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Adaptive controller with PID structure for a mobile platform application

Regulator adaptacyjny ze strukturą PID dla aplikacji na platformę mobilną

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Abstract: The features of building a control system for a moving platform based on an adaptive controller with a PID structure, whose parameters are tuned using a method derived from ANN learning algorithms, are considered. A proportional-integral-differential control law was selected, as it best meets the needs of mobile platform control. The input circuit of the controller was selected using a discrete representation of the selected control law and the reference equation, which provides the required speed of the control system. Simulation of the system for stabilizing the position of a moving platform in the Simulink environment allows us to determine ways of its further improvement.

Keywords: moving platform, control, system, PID law, simulation, modelling, Simulink

Streszczenie: Rozważono cechy budowy układu sterowania platformą ruchomą opartego na regulatorze adaptacyjnym ze strukturą PID, którego parametry są dostrajane za pomocą metody wywodzącej się z algorytmów uczenia sieci neuronowych. Wybrano proporcjonalno-całkująco-różniczkowe prawo sterowania, jak najlepiej spełniające wymagania sterowania platformą. Obwód wejściowy neurokontrolera wybrano, wykorzystując dyskretną reprezentację wybranego prawa i równanie odniesienia, które zapewnia wymaganą prędkość układu sterowania. Symulacja układu stabilizacji położenia platformy ruchomej w środowisku Simulink pozwala na określenie sposobów jego dalszego udoskonalenia.

Słowa kluczowe: ruchoma platforma, sterowanie, system, struktura PID, symulacja, modelowanie, Simulink

Introduction

The study of the dynamics of ground robotic complexes is a topical task [1], [2] related, in particular, to the problem of digitalization of society [3], and to intelligent autonomous mobile platforms [4] – [5], which are an important element in various sectors of the world economy [6], [7]. Mobile platforms are actively used in testing and training unmanned aerial vehicles [8] – [10].

Let us consider the features of building a mobile platform control system, which allows it to be kept in a given position and prevent deviation from a given state of equilibrium in the event of external influence or load change. Using the Simulink package [11], we will build a structural diagram of the platform control system and conduct its simulation.

The algorithm for stabilizing a mobile platform consists in maintaining its given position when a disturbance acts on it or when its weight changes. The range of angles in which the platform position is stabilized in the range of $0^o \pm 90^o$ (Fig. 1).

The given position of the platform is achieved by balancing the engine thrust, which is directed in the direction of the air flow and the projection of the platform gravity, directed in the opposite direction to the air flow (Fig. 1, a). In the case when the projection of the platform gravity on the longitudinal axis is greater than the engine thrust, the speed of rotation of the engine shaft increases and the platform begins to rise (Fig. 1, b). When the engine thrust is greater than the platform gravity, the speed of the engine shaft decreases and the platform begins to descend (Fig. 1, c). The platform gains equilibrium when the projection of the platform gravity is balanced by the engine thrust. The external forces applied to the platform, we will highlight the main ones: the lifting force of the engine thrust F (or, if it is negative, the braking force), which is transmitted through the moving screw and the projection of the gravitational force P, directed in the opposite direction to the engine thrust.

The equation of the platform motion has the form as follows:

$$\frac{d^2\theta}{dt2} + \beta\frac{d\theta}{dt} + P\sin\theta = \alpha U \quad (1)$$

where P is the force of gravity of the platform, Θ is the angular displacement of the platform, β is the coefficient of viscous friction (damping coefficient), α is the conversion coefficient of the actuator, U is the control signal at the input of the actuator (voltage at the motor input).

The static state of the platform is described by an equation of the form as follows:

$$\theta = \arcsin(\alpha\frac{U}{P})$$

Remark that correspondence between the platform arm l and angle θ is as follows:

$$y = l\sin\theta, \quad (2)$$

where y is platform displacement at the vertical axis.

As can be seen from the expression (1), the platform motion is governed by a nonlinear second-order differential equation, which indicates the impossibility of conducting research related to the use of methods of linear theory of automatic control [12]. In the process of operation of the system for controlling the movement of a moving platform, the following requirements must be met:

1. ensure that the moving platform reaches the specified angular position with minimal overshoot;
2. achieve the desired system performance.

Since the dynamics of the processes occurring in the mobile platform control system depends on the type and parameters of the selected controller, to ensure the specified performance indicators of the system, we synthesize a proportional-integral-differential (PID –) controller [12].

