1. * Amor OUNISSI[1], 2. Azeddine KADDOURI[2] ,3. Rachid ABDESSEMED[1]

[1]Department of Electrical Engineering, Faculty of Technology, University Batna 2,Batna, Algeria.
[2]Department of Electrical Engineering, Faculty of Technology, University of Moncton, Moncton, Canada.
ORCID: 1.0000-0002-9822-2191; 2 .0000-0001-8758-1028 ; 3 .0000-0001-9062-7410

doi:10.15199/48.2024.03.23

Radial Basis Function Networks Based Synergetic Terminal Controller For Piezoelectric Actuator With Colman-Hodgdon Hysteresis Model

***Abstract**. This article proposes an intelligent nonlinear control approach based on the concept of combining neural networks and the methodology of synergistic terminal control. We have introduced the notion of convergence in finite time through the improvement induced on the macrovariable. This approach is associated with the approximation criteria of unknown nonlinearities by a radial basis function neural network to a class of PEA piezoelectric actuator positioning mechanisms.RBF weights are adjusted using the terminal attractor concept in the PEA finite time control process.the stability of a closed-loop system is ensured by the Lyapunov method.The simulation results have demonstrated the robustness of the proposed approach and provide good results in terms of tracking the trajectory and provides a better overall performance than that of classical synergetic control.*

Streszczenie.** W artykule zaproponowano inteligentne podejście do sterowania nieliniowego, oparte na koncepcji łączenia sieci neuronowych i metodologii synergistycznego sterowania terminalami. Wprowadziliśmy pojęcie zbieżności w skończonym czasie poprzez poprawę wywołaną makrozmienną. Podejście to wiąże się z aproksymacją kryteriów nieznanych nieliniowości za pomocą sieci neuronowej o promieniowej funkcji bazowej do klasy mechanizmów pozycjonowania siłowników piezoelektrycznych PEA. Wagi RBF są regulowane za pomocą koncepcji atraktora końcowego w procesie kontroli czasu skończonego PEA. Stabilność zamkniętego -pętlę zapewnia metoda Lapunowa. Wyniki symulacji wykazały solidność proponowanego podejścia i zapewniają dobre wyniki w zakresie śledzenia trajektorii oraz zapewniają lepszą ogólną wydajność niż w przypadku klasycznego sterowania synergicznego.* (Funkcja podstawy promieniowej Synergiczny kontroler terminala oparty na sieci dla siłownika piezoelektrycznego z modelem histerezy Colmana-Hodgdona***)

Keywords: Coleman-Hodgdon model, Identification with particle swarm optimization approache, Radial Basis Function Newtworks.
Słowa kluczowe: Model Colemana-Hodgdona, Identyfikacja metodą optymalizacji roju cząstek, Radialne sieci funkcyjne

Introduction

Scientific research and industry frequently call for precision positioning mechanisms with large millimeters order stroke and Micro/Nanoscale positioning resolution. Uncertainties such non-linearities, hysteresis phenomena, and drift that reduce positioning and/or tracking accuracy have spurred research in positioning systems control theory [1]. Furthermore, resonance vibrations can result in vibrational reactions that upset a system [2]. A system is typically controlled via its modeling, or by figuring out the relationships between its variables[3].A mathematical model that is based on an experimental analysis, a theoretical analysis, or even a theoretical-experimental analysis can describe a system [4].

To model the system, one must first select the model's structural elements that best explain and forecast the system's behavior and are compatible with the synthesis of the control. Identification, or figuring out the parameters of the selected model, comes next in the second step[5].Due to several considerations, such as measurement noise, the positioning systems in use today have unmodeled dynamics[6]. The motion detector essentially consists of a displacement sensor and hardware circuit [7] .For closed loop control, it may measure the output displacement and relay it back to the control system[8].It is also a crucial component because the detector's performance directly affects the system's accuracy[9]. By mathematical modeling and control strategies, remarkable attempts have been made to account for the non-linearities of the piezoelectric actuator[10]. Consequently, it would seem that both theoretical and practical parts of nonlinear system control strategies are inadequate [11].

