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Using Neural Network and Reference Model Techniques for Unmanned Quadcopter Controllers Design

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Abstract— **This paper describes nonlinear dynamics model of an unmanned aerial vehicle of type quadcopter using Newton-Euler modeling technique. Usually UAVs systems are unstable and stabilization control plays a very important role. More than half of industrial controllers in use today are PID. Thus, the adjustment aspect of proportional integral derivative (PID) controllers becomes a challenge for research. To tune the controller, two main approaches are proposed. One is linear; the PD gains are fixed in optimal way by using reference model method, while the other is nonlinear and consists of an adaptive hybrid Neural Network based PD (NNPD) control. Hence, simulation results have been performed under MATLAB/Simulink and prove that proposed adaptive hybrid Neural Network based PD (NNPD) controller and reference model method give better results in the term of settling time and precision in Quadrotor UAV application.**

Keywords— **Quadcopter; PD tuning; Neural Network; Reference model.**

NOMENCLATURE

AFGS-SMC	Adaptive Fuzzy Gain-Scheduling Sliding Mode Control
ANNs	Artificial Neural Networks
BP	Backpropagation
DOF	Degree of freedom
IntSMC	Integral Sliding Mode Control
MLP	MultiLayer Perceptron
NN	Neural Network
NNPID	Neural Netwok based PID
PID, PD	Proportional, Integral and Derivative
RBFNN	Radial Basis Function Neural Network
RM	Reference Model
RMPD	Reference Model based PD
UAVs	Unmanned Aerial Vehicles
VTOL	Vertical Take-Off and Landing
b, d	Lift and Drag coefficients
g	Gravitational constant
I_x, I_y, I_z	Inertias around x, y and z axis
J_r	Rotor inertia
k_{ftx}, k_{fty}, k_{ftz}	Translation drags coefficients
k_{fax}, k_{fay}, k_{faz}	Frictions aerodynamics coefficients.
L	Half size of Quadcopter
m	Total mass of the Quadcopter
x, y, z	Cartesian coordinates
ϕ	Roll angle (Rotation around x-axis)
θ	Pitch angle (Rotation around y-axis)
ψ	Yaw angle (Rotation around z-axis)
ω_i	Angular speed of the ith rotor

I. INTRODUCTION

Nowadays, UAVs (unmanned aerial vehicles) have obtained considerable development and are becoming more popular. This can be easily observed in the military and civil areas. It is constituted by four rotors placed at the end of a cross, where two diagonal motors turn in the same direction whereas the others turn in the other direction to eliminate the anti-torque. This vehicle has six degrees of freedom with four independent thrust forces generated by four rotors. Therefore, is an under-actuated dynamic vehicle (four input and six outputs). Thus it can be controlled by varying the speed of the rotors in order to produce the required forces and moments [1][2].

Several studies related to design control techniques of Quadcopter have been proposed. In [3], the second order sliding mode control to direct the position and attitude tracking of a small Quadcopter UAV is considered. The backstepping technique has been used to solve the stabilization and trajectory tracking problems[4][5]. A novel adaptive fuzzy gain-scheduling sliding mode control (AFGS-SMC) approach is proposed [6]. PID and Fuzzy-PID control model for Quadcopter Attitude with disturbance parameter [7][8]. PID and LQR controllers were proposed to stabilize the attitude [9]. An attitude control strategy based on Ziegler-Nichols rules for tuning PD is proposed in [10]. A generalized proportional integral (GPI) control approach is presented in [11] for regulation and trajectory tracking problems in a nonlinear, multivariable Quadcopter system model.

Artificial neural network has several features such as nonlinear, self-learning and adaptability [12]. In recent years, it has attracted great attention, by fact that is nowadays

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becoming widely used in many applications. The NN control has been proved to be effective for controlling uncertain nonlinear systems. Recently, the researchers have focused on the study of Quadcopters for its increasing importance. A decentralized PID neural network (PIDNN) control scheme was applied to a Quadcopter subjected to wind disturbance [12]. Adaptive RBFNNs and double-loop integral sliding mode control (IntSMC) control is introduced for the position tracking [13]. Artificial neural network's direct inverse control system for Quadcopter attitude dynamics is suggested [14]. An adaptive neural network control to stabilize a Quadcopter under the presence of external disturbances is proposed in [15]. The lack of the neural network is to define the best topology of the network, the number of neurons to place in the hidden layer (s), the choice of the initial values of the neural weights and the setting of the learning rate, which play an important role in the speed of convergence.