According to the scheme of the mobile platform control system, the specified angle is compared with the angle at the output of the object. There is supplied by the feedback channel to the comparison element and the resulting difference signal is fed to the input of the PID – controller, in which, in accordance with the selected control law, the value of the control variable is calculated, which is supplied to the control object. In the process of synthesizing the controller, three parameters are to be determined: the proportionality coefficient – K_p, the coefficient at the integral component K_i, and the coefficient at the derivative component K_d. In a particular case, any of these coefficients can be equal to zero.

The proportional component provides signal amplification, the integral component provides its phase lag, and the differential causes its lead. Therefore, the integral component forms the controller characteris-

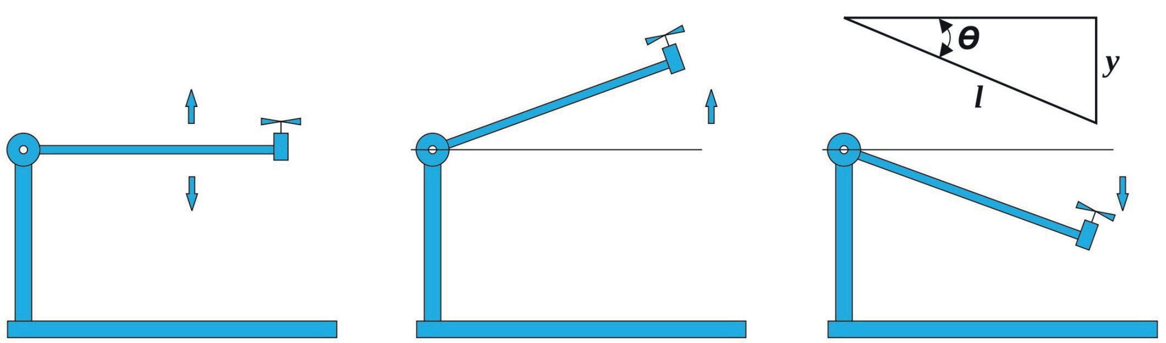

Fig. 1. Model of a moving platform

tics in the low-frequency range, and the differential – in the high-frequency range.

Principles of constructing controllers based on dynamic neural networks

The use of digital controllers [13], [14] has a number of advantages over analog ones: changing the controller parameters can be easily done by reprogramming it. Information processing occurs in digital form, which allows implementing complex data processing algorithms, in the process of digital information processing; the calculation results do not depend on the drift of the circuit parameters and the presence of noise.

Since the differential equation of the object (mobile platform) is nonlinear, when constructing a neural network, it is necessary to take into account both the dynamics of the model and the influence of the nonlinearities present in it. These nonlinearities can be taken into account by introducing nonlinear activation functions into the neural network and increasing the number of its layers.

To control processes in nonlinear dynamic objects, it is advisable to use controllers based on dynamic neural networks, in which, taking into account the main dynamic characteristics of the object, one or another control law is implemented [15].

The main advantage of a neural network is its ability to learn, which allows you to adapt a neural controller to a specific controlled object. Since in this case the controller is synthesized based on experimentally obtained sequences. The real controlled object has certain ranges of permissible values of input and output signals, the coefficients of the neural controller cannot acquire random values, they must either be pre-calculated on the basis of certain assumptions, or obtained by preliminary training using a mathematical model of the object. To accomplish the tasks set, a number of important steps must be taken as follows [16]:

1. First of all, it is necessary to have a specific nonlinear object or its mathematical model. In accordance with the selected control law, it is necessary to form the structure of the controller input circuit.
2. Select a mathematical model of the standard, based on the desired process dynamics, which sets the duration of the transient process, possible overshoots as the necessary indicators of the control law. This standard ensures the creation of an appropriate sequence that is used when training the controller. The goal of training is to select such weight coefficients of all controller neurons that ensure the minimum possible discrepancy between the output signals of the object and the standard. Due to the serial connection of the primary neural network and the object, these coefficients take into account the nonlinear features of the object during training.
3. After completing the training procedure, the resulting structure, the values of the weight coefficients, the set of delay elements and their durations are transferred to the Simulink environment. The convergence of the signals from the outputs of the reference and the object controlled by the synthesized controller is compared.
4. The controller is combined with the object and the duration of the transient process, the duration of delays, the quality of response to disturbances (training) and the stability of control are monitored.