The structure of the internal dynamics of nonlinear systems is revealed by recent approaches to nonlinear systems, such as differential geometry theory [12].Nonlinear inversion dynamics [13], backstepping [14]-[15], and feedback linearization [16] are three nonlinear control design techniques that have been created and successfully used to solve control issues. Advanced nonlinear control design techniques typically rely on an analytical model of the dynamic system, which is either unreliable or unavailable in many control applications[17].

While the adaptive component automatically corrects for the modeling error created by the simplification, nonlinear adaptive control approaches also permit the use of a simplified dynamic model in the design of the controller[18]. The assumption that the unknown dynamics have a defined structure and that unknown parameters enter the dynamics linearly is a key flaw in these nonlinear adaptive control systems[19].The employment of adaptive control methods in real applications is severely hampered by the linear parameterization of the unknown dynamics because it is challenging or impossible to fix the structure of the unknown non-linearities [20].

Therefore, smart control attracts great attention.It offers a fresh concept for resolving challenging system control issues. A standard and workable structure for the representation of nonlinear dynamical systems is provided by neural networks, which can approximate a broad class of nonlinear functions[21]. In order to improve applications when a mathematical model of a nonlinear system is available but imprecise or to create a model of the system from experimental data when a theoretical and fundamental model is impractical, neural networks are a strong tool [22]. While in adaptive control, the change of the neural network parameters is driven by a tracking error, which by definition contains no information about the entry, the weights of the neural network are updated according to input-output information in offline applications[23].

loop are bounded[24]. Approximation of nonlinear systems using function basis radial networks has some interesting advantages[25].The general RBF network approximation capabilities provide the theoretical basis for complex process representation.Also, the RBF network response is linear with respect to the network connection weights[26].Provided that the other parameters, the centers of RBF, can be chosen appropriately. One relies mainly on the use of RBF network, in order to approximate the unknown non-linearities of an uncertain model[27]-[28].More precisely, we will be interested in the terminal synergetic control associated with the approximation criteria of the non-linearities unknown by RBF to a class of piezo actuator PEA positioning mechanism.

1. Experimental investigation

1.1 *Modeling and Identification of C-H model*

The Coleman-Hodgdon model of Piezoelectric Actuator is described by the following equations :

(1) $$x(U)=\begin{cases}(a_1-a_2e^{-a_3V_f})U-a_4\left(1-\dfrac{2e^{-a_5U}}{e^{-a_5V_m}+e^{-a_5V_M}}\right) & Si \quad \dot{U}\geq 0\\ (a_1-a_2e^{-a_3V_f})U+a_4\left(1-\dfrac{2e^{a_5U}}{e^{a_5V_m}+e^{a_5V_M}}\right) & Si \quad \dot{U}<0\end{cases}$$

where x is the mechanism's output displacement, U is the control input and its derivative for the PEA, $V_f=V_M-V_m$ is the voltage range, and V_M, V_m are the maximum and minimum input voltages, and a_1-a_5 a re constant parameters. The application of the PSO algorithm in the determination of the optimal position has been described and validated by the experimental configuration used for the modeling and the identification of the C-H PEA model [29]. Figure 1 compares the C-H model's tracking performance to that of experiments when the piezoelectric positioning stage is driven by a sinusoidal input. The experimental results match the C-H modeling results very well.

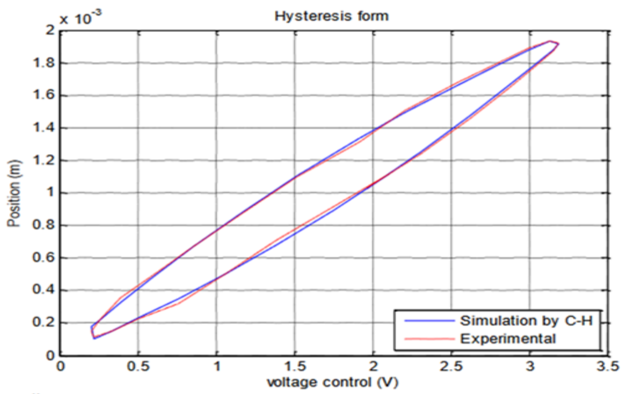

Fig.1. shows the experimental and PSO-based C-H model hysteresis with a 1 Hz input voltage

2. *Description the control system*

The dynamic of the nonlinear system can be expressed in the following state space model:

(2) $$\begin{cases}\dot{x}_1=x_2\\ \dot{x}_2=f(x_1,x_2,t)+g(x_1,x_2,t)U+d(t)\end{cases}$$

Where $x=[x_1,x_2]^T$ the state space vector, the vector of outputs is given by $y=[x_1,x_2]^T$, $U, and\ d(t)$ The control input and disturbances.The dynamic behavior of our system is described by a nonlinear C-H model. This model requires robust control and must be insensitive and stable to the variation of the parameters and disturbances. These expected characteristics of the control can be realized by a synthesis based on the technique of synergistic control [30].