The Proportional-Integral Derivative (PID) controller is one of the earlier developed control strategies widely used in industrial because of its easy implementation. For achieving appropriate closed loop performance, three parameters of the PID controller must be tuned, the proportional gain K_P, the integral gain K_I and the derivative gain K_D. Many studies have been proposed the Proportional-Integral Derivative (PID) control of a Quadcopter by using linearized model [16]-[18]. Tuning methods of PID parameters are classified as traditional and intelligent methods. Usually conventional methods such as Ziegler and Nichols not give good tuning. Recently, the intelligent approaches such as genetic algorithm, Particle Swarm Optimization (PSO) and neural network were used in PID tuning for controlling of Quadcopter [2][19].

The hybrid systems of PID control and the artificial neural networks control have been widely studied [20]-[22]. Commonly, neural network is used to tune the control gains of PID controllers. Therefore, PID Neural Network (PIDNN) is a novel control strategy that includes the advantages of PID control and neural network control.

The aim of this paper is to get an ideal response for the highly nonlinear Quadcopter focus on attitude and altitude stabilization during control. Reference model method and a Neural Network approaches are chosen to obtain optimal gains of PD controller.

This paper is organized into five sections. Section II presents the stages of modeling of the Quadcopter using Newton Euler formalism. The control techniques used to adjust the controllers parameters are presented in sections III and IV. Section V describes the obtained results. Finally, Section VI provides concluding remarks.

II. THE DYNAMIC MODEL OF QUADCOPTER

The Quadcopter UAV, shown in Fig. 1, has four rotors to generate the propeller forces Fi=1,2,3,4. Two reference frames are used, the body coordinate system B and the ground coordinate system E. Rotor 1 and rotor 2 rotate in the clockwise direction, while the rotor 3 and 4 rotate in the counter-clockwise direction to balance the torques and produce yaw motion as needed. The motion of Quadcopter can be controlled to desired values by changing the rotation speed of four rotors. The vertical take-off/Landing can be adjusted by increasing or decreasing the rotation speed of the four rotors simultaneously. The yaw motion is obtained from the difference in the counter torque between each pair of propellers. The up (down) motion is achieved by increasing (decreasing) the rotor speeds altogether with the same magnitude. Forward (backward) motion which is related to the pitch, angle can be obtained by increasing the back (front) rotor thrust and decreasing the front (back) rotor thrust. Finally, a laterally motion which is related to the roll, angle can be achieved by increasing the left (right) rotor thrust and decreasing the right (left) rotor thrust. The Quadcopter has six degrees of freedom, nonlinear, unstable, and multivariable, strongly coupled [12][5].

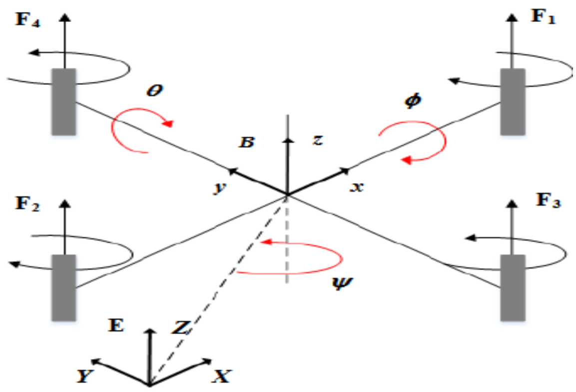

Fig.1 Quadcopter Configuration

Using the Euler- Newton formalism, the dynamic equations are written in the following form :

$$\begin{cases} \dot{\zeta} = \mathrm{v} \\ \mathrm{m}\ddot{\zeta} = \mathrm{F_f} + \mathrm{F_t} + \mathrm{F_g} \\ \dot{\mathrm{R}} = \mathrm{R}S(\Omega) \\ \mathrm{J}.\dot{\Omega} = -\mathrm{M_{gm}} - \mathrm{M_{gh}} - \mathrm{M_a} + \mathrm{M_f} \end{cases} \quad (1)$$