The number of delay lines and their introduction into the input and feedback circuits determines the dynamic properties of the neural network. Thus, to build a neural controller taking into account the specified properties of the system, it is necessary to choose the number of introduced delay lines so that these properties can be implemented.

Since our task is to create a dynamic neural network that should perform the functions of a controller, it is advisable to take the proportional-integral-differential law (PID law) as the basis for its implementation, as one of the most universal control laws [12], [17], [18]. A dynamic neural network functions as a discrete system, so this law must be presented in a discrete form [19].

Dynamic neural networks creation

A linear controller is used to control a nonlinear object; and the features of the nonlinear object are taken into account by choosing the corresponding weight coefficients of the neural network during its training (we see a similar use in other authors [11]. That is, a nonlinear system is not considered as linearized linear, and nonlinearity is taken into account by the neural network itself. The structure of the controller input circuit is given by the selected control law (in our case, proportional-integral-differential).

The dependence between the input and output signals for a continuous PID controller has the form as follows [17]:

$$u(t)=K_d\frac{d\Delta y(t)}{dt}+K_p\Delta y(t)+K_i\int_0^t \Delta y(t)dt \quad (3)$$

where

$\Delta y(t)$ – the difference signal at the controller input,
$u(t)$ – the controller output signal,
K_d, K_p, K_i – the coefficients for the differential, proportional and integral components, respectively.

Having presented equation (3) in operator form as follows (X – the input signal):

$$Y(s)=\left(K_d s+K_p+\frac{K_i}{s}\right)X(s) \tag{4}$$

Let's write the transfer function of the PID controller in the following form:

$$W(s)=K_d s+K_p+\frac{K_i}{s} \tag{5}$$

We use the relation [19], which connects the operators of the continuous and discrete z transformations, namely: $s=(1-z^{-1})/\Delta\ t$, due to which we obtain the given control law (5) in discrete form as follows:

$$W(z)=K_d\frac{(1-z^{-1})}{\Delta t}+K_p+\frac{K_i\Delta t}{(1-z^{-1})} \tag{6}$$

Reducing the right side of the resulting expression to a common denominator as follows:

$$W(z)=\frac{\frac{K_d}{\Delta t}(1-z^{-1})^2+K_p(1-z^{-1})+K_i\Delta t}{(1-z^{-1})}= \tag{7}$$

$$=\frac{\frac{K_d}{\Delta t}-2\frac{K_d}{\Delta t}z^{-1}+\frac{K_d}{\Delta t}z^{-2}+K_p-K_p z^{-1}+K_i\Delta t}{(1-z^{-1})}$$

and grouping the terms at negative powers of argument z, we obtain as follows:

$$W(z)=\frac{\frac{K_d}{\Delta t}+K_p+K_i\Delta t-\left(2\frac{K_d}{\Delta t}+K_p\right)z^{-1}+\frac{K_d}{\Delta t}z^{-2}}{1-z^{-1}}= \tag{8}$$

$$=\frac{w_{11}+w_{12}z^{-1}+w_{13}z^{-2}}{1-w_{14}z^{-1}}$$

where the proper weight coefficients are as follows:

$$w_{11}=\frac{K_d+K_p\Delta t+K_i\Delta t^2}{\Delta t}$$

$$w_{12}=-\frac{2K_d+K_p\Delta t}{\Delta t}$$

$$w_{13}=\frac{K_d}{\Delta t} \qquad w_{14}=1$$

The corresponding difference equation, which corresponds to expression (8), will have the form as follows:

$$u_k=w_{11}\Delta y_k+w_{12}\Delta y_{k-1}+w_{13}\Delta y_{k-2}+w_{14}u_{k-1} \tag{9}$$

A certain scheme of a neural network corresponds to equation (9) is presented at Fig. 2. It is based on one neuron with purelin activation function.

Training a neural controller using a neural model of an object

Taking the scheme (Fig. 2) as a basis and supplementing it with a standard, we obtain a system structure that allows us to synthesize a controller based on a discrete representation of the PID control law (Fig. 3).

