to move. The weight value V_{jk} between the j-th hidden layer and the k-th output layer is calculated through Equation (11).

$$\Delta V_{jk} = -\rho\frac{\partial E}{\partial V_{jk}} = \rho\delta_k z_j \tag{11}$$

Therefore, the amount of change in the weight for reducing the error value is as shown in Equation (12).

$$\Delta V_{jk}(n+1) = \rho\delta_k z_j + \alpha\Delta V_{jk}(n) \tag{12}$$

Here, α is used as an arbitrary constant value to prevent falling into the local minima. The weight value U_{ij} between the i-th input layer and the j-th hidden layer is equal to the weight value induction between the $j-th$ hidden layer and the k-th output layer, and thus can be expressed as Equation (13).

$$\Delta U_{jk}(n+1) = \rho\eta_k x_i + \alpha\Delta U_{ij}(n) \tag{13}$$

The input data is set to the compressor rotation speed target data at the reference speed, and the PID control gain is defined as Equation (14) using the output value O.

$$K_p = O * \mathrm{k}_1, K_I = O * \mathrm{k}_2, K_D = O * \mathrm{k}_3 \tag{14}$$

where k_1, k_2, k_3 is a constant.

3.2 Design of Artificial Neural Network(ANN) Controller

Figure 4 shows the structure of an artificial neural network PID fuel flow control system that sets the reference speed considering surge and flame-out and allows the engine to follow the reference command. The required thrust of the turbojet engine control system to be designed is obtained by controlling the fuel flow rate. In order to produce high operation and high performance, rapid changes in air flow rate during engine acceleration and deceleration cause surge or flame loss, which causes combustion stop, damage to engine elements, and loss of power. Therefore, the engine must be accelerated along the operating line adjacent to the surge limit for efficient surge control[11][12].

It can be seen that the compressor surge operating point of the target engine is very close to the surge control line. Since the engine's operating line must be controlled so that it is close to the surge limit to maximize the engine's performance, the engine is accelerated while maintaining minimum surge margin [13]. And prior to the simulation, the control system must set a control line in consideration of surge phenomenon and flame loss. The controller shall set the control line in consideration of surge phenomenon and flame loss. The control line for surge and flame loss is defined by Equations (15) and (16), and N represents the rotational speed of the compressor rotor.

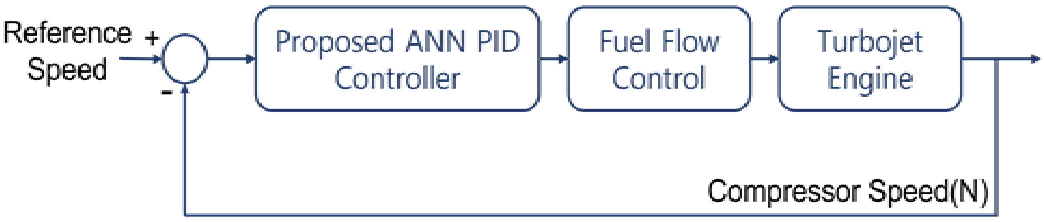

Fig.4 Structure of the engine control system.

$$P_{surge} = \begin{cases} \dfrac{(2.912-2.082)(N-20000)}{4000} + 2.082, & N < 24000 \\ \dfrac{(3.622-2.912)(N-24000)}{3000} + 2.912, & 24000 \le N < 27000 \\ \dfrac{(3.938-3.622)(N-27000)}{1000} + 3.622, & 27000 \le N < 28000 \\ \dfrac{(4.088-3.938)(N-28000)}{1000} + 3.938, & 28000 \le N < 29000 \\ \dfrac{(4.135-4.088)(N-29000)}{1000} + 4.088, & 29000 \le N < 29500 \\ 4.135 & 29500 \le N \end{cases} \tag{15}$$

$$P_{frame-out} = \begin{cases} \dfrac{(2.5835-1.5250)(N-20000)}{7000} + 1.5250, & N < 27000 \\ \dfrac{(2.8920-2.5835)(N-27000)}{1000} + 2.5835, & 27000 \le N < 28000 \\ \dfrac{(3.0260-2.8920)(N-28000)}{1500} + 2.8920, & 28000 \le N < 29500 \\ 3.0260 & 29500 \le N \end{cases} \tag{16}$$