J is a symmetric positive definite constant inertia matrix.

$$J = \begin{pmatrix} I_X & 0 & 0 \\ 0 & I_Y & 0 \\ 0 & 0 & I_Z \end{pmatrix} \quad (2)$$

Ω : is the angular velocity of the fixed airframe

$$\Omega = \begin{bmatrix} 1 & 0 & -\sin\theta \\ 0 & \cos\phi & \sin\phi \\ 0 & -\sin\phi & \cos\phi\cos\theta \end{bmatrix} \times \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \quad (3)$$

R is the rotation matrix defined by Euler angles.

$$R = \begin{pmatrix} C\psi C\theta & S\phi S\theta C\psi - S\psi C\phi & C\phi S\theta C\psi + S\psi C\phi \\ S\psi C\theta & S\phi S\theta S\psi + C\psi C\theta & C\phi S\theta S\psi - S\psi S\phi \\ -S\theta & S\phi C\theta & C\phi C\theta \end{pmatrix} \quad (4)$$

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$S(\Omega)$ is a skew-symmetric matrix. For a given vector $\Omega = [\Omega_1 \quad \Omega_2 \quad \Omega_3]^T$ it is defined as in (5).

$$S(\Omega) = \begin{bmatrix} 0 & -\Omega_3 & \Omega_2 \\ \Omega_3 & 0 & -\Omega_1 \\ -\Omega_2 & \Omega_1 & 0 \end{bmatrix} \quad (5)$$

F_f is the resultant of the forces generated by the four rotors.

$$F_f = R \times [0 \quad 0 \quad \textstyle\sum_{i=1}^{4} F_i]^T \quad (6)$$

$$F_i = b\omega_i{}^2 \quad (7)$$

Where F_i the thrust force produced by the *ith* rotor.

F_t is the resultant of the drag forces along (*x*, *y*, *z*) axis, it is defined by (8).

$$F_t = \begin{bmatrix} -K_{ftx} & 0 & 0 \\ 0 & -K_{fty} & 0 \\ 0 & 0 & -K_{ftz} \end{bmatrix} \dot{\zeta} \quad (8)$$

F_g is the gravitational force:

$$F_g = \begin{bmatrix} 0 \\ 0 \\ -mg \end{bmatrix} \quad (9)$$

M_f is the moment developed by the quadrotor according to the body fixed frame. It is expressed as in (10).

$$M_f = \begin{bmatrix} l(F_4 - F_2) \\ l(F_3 - F_1) \\ d(\omega_1{}^2 - \omega_2{}^2 + \omega_3{}^2 - \omega_4{}^2) \end{bmatrix} \quad (10)$$

M_a is the resultant of aerodynamics frictions torques, it is expressed in (11).

$$M_a = \begin{bmatrix} -K_{fax} & 0 & 0 \\ 0 & -K_{fay} & 0 \\ 0 & 0 & -K_{faz} \end{bmatrix} \Omega^2 \quad (11)$$

M_{gh} is the resultant of torques due to the gyroscopic effects.

$$M_{gh} = \textstyle\sum_{i=1}^{4} \Omega \wedge J_r [0 \quad 0 \quad (1)^{1+i}\omega_i]^T \quad (12)$$

M_{gm} is the gyroscopic moment due to movements of the Quadcopter:

$$M_{gm} = \Omega \wedge J.\Omega \quad (13)$$

Consequently, the Quadcopter is an underactuated system with six outputs (ϕ, θ, ψ, x, y, z) and four control inputs (u_1, u_2, u_3, u_4). Finally, the dynamic model is written as follows:

$$\ddot{\phi} = \left(-\dot{\theta}\, s\phi + \dot{\psi}\, c\phi\, c\theta\right)\left(\dot{\theta}\, c\phi + \dot{\psi}\, c\theta\, c\phi\right)\frac{(I_y - I_z)}{I_x}$$
$$\left(\dot{\theta}\, c\phi + \dot{\psi}\, c\theta\, s\phi\right)\frac{J_r\Omega_r}{I_x} - \left(\dot{\phi}^2 - 2\dot{\phi}\,\dot{\psi}\, s\theta^2\right)\frac{k_{fax}}{I_x} + \frac{l\,u_2}{I_x} \quad (14)$$