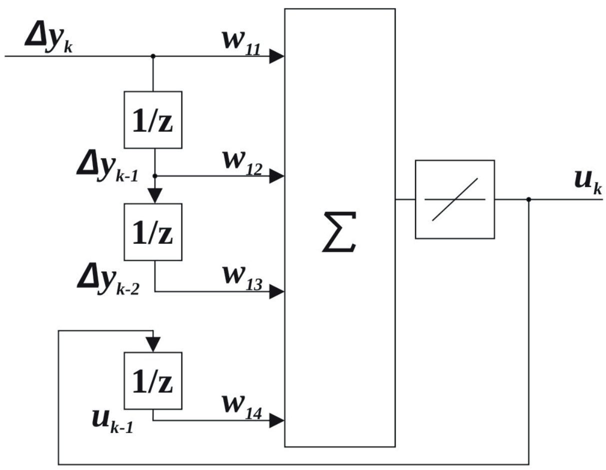

Fig. 2. Discrete representation of a PID controller based on the relation (8)

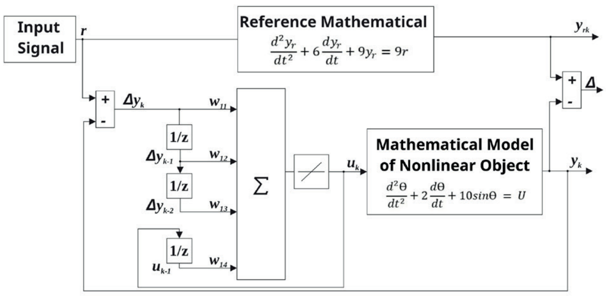

Fig. 3. Structural diagram of an automatic control system using a neural controller, which is implemented on the basis of the relation (8)

The model of a nonlinear object is given by a differential equation of the form (1). To implement the training procedure, we introduce a standard to which it is necessary to bring the system (object with a controller) as close as possible. That is, we select the coefficients w_{11}, w_{12}, w_{13}, w_{14} so that when any the same signal simultaneously enters the inputs of the system and the standard, the values of their output signals are as close as possible. Taking into account the requirements for ensuring a given system operating speed, the equation of the standard is chosen in the following form, i.e., with following values of coefficients alfa = 1, beta = 6 and P = 9:

$$\frac{d^2 y_r}{dt^2} + 6\frac{dy_r}{dt} + 9y_r = 9r \tag{10}$$

The neural controller is introduced into the automatic control system (Fig. 4). We assume that the nonlinear object is given by equation (1), the standard is given by equation (9), the architecture of the neural controller is already known (Fig. 2). In the learning process, it is only necessary to determine its weight coefficients of the controller (remark, that in the equation (1) there are taken the following values of coefficients alfa=1, beta=6 i P=10).

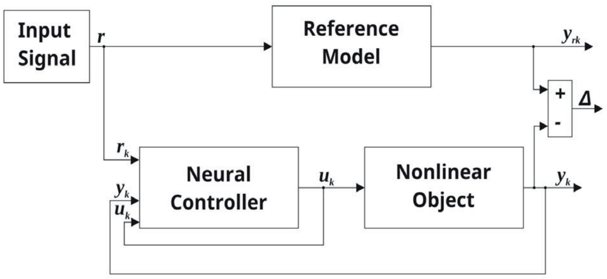

Fig. 4. Scheme of introducing a neural controller into an automatic control system

In this case, the neural controller complements the nonlinear object so that when any actually permissible sequence r_k is received, the resulting system approaches the standard as closely as possible (ideally $y_{rk} = y_k$).

The peculiarity of this approach is that when implementing the learning process, only two numerical sequences out of three given ones are used [16]. In this case, based on the sequences obtained when measuring the values of the signals at the input and output of the object (u_{ko} and y_{ko}), a neural model of the object is formed through training the neural network, which is supplemented by a neural controller and closed by feedback, which corresponds to the real system. The formed neural network reproduces the model of the combination of the controller and the object. Since it is necessary that this model be equivalent to the standard, the controller coefficients can be obtained by training this combined network. There is realized with sequences from the input and output of the standard (r_k and y_k), while the values of those coefficients that correspond to the subnet of the object must be fixed, i.e., only the controller coefficients must change during the learning process. In other words, the neural model of the object (Fig. 5) is used so that the error "reversely propagates" to the controller network through it [15].

After training from the combined network, you can select the part that corresponds to the controller and use it to control a real object. The described method has the advantage that the controller is trained only on the sequences r_k and y_k without using the sequence u_k. but in this case there is feedback inside the network, and training such networks is not an easy task.