The turbine inlet temperature control line is defined as shown in Equation (17), and the compressor outlet pressure control line is defined as shown in Equation (18).

$$P_{temp} = \begin{cases} \dfrac{(2000-1700)(N-20000)}{6000} + 1700, & N < 26000 \\ \dfrac{(2500-2000)(N-26000)}{4000} + 2000, & 26000 \le N \end{cases} \tag{17}$$

$$P_{pressure} = \begin{cases} \dfrac{(2.5132-1.9568)(N-20653)}{3505} + 1.9568, & N < 24160 \\ \dfrac{(3.2783-2.5132)(N-24160)}{3490} + 2.5132, & 24160 \le N < 27650 \\ \dfrac{(3.7087-3.2783)(N-27650)}{1731} + 3.2783, & 27650 \le N < 29380 \\ 3.7087 & 29380 \le N \end{cases} \tag{18}$$

For the application of artificial neural networks, an artificial neural network algorithm is applied by setting the compressor rotation speed as input data and setting the reference speed as target data. Neural networks were prepared using MATLAB.

4. SIMULATION

The performance of the PID engine control method proposed in this paper was confirmed by simulation using MATLAB. We use a linear model represented by the state space equation in the following equation (19).

$$\dot{x_{p1}}(t) = A_p x_p(t) + B_p u_p(t) \tag{19}$$

Where, $x_p = [x_{p1} \;\; x_{p2} \;\; x_{p3}]^T$

x_{p1} : compressor rotation speed

x_{p2} : turbine inlet temperature

x_{p3} : compressor outlet pressure

u_p : fuel flow

Figure 5 and 6 show the performance test execution result index of the proposed artificial neural network PID control system. The solid blue line in Figure 5 and Figure 6 is the result of the proposed algorithm, and the red dot-decision line is the result of a classical PID control system. The PID speed of the artificial neural network according to the reference speed reacts quickly within 0.2 seconds, maintaining its performance within a stable range without exceeding surge and flame-out control lines and turbine inlet temperature limits. The control gain values $K_P, K_I, and K_D$ of the PID controller are $K_P = 0.00004, K_I = 0.0025, and\ K_D = 0.00002$, respectively, and the weight O is determined by the results of the artificial neural network.

Figure 5 shows the experimental results comparing the performance changes for (A) Rotro Speed, (B) Compressor exit pressure ratio, (C) Turbine inlet Temperature, and (D) Fuel Flow Rate according to the reference speed of the simulation. It can be seen that the artificial neural network PID controller exhibits faster response characteristics to the reference speed than the classical PID controller. For surge control, both artificial neural network PID controllers and classical PID controllers show excellent performance. The designed artificial neural network PID controller shows that compressor rotation speed exhibits rapid response characteristics, and compressor outlet pressure and turbine inlet temperature maintain performance within a stable range without exceeding the limit. On the other hand, when the PID controller is used, it can be seen that the compressor rotation speed is greater than that of the artificial neural network PID controller, and it does not cause surge or flame loss, but it shows instability in a specific section. Figure 6 is the result of simulation for a shorter time than Figure 5. Similarly, it can be seen that the performance of the proposed ANN-PID controller is better. We also confirm that the proposed algorithm exhibits a faster and more stable steady-state response.