$$\ddot{\theta} = \left(\dot{\psi}\, c\phi\, c\theta - \dot{\theta}\, s\phi\right)\left(\dot{\phi} - \dot{\psi}\, s\theta\right)\frac{(I_z - I_x)}{I_y} - \left(\dot{\psi}\, s\theta - \dot{\phi}\right)\frac{J_r\Omega_r}{I_y}$$
$$-\left(\dot{\theta}^2\, c\phi^2 + 2\dot{\theta}\,\dot{\psi}\, c\theta\, s\phi\, c\phi + \dot{\psi}^2\, c\theta^2\, s\phi^2\right)\frac{k_{fay}}{I_y} + \frac{l\,u_3}{I_y} \quad (15)$$

$$\ddot{\psi} = \left(\dot{\psi}\, s\phi\, c\theta + \dot{\theta}\, c\phi\right)\left(\dot{\phi} - \dot{\psi}\, s\theta\right)\frac{(I_x - I_y)}{I_z} - \left(\dot{\psi}\, s\theta - \dot{\phi}\right)$$
$$-\left(\dot{\theta}^2\, s\phi^2 - 2\dot{\theta}\,\dot{\psi}\, c\theta\, s\phi\, c\phi + \dot{\psi}^2\, c\theta^2\, c\phi^2\right)\frac{k_{faz}}{I_z} + \frac{l\,u_4}{I_z} \quad (16)$$

$$\ddot{x} = \frac{c\psi\, s\theta\, c\phi + s\psi\, s\phi}{m} u_1 - \frac{k_{ftx}}{m}\dot{x} \quad (17)$$

$$\ddot{y} = \frac{s\psi\, s\theta\, c\phi - c\psi\, s\phi}{m} u_1 - \frac{k_{fty}}{m}\dot{y} \quad (18)$$

$$\ddot{z} = -g + \frac{c\theta\, c\phi}{m} u_1 - \frac{k_{ftz}}{m}\dot{z} \quad (19)$$

Where c(.) and s(.) are abbreviations for cos(.) and sin(.), respectively.

The control inputs u_1, u_2, u_3, u_4 and Ω_r are given in (20).

$$\begin{cases} u_1 = b\,(\omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2) \\ u_2 = b\,(\omega_4^2 - \omega_2^2) \\ u_3 = b\,(\omega_3^2 - \omega_1^2) \\ u_4 = d\,(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2) \\ \Omega_r = \omega_2 + \omega_4 - \omega_3 - \omega_1 \end{cases} \quad (20)$$

The model parameter values of the Quadcopter are listed in Table I.

TABLE I.
QUADCOPTER PARAMETERS

Parameter	**Value and unite**	**Parameter**	**Value and unite**
M	0.65Kg	I_x, I_y	7.5 10^{-3} Kg.m²
g	9.81m/s²	I_z	1.3 10^{-3} Kg.m²
L	0.23m	K_{fax} , K_{fay}	5.567 10^{-4}N/rad/s
b	3.13 10^{-5}N/rad/s	K_{faz}	6.354 10^{-4}N/rad/s
d	7.5 10^{-7}N.m/rad/s	K_{ftx} , K_{fty}	5.567 10^{-4}N/rad/s
J_r	6.5 10^{-5}Kg.m²	K_{ftz}	6.354 10^{-4}N/rad/s

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III. Reference model Based PD Controller

In the first part of this work, the reference model is used to determine the parameter's values of the PD controllers, giving thus the RMPD approach.

The general idea behind this method is to have a system that follows a certain system as a reference model which is imposed in some desired specifications.

For a controlled system of order n and characteristic equation:

$$D(p) = a_0 + a_1 p + a_2 p^2 + \cdots + a_n p^n \qquad (21)$$

The performance may be those of a dominant mode of first order or second order.

When it is desired to have the behavior of a first order system with a specified settling time $T_{r5\%}$, the dominant pole is placed at -1/ τ and the (n-1) others must be placed sufficiently left of -1/ τ in the complex plan.

If the desired behavior is of the second order with damping factor ξ and the natural pulsation, the dominant poles are placed at $-\xi\omega n \pm j\omega n\sqrt{(1-\xi^2)}$ and the (n-2) others must be placed sufficiently left of $-\xi\omega_n$ in the complex plan [23][24].