The synergetic control theory is one of the new promoter options in modern and emerging control theory. The purpose of the control is to regulate the tracking of the trajectory of the position of the PEA [31].

We define the error

(3) $$e=x_{ref}-x$$

Where x_{ref} denotes the desired trajectory, the choice of a terminal macro variable is defined by:

(4) $$\psi=\dot{e}+\beta e^{\frac{q}{p}}$$

Where $\beta>0$ is constant, and p and q are odd positive constants, such that $p>q$ .To create a control law, RBF NN uses the macro variable's variable as input. A hidden layer, an output layer, and an input layer make up the Radial Basis Function Network. For each neuron in the bued layer, the activation function is selected as the Gaussian function. These Gaussian functions' excitation values are chosen as the distances between the input value and the function's center point.

(5) $$\varphi_i(\psi)=exp\left(-\frac{|\psi-c_i|^2}{2b_i^2}\right)$$

Where c_i the central position of the i^{eme} neuron et b_i is the spreading factor of the corresponding Gaussian function.

The weight of the parameters w_i between the neurons of the hidden layer and the output layer are adjusted according to an adaptation law $\dot{w}_i$ .The control law is:

(6) $$U_{RBF}=\sum_{i=1}^{n}w_i\varphi_i(\psi)=\sum_{i=1}^{n}w_i\,exp\left(-\frac{|\psi-c_i|^2}{2b_i}\right)$$

Where n is the number of neurons in the hidden layer.

Weight adjustment is established by gradient descent, the weight adaptation law is:

(7) $$\dot{w}_i=-\rho\frac{\partial E}{\partial w_i}=-\rho\frac{\partial\psi\partial\dot{\psi}}{\partial w_i}=-\rho\frac{\partial\psi\partial\dot{\psi}}{\partial U}\frac{\partial U}{\partial w_i}$$

Then

(8) $$\frac{\partial\psi\partial\dot{\psi}}{\partial U}=-\rho g\psi$$

(9) $$\frac{\partial U}{\partial w_i}=exp\left(-\frac{|\psi-c_i|^2}{2b_i^2}\right)$$

From where

(10) $$\dot{w}_i=-\gamma\psi\,exp\left(-\frac{|\psi-c_i|^2}{2b_i^2}\right)$$

Where $\gamma=\rho g$, the learning rate parameter

We derive the equation (4), and we use the system equation (2), we will have:

(11) $$\begin{aligned}\dot{\psi}&=\ddot{e}+\beta\frac{q}{p}\|\dot{e}\|^{\frac{q}{p}-1}\\ &=\dot{x}_2-\ddot{x}_{ref}+\beta\frac{q}{p}\|\dot{e}\|^{\frac{q}{p}-1}\\ &=f(x_1,x_2,t)+g(x_1,x_2,t)U+d(t)-\ddot{x}_{ref}+\beta\frac{q}{p}\|\dot{e}\|^{\frac{q}{p}-1}\end{aligned}$$

Then, the control law is:

(12) $$\bar{U}=\frac{1}{g(x)}\left[\ddot{x}_{ref}-f(x)-d(t)-\beta\frac{q}{p}\|\dot{e}\|^{\frac{q}{p}-1}+\gamma\psi\right]$$

$$\gamma>0$$

The control law may have some difference from the $\overline{\mathrm{U}}$ control law. From (2) and (8) we get:

(13) $$\dot{\psi} = -\mathrm{T}\psi + g(\widetilde{w}^{\mathrm{T}}\varphi + \in)$$

2.1 Theorem.

$x_{ref=500}$For the Piezoelectric Actuator system (1), and if the control signal is designed as

(14) $$U = U_{\mathrm{RFB}} + \overline{U}$$

And the update law for weight vector is chosen by:

(15) $$\hat{\widetilde{w}} = -\gamma\psi^{\mathrm{T}}\beta\frac{\mathrm{q}}{\mathrm{p}}\|e\|^{\frac{\mathrm{q}}{\mathrm{p}}-1}$$

Where $\gamma > 0$, is the learning rate

The system errors and the error rate asymptotically converge to zero in finite time, the rate of convergence depending on the parameters γ , p and q.