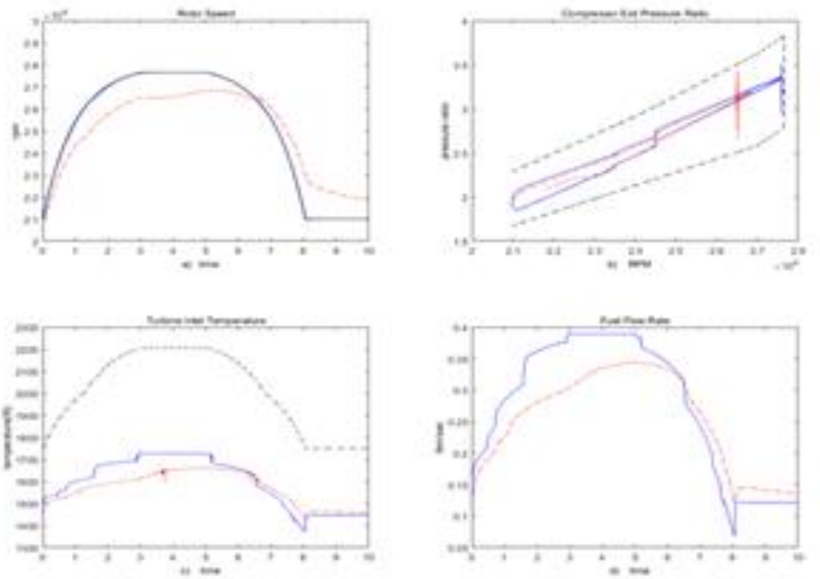

Fig. 5 Simulation result value of proposed algorithm (Blue Line : proposed ANN PID , Red dot-decision Line : PID)

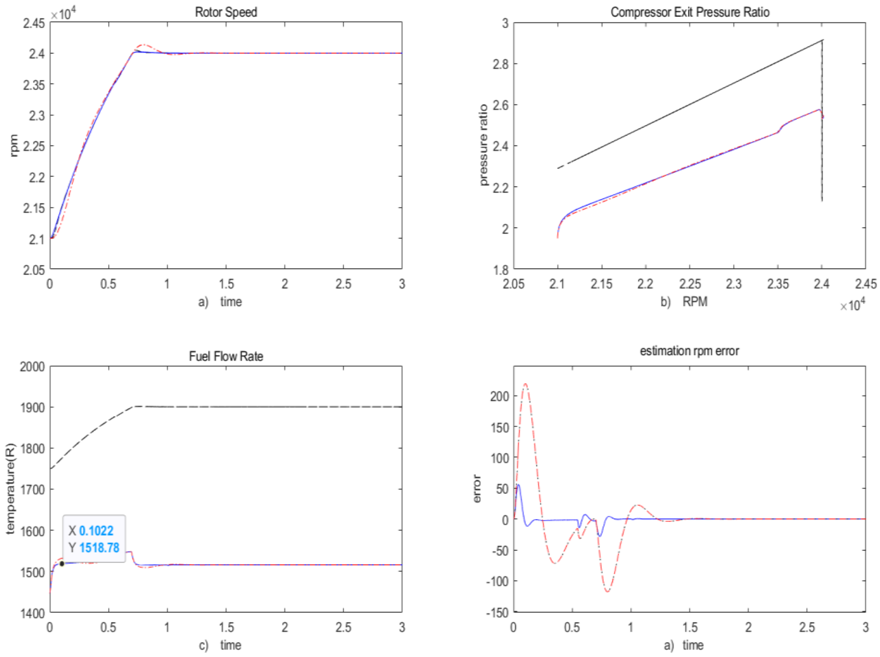

Fig. 6 Simulation result value of proposed algorithm (Blue Line : proposed ANN PID , Red dot-decision Line : PID)

5. CONCLUSION

In this paper, a turbojet engine speed controller for a small unmanned aerial vehicle to which an artificial neural network PID control technique is applied was designed. Through simulation using MATLAB, it is safe, maintains the required performance for speed, pressure, temperature, and fuel flow in a normal state, and confirms the fast response characteristics, and demonstrates the superiority of artificial neural network PID controller performance by comparing with classical PID controllers.

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