Tuning the controller requires knowledge of the relationship between the input and output variables of the system to be controlled. Since the UAV is a complex nonlinear system, this relationship between the input signal and the output signal is not so simple. However around some assumption, the relationship between the signals can be described by a linear model. Then, we can present a very simplified model of quadcopter in equations 22-25, the equation become simpler as equations 14-19:

$$\ddot{\phi} = \frac{l\, u_2}{I_x} \qquad (22)$$

$$\ddot{\theta} = \frac{l\, u_3}{I_y} \qquad (23)$$

$$\ddot{\psi} = \frac{l\, u_4}{I_z} \qquad (24)$$

$$\ddot{z} = \frac{1}{m} u_1 - \frac{k_{ftz}}{m} \dot{z} \qquad (25)$$

By applying Laplace transform on equation (22-25), the transfer function of the open-loop system is given by:

$$G_\phi(p) = \frac{\phi}{u_2}(p) = \frac{l}{I_x p^2} \qquad (26)$$

$$G_\theta(p) = \frac{\theta}{u_3}(p) = \frac{l}{I_y p^2} \qquad (27)$$

$$G_\psi(p) = \frac{\psi}{u_4}(p) = \frac{l}{I_z p^2} \qquad (28)$$

$$G_z(p) = \frac{z}{u_1}(p) = \frac{1/m}{p(\frac{k_{ftz}}{m} + p)} \qquad (29)$$

There are four PD controllers, one controller to each flight parameter (ϕ, θ, ψ, z) :

$$u_i(t) = k_{pj} e_j(t) + k_{dj} \frac{d}{dt} e_j(t) \qquad (30)$$

Where i=1, 2, 3, 4 and $j = \phi, \theta, \psi, z$.

The characteristic polynomial of the desired behavior for attitude and altitude motions is defined by:

$$D_{\varphi,\theta,\psi}(p) = p^2 + \frac{L}{Ix} K_{d\Phi,\theta,\psi} p + \frac{L}{Ix} K_{p\Phi,\theta,\psi} = \left(p + \frac{1}{\tau}\right)\left(p + \frac{\alpha}{\tau}\right) \qquad (31)$$

$$D_z = p^2 + \left(\frac{K_{dz}}{m} + \frac{Kftz}{m}\right)p + \frac{1}{m} K_{pz} = \left(p + \frac{1}{\tau}\right)\left(p + \frac{\alpha}{\tau}\right) \qquad (32)$$

By identifying with the reference model, the PD parameters are then extracted:

$$K_{p\varphi} = \frac{I_x}{l}\frac{\alpha}{\tau^2} \quad ; \quad K_{d\varphi} = \frac{I_x\,(\alpha+1)}{l.\tau} \qquad (33)$$

$$K_{p\theta} = \frac{I_y}{l}\frac{\alpha}{\tau^2} \quad ; \quad K_{d\theta} = \frac{I_y\,(\alpha+1)}{l.\tau} \qquad (34)$$

$$K_{p\psi} = \frac{I_z\,(\alpha+1)}{\tau} \quad ; \quad K_{d\psi} = \frac{I_z\,(\alpha+1)}{\tau} \qquad (35)$$

$$K_{pz} = \frac{m\alpha}{\tau^2} \quad ; \quad K_{dz} = \frac{m(\alpha+1)}{\tau} \qquad (36)$$

The desired closed loop performances are:

- Position error $\varepsilon_p = 0$
- zero overshoot
- Settling time Tr(5%/) =0.5 s

IV. Neural Network based PD tuning

The adjustment of the PD controllers depends on the setting of its parameters (i.e., K_p, K_d), so that the performance of the controlled system becomes powerful and accurate according to the established performance criteria.

The neural network has the ability of nonlinear mapping, which can realize the best combination of PID control by learning the system performance. The proposed Neural Network based PD (NNPD) approach for Quadcopter attitude and altitude stabilization consist of a Neural Network controller which adjust the PD parameters (i.e. proportional and derivative gains) online in optimal manner according to the dynamic characteristics and behavior of the quadcopter UAV. The hybrid control block diagram of proposed NNPD is given in Fig.2.