$\widetilde{\mathrm{w}} = \mathrm{w}^{*} - \hat{\mathrm{w}}$***2.2 Poof.***

wLet be the estimation error of the weight vector Consider the Lyapunov candidate function as:

(16) $$V = \frac{1}{2}\psi^{\mathrm{T}}\psi + \frac{1}{2\rho}\widetilde{w}^{\mathrm{T}}\widetilde{w}$$

We derive (16), we get

(17) $$\dot{V} = \psi\dot{\psi} + \frac{1}{\rho}\widetilde{w}^{\mathrm{T}}\hat{\widetilde{w}}$$

$$\dot{V} = \psi^{T}\left[-\mathrm{T}\psi + g(w^{\mathrm{T}}\varphi + \varepsilon)\right] + \frac{1}{\rho}\widetilde{w}^{T}\hat{\widetilde{w}}$$

We replace (15) in (17), we get:

(18) $$\dot{V} = -\mathrm{T}\psi^{\mathrm{T}}\psi + g\psi^{\mathrm{T}}\varepsilon \leq \|\psi\|(-\mathrm{T}\|\psi\| + g\varepsilon)$$

(19) $$\dot{V} \leq -\mathrm{T}\|\psi\|^{2} + \sigma\|\psi\|$$

$\sigma = g\epsilon$

Where

The influence of the $\alpha\|\Psi\|$ term is minimal, of the order of the minimum approximation error which is by design very small.As a result, all signals in the system to be controlled are bounded. Obviously, $\mathrm{e}(0)$ is bounded, then $\mathrm{e}(\mathrm{t})$ is also bounded.The reference signal $\mathrm{x}_{\mathrm{ref}}$ is bounded, then the state of the system $\mathrm{x}(\mathrm{t})$ is also bounded.To complete the proof and establish the asymptotic convergence of the tracking error.We need to prove that $\Psi_{\rightarrow 0}$ when $t_{\rightarrow\infty}$, assume $\|\Psi\| \leq \alpha$, then equation (18) can be rewritten as:

(20) $$\dot{V} \leq -\mathrm{T}\alpha|\psi| + \alpha|\sigma|$$

Integrating both sides of (20) leads to:

(21) $$\int_{0}^{t}|\psi|d\tau \leq \frac{1}{\mathrm{T}\alpha}\left[|\mathrm{V}(0)| + |\mathcal{V}(t)|\right] + \mathrm{T}\int_{0}^{t}|\sigma|d\tau$$

Since $\Psi \in \mathrm{L}_1$, from (19), the macro-variable is bounded and that Ψ, $\dot{\Psi} \in L_{\infty}$ consequently by the use of Barbalat (t)'s lemma[31],we also have $\Psi_{\rightarrow 0}$ when $t_{\rightarrow\infty}$,the system is stable and the error converges asymptotically to zero.

3. Results and discussion

To show the performance of the proposed terminal synergistic radial neural base function control. this part, presents a numerical simulation carried out on the dynamic model of hysteresis C-H.The purpose of the control is to force the system output to follow a desired set point

micron meter. Figure 2.a, show rapid convergence of system states to their reference.From figure 2.b, shows that the tracking error is about 5.797 e-05 m. Figure 3.a shows the control signal which is bounded. As well as the system is stable that presented by the figure 3.b. To demonstrate the superior qualities of the suggested controller compared to the synergetic terminal controller.We have seen in figure 4, the results of the responses of the system in the cases a) Trajectory tracking response of position b) Control voltage. c) Tracking error d) the phase plane, by an application of a disturbance of a load of 10 N. Figure 5 compares the error position tracking inaccuracy between the synergistic terminal controller and the suggested control approach, the latter being inferior to the synergistic terminal controller.