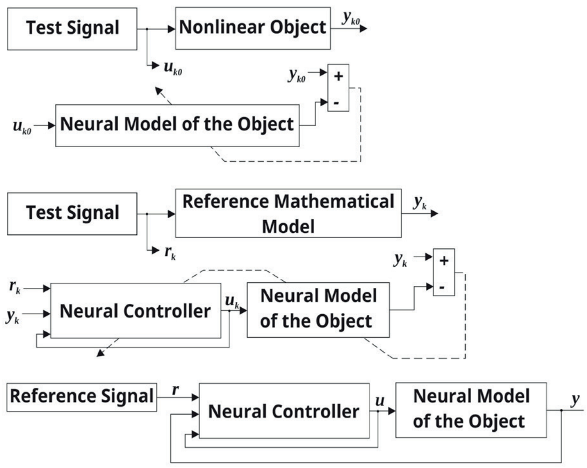

Fig. 5. Generalized scheme of training a neural controller using a neural model of an object

Dynamics of a neural controller using a neural model of an object training is presented (Fig. 6) as well.

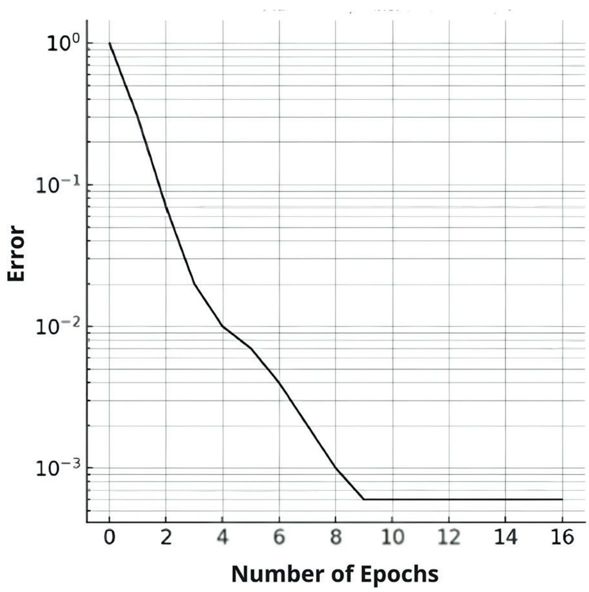

Fig. 6. Dynamics of training a neural controller using a neural model of an object

After completing the general network training process, we will select the controller and export it to the SIMULINK system. The quality of the constructed controller can be assessed using the time characteristics (Fig. 7), using the step excitation function. According to the simulation results, the root mean square error between the output signals of the object and the standard was equal to 0.009, which indicates high control accuracy.

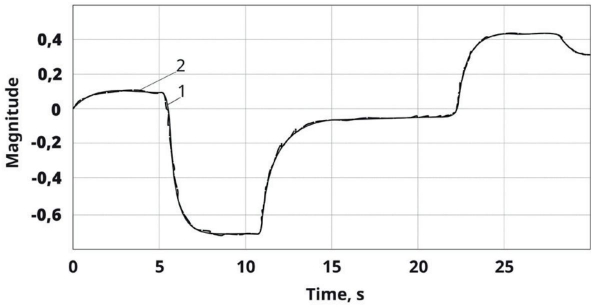

Fig. 7. Comparison of signals at the outputs of the reference (1) and the object (2) controlled by the synthesized neural controller

Conclusions

1. A control system for a moving platform based on an adaptive controller with a PID structure, whose parameters are tuned using a method derived from ANN learning algorithms, is justified.
2. It is established that in the simplest case, the proportional-integral-differential (PID) control law can be implemented on the basis of one neuron with a linear activation function and two delay lines at one input and one delay line from the output of the neuron to its second input
3. The learning duration is somewhat too large (tens of epochs).
4. The implementation of the control system has some difficulties due to problems with the selection of an appropriate element base.