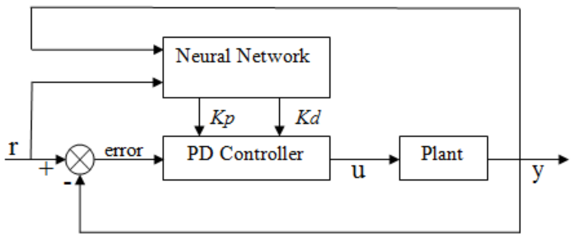

Fig.2 Structure of PD Control System Based on Neural Network

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Following this structure, there were implemented four independent PD controllers, one for each angle of the attitude (pitch, yaw, and roll) and one for the altitude (z).

Through self-learning and adjusting the weights of the neural network, we obtain optimal PD controller parameters.

A basic structure of MLP is shown in Fig.3, which consists of a series of layers. In addition to the input and output nodes, the network contains one or more hidden layers. The first layer has a connection from the network input. Each subsequent layer has a connection from the previous layer. The final layer produces the network's output [11].

In this study feed forward neural network with three layers and no inner feedback loop was used such that the neural network's output follows the desired output. Then using neural network to adjust the parameters of the conventional PD controller in the same way as when they are set by a human operator. The basic structure for estimating these parameters is detailed in Fig.4.

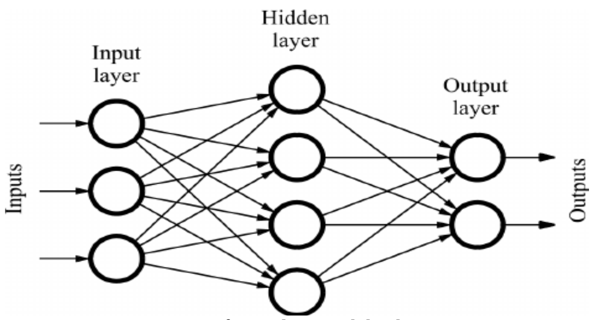

Fig.3. Structure of neural network back propagation

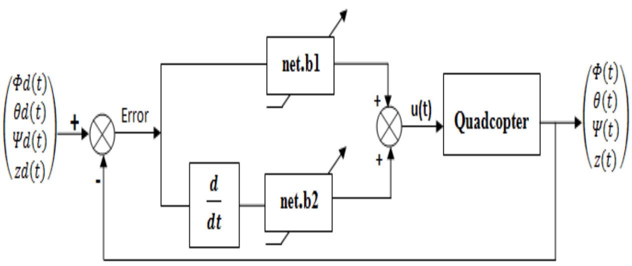

Fig.4. Structure of the neuronal PD control

The input vector of the network has two components: the desired output and the actual output. The bias *net.b1* weighting the input error will be associated with the factor P and the bias *net.b2* weighting the input of the derivative of the error will be associated with the factor D. The proportional and derivative gains are determined in real time by the neural network. This approach is the direct application of traditional control techniques including an adaptive control method. The back-propagation neural network (BPNN) [9] with one sigmoid-type hidden layer and linear output layer was used during this work.

The activation function of the hidden layer neurons is hyperbolic tangent sigmoid transfer function:

$$f(x) = \frac{2}{1+\exp(-2x)} \quad (37)$$

The backpropagation learning algorithm has been used to minimize the error function:

$$E = \frac{1}{2}e^2(t) = \frac{1}{2}(y_d(t) - y(t))^2 \quad (38)$$

Where y_d(t) and y(t) are respectively the desired and the actual outputs.

The weight change takes into account the information of the previous changes of the network. So the rule of adaptation of the weights becomes (eqs. 39-40).

$$w_{jk}(t) = w_{jk}(t-1) + \Delta w_{jk}(t) \quad (39)$$
$$w_{ij}(t) = w_{ij}(t-1) + \Delta w_{ij}(t) \quad (40)$$

According to the gradient descent method, the connection weights at the output layer and hidden layer are updated by the following equations:

$$\Delta w_{kj}(t) = -\eta \frac{\partial E}{\partial w_{kj}} + \alpha \Delta w_{kj}(t-1) + \beta \Delta w_{kj}(t-1) \quad (41)$$
$$\Delta w_{ji}(t) = -\eta \frac{\partial E}{\partial w_{ji}} + \alpha \Delta w_{ji}(t-1) + \beta \Delta w_{ji}(t-1) \quad (42)$$

Where w_{ij} is a vector of weights from input node i to hidden neuron j, w_{jk} is a vector weights from hidden neuron j to output neuron k, η is the learning rate, α is the momentum term, *t* is the present iteration and *Δw(t)* is the weight increment.