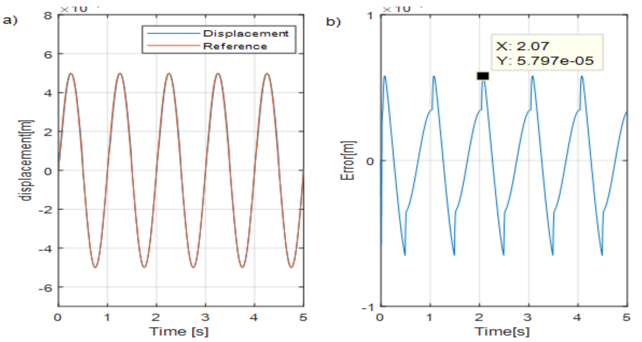

Fig.2. Results Simulation of the RBF network Synergetic Terminal Controller: a) Trajectory tracking response of the position b) Tracking error.

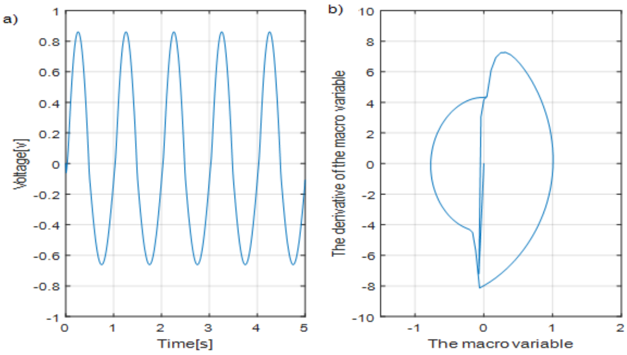

Fig.3. Results Simulation of the RBF network Synergetic Terminal Controlle

r: a) Control voltage b) phase diagram

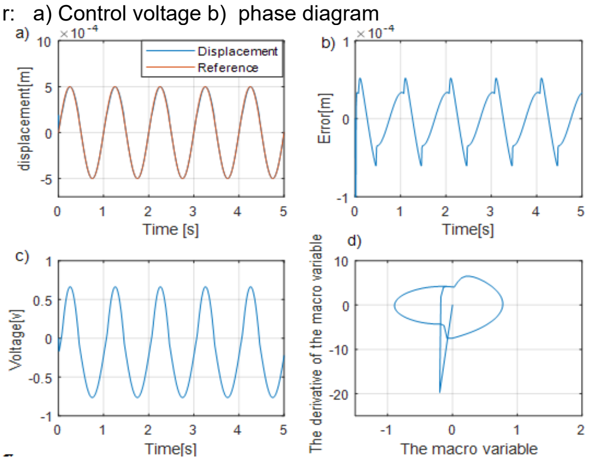

Fig.4. Simulation of the RBF network Synergetic Terminal Controller with a load of 10 N: a) Trajectory tracking response of the position b)Tracking error c)Control voltage d) phase diagram

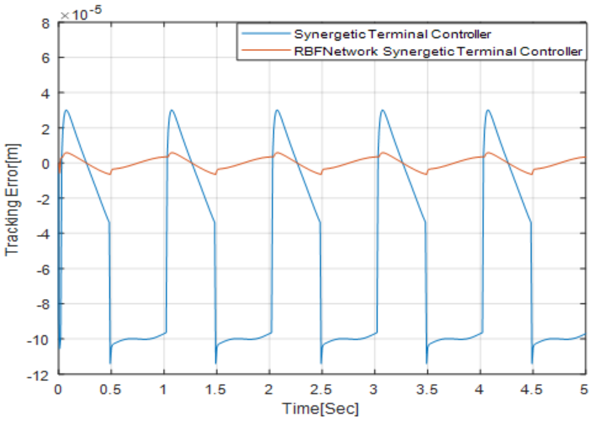

Fig.5. Evolution of the tracking error for the RBF network Synergetic Terminal Controller and the Synergetic Terminal Controller