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REFERENCES

[1] Strutynskyi S.V., Semenchuk R.V. Research on linear and angular oscillations of a mobile platform of a ground robotic complex, Mechanics and Advanced Technologies, Vol. 7, No. 1(97), pp. 129–137, DOI: https://doi.org/10.20535/2521-1943.2023.7.1.266626
[2] Hao X. R., Jun Y. J. and Qi Tang. Stability Control Method of opto-electronic platform's view-axis BasedonAuto-disturbance Rejection Controller. Modern Industrial Economy and Information Technology, 2021, 11(12):3
[3] João Barata, Ina Kayser. Industry 5.0 – Past, Present, and Near Future, Procedia Computer Science, Volume 219, 2023, Pages 778–788
[4] Jun Yang; Nadra Guizani; Long Hu; Ahmed Ghoneim; Mubarak Alrashoud; M. Shamim Hossain. Smart Autonomous Moving Platforms, IEEE Network, Volume 34, Issue 3, May/June 2020), page(s): 116–123, DOI: 10.1109/MNET.011.1900263
[5] Chip Huyen, AI Engineering: Building Applications with Foundation Models, O'Reilly Media, Inc., 2024.
[6] Shreya Talati, Darshan Vekaria, Aparna Kumari, Sudeep Tanwar. An AI-driven object segmentation and speed control scheme for autonomous moving platforms, Computer Networks, Volume 186, 26 February 2021, 107783
[7] Yulei Wu, Yuxiang Ma, Hong-Ning Dai, Hao Wang. Deep learning for privacy preservation in autonomous moving platforms enhanced 5G heterogeneous networks. Computer Networks, Volume 185, 11 February 2021, 107743; https://doi.org/10.1016/j.comnet.2020.107743
[8] Liu Yang, An Zhe. Research on line-of-sight stabilization control technology under moving platform, Proc. of SPIE, Vol. 12557, 2023, pp. 125570 K-1 – 125570 K-6. https://doi.org/10.1117/12.264/469
[9] Wei J., Qi L. Gyro stabilized platform visual axis stable adaptive fuzzy PID control system. Journal of aviation, 2007, 28 (1) :5
[10] Lintao Lan, Wei Jiang and Fangwu Hua. Research on the Line of Sight Stabilization Control Technology of Optronic Mast under High Oceanic Condition and Big Swaying Movement of Platform, Sensors 2023, 23(6), 3182; https://doi.org/10.3390/s23063182
[11] Aggarwal C. C. Neural Networks and Deep Learning, Springer International Publishing AG, part of Springer Nature 2018 /https://doi.org/10.1007/978-3-319-94463-0 2.
[12] Charles L. Phillips, H. Troy Nagle, Aranya Chakrabortty. Digital Control System Analysis and Design, 4-th ed. – Englewood Cliffs, New Jersey: Prentice Hall, 2015
[13] Hamid Khodabandehlou and M. Sami Fadali. Nonlinear System Identification using Neural Networks and Trajectory-based Optimization, Proceedings of the 16th International Conference on Informatics in Control, Automation and Robotics (ICINCO), 2019, pages 579–586, ISBN: 978–989–758–380–3
[14] Eric Aislan Antonelo, Eduardo Camponogara, Laio Oriel Seman, Eduardo Rehbein de Souza, Jean P. Jordanou, Jomi F. Hubner. Physics-Informed Neural Nets for Control of Dynamical Systems, arXiv:2104.02556, [Submitted on 6 Apr 2021 (v1), last revised 31 May 2022 (this version, v3)]
[15] Gao Huang, Dynamic neural networks: advantages and challenges, National Science Review, Volume 11, Issue 8, August 2024, nwae088, https://doi.org/10.1093/nsr/nwae088
[16] Hirnyak Yuriy, Ivakhiv Orest, Nakonechnyi Markiyan, Repetylo Taras. Control System of Robot Movement / IDAACS`2013. The 7 IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS). Volume 1, September 12–14, 2013, Berlin, Germany, P. 334-337.
[1] Chakrabortty, A., Nagle, H. T., & Phillips, C. L. (2015). Digital control system analysis & design: Global edition (4th ed.). Pearson.ISBN: 1–292–06122–7, 978–1–292–06122–1, 978–1–292–06188–7.
[2] Emami-Naeini,A.,Powell,D.,&Franklin,G.F.(2019).Feedback control of dynamic systems (8th ed.). Pearson. ISBN: 978–0–13–480230–2.
[3] Granino A. Korn, Theresa M. Korn, Mathematical Handbook for Scientists and Engineers: Definitions, Theorems, and Formulas for Reference and Review, Courier Corporation, 2013, 1152 pages