The learning will be stopped when the system manages to follow the planned path according to the criteria set by the user. If large variations occur in the system to be controlled, learning can restart. The last session contains the application and validation of this approach.

V. SIMULATION RESULTS

The mathematical dynamical model of the Quadcopter vehicle is derived first in Matlab Simulink. The goal of this analysis is to test how well the controllers can stabilize and guide the Quadcopter to reach the desired response.

The proposed adaptive hybrid Neural network NNPD and reference model RMPD controllers for stabilization of Quadcopter were simulated. During simulation step input was used to analyze the response of attitude and altitude control of Quadcopter UAV. The control objectives are to reach and maintain Quadcopter at a desired altitude/attitude, such that the quadcopter can hover at a fixed point. In this simulation, initially, ϕ, θ, ψ and z are set at 0. The simulation times are set from 0 to 4 s. Desired ϕ, θ and ψ are fixed to 1 radian, while desired *z* is set at 10 meters.

In addition, to construct a neural network with three layers of 1-2-1 structure, we select learning rate η=0.3 and number of iteration at 100. The initial gains in the developed neural network are selected randomly. However, by putting the PD gains as threshold's weights and adjusting them using the back-propagation learning algorithm, the desired bias in the neural network can be fast obtained for achieving the

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desired system output. The result shows that the desired output has been well tracked.

The simulation shown in Fig.5-8, it is done for three axes of Quadcopter which are roll, pitch and yaw, and the optimal parameters of PD controllers are presented in Tables II and III.

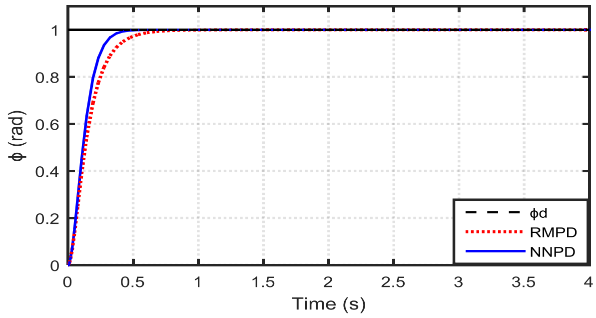

Fig.5 Step response of roll angle

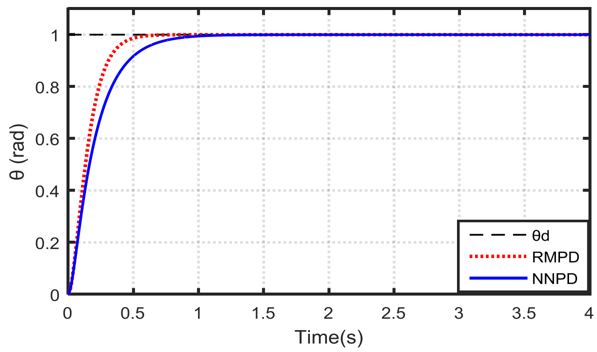

Fig.6 Step response of pitch angle

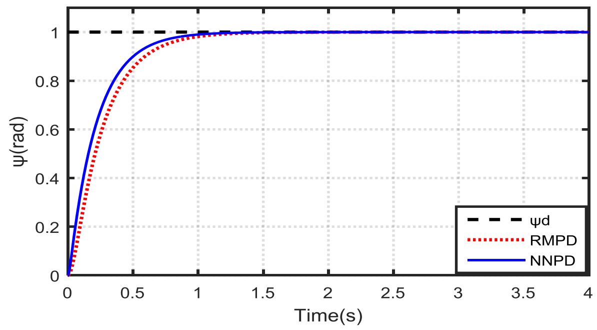

Fig.7 Step response of yaw angle

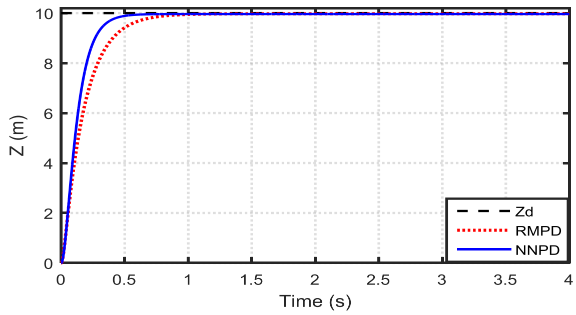

Fig.8 Step response of altitude position

TABLE II.
PD GAINS OPTIMISED BY REFERENCE MODEL METHOD

	Kp	Kd	Settling Time (s)
Roll Angle	2.4178	0.3848	0.45
Pitch Angle	2.4178	0.3848	0.37
Yaw angle	1.1948	0.1902	0.75
Altitude z	234	42.9	0.56

TABLE III.
PD GAINS OPTIMISED BY NEURAL NETWORK

	Kp	Kd	Settling Time (s)
Roll Angle	5.4561	0.6849	0.3
Pitch Angle	6.5392	1.1968	0.5
Yaw angle	6.5546	0.9362	0.41
Altitude z	169.6365	22.4686	0.33

According to the simulation results, the system has fast response and stable, without overshoot. As shown the both approaches controller produced better result on all axes of Quadcopter. This means that the PD parameters have been regulated accurately and the control designs are able to stabilize the Quadcopter.

Finally, in Fig. 9 and Fig. 10 is displayed the evolution of the variable input using NNPD and RMPD controllers for altitude position. In these Figures the high robustness of the both controllers is demonstrated when the control inputs are affected by noise.

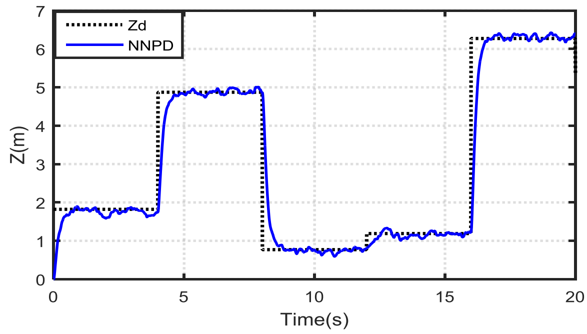

Fig.9 system output response to variable input with NNPD

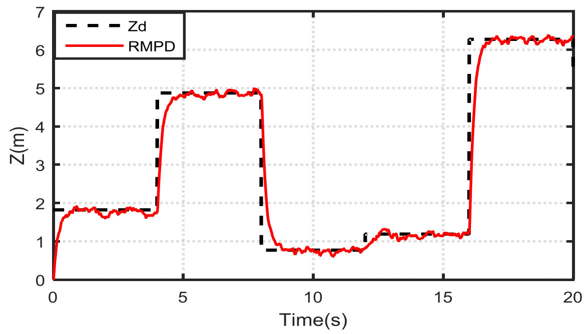

Fig.10 system output response to variable input with RMPD

VI. CONCLUSIONS

In this paper, the application of an optimal PD controller for the stabilization of Quadcopter UAV is successfully demonstrated.

First, the mathematical model of the quadcopter is introduced using Newton Euler formalism. Then, two control approaches using PD controller have been realized. A first,

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the PD controller based on reference model is proposed where the set of poles are placed in the desired closed-loop places. A second approach uses the principle of a PD controller and uses a neural network to adapt the proportional, integral and derivative parameters. Finally, the proposed control scheme is applied to autonomous Quadcopter UAV.

Concerning the last approach, a neuronal PD controller with adaptive coefficients for attitude and altitude stabilizing flight control system has been studied and is successfully simulated. The learning is done online with three layers and back propagation algorithm. The use of neural networks has been an effective means for determining PD parameters with avoiding the tedious manual tuning.

Several validation analyses of these approaches have been tested, particularly the step responses and the variable inputs responses with disturbances. Notice that the Quadcopter can reject the perturbation and the high performance response can be achieved by using the proposed control system and despite the nonlinearity present in the system the stability of the system can be guaranteed.

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