4. Conclusion

The work considered in this article is a neural network of RBF type combined with the methodology of synergetic terminal control.The developed algorithm has been applied to the PEA. This interest is justified by the fact that piezoelectric actuator positioning systems are, for the most part, non-linear systems subject to modeling and parametric uncertainties, as well as to external disturbances. The algorithm is based on the RBF type neural network, with a hidden layer, to achieve the necessary approximations. The adjustment laws used made it possible to ensure the boundedness of the adjustable parameters.Lyapunov's analysis has guaranteed the stability of the control loop, under certain assumptions, even in the presence of uncertainties and external disturbances.Based on simulation results and performance comparison with traditional synergetic control.Our control strategy offers the best performance in terms of positioning tracking accuracy, small tracking errors, fast convergence and chattering rejection

***Authors**:*
**Dr O.amor. University of BATNA -2-, Department of Electrical Engineering, Faculty of Technology, Batna, Algeria,*
E-mail: amor.ounissi@univ-batna2.dz;
Prof. Dr A.Rachid. University of BATNA -2-, Department of Electrical Engineering, Faculty of Technology, Batna, Algeria;
E-mail: rachid.abdessemed@gmail.com;
Prof. Dr K.azeddine. University of Moncton,Department of Electrical Engineering, Faculty of Technology, Moncton, Canada;
E-mail: azeddine.kaddouri@umoncton.ca

REFERENCES

[1] Qinou. Z,Nicholas. T, Ferreira. P."Dynamics Modeling and Verification of a large displacement precision preloaded-flexure stage, 43 (2019): 36-45.

[2] Andrew J.Fleming .,Nanopositioning System With Force Feedback for High- Performance Tracking and Vibration Control, *IEEE/ASME Transactions On Mechatronics,* 15(2010) ,No. 3, 433-447.

[3] QW. He, T. Wang, and X. HE., Dynamical modeling and boundary vibration control of a rigid- flexible wing system, *IEEE/ASME Transaction on Mechatronics*, 25,(2020), No 06, 2711-2721.

[4] J. Siepmann, F. Siepmann.,Review Modeling of diffusion controlled drug delivery, *Journal of Controlled Release,* 161(2011), No.02, 351-362

[5] Krzysztof W, Grzegorz. K, Grzegorz. W, and Jan. A .,Mathematical modelling, numerical and experimental analysis of one-degree- of-freedom oscillator with Duffing-type stiffness, *International Journal Of Non-Linear Mechanics,* 138, (2022).

[6] F. Ferrante, F. Gouaisbaut, R. G. Sanfelice, and S.Tarbouriech., State estimation of linear systems in the presence of sporadic measurements,*Automatica,* . 73(2016), 101-109.

[7] Chulki Kim, Robert Marsland, and Robert H.Blick.,The Nanomechanical Bit, *Review Nano.Micro Small.6136829, 2020,33,Downloaded .from .http://www.doi/10.1002/smll.202001580.*

[8] Haitao Wu, Leijie Lai, Liqiang Zhang and Limin Zhu., Fractional order zero phase error racking control of a novel decoupled 2-DOF compliant micro-positioning stage, *J. Micromech. Microeng.* 31(2021) p. 12.

[9] Ziqiang Chi and Qing Xu "Recent Advances in the Control of Piezoelectric Actuator", *International Journal of Advanced Robotic Systems.(*2014), 11:182.

[10] Eneko Artexe,Oscar Barambones,Isidro Calvo, Pablo Femandez-Bustamante and ImanolMartin.,Ultraprecise Controller for Piezoelectric Actuators Basedon Deep Learning and Model Predictive Control, *Sensors, 23, (*2023) 1690.

[11] Ali Bazei, Mokrane Boudaoud, Massoud Hammasian Ettefagh, Zhiyong Chen, and Steph Régnier., "Displacement sensing by piezoelectric transducers in high-speed lateral nanopositioning, *IEEE Sensors Journal, 19, 20, (*2019), 9156 - 9165.

[12] Andrew D. Lewis.,The bountiful intersection of differential geometry,mechanics, and control theory, *Annual Review of Control, Robotics, and Autonomous Systems 1,(2018),* 1.1–1.24,*http://www.annualreviews.org/http://doi: 10.1146/annurev-control-060117-105033.*

[13] Josef F.,HornNon-Linear Dynamic Inversion Control Design for Rotorcraf, *Erospace 6 (2019),* 38.doi:10.3390/aerospace603003.

[14] Zhao. Ferg, Winyu. Liang, Jie.Ling, Xiaohio. Xiao and Kok Kiong Tan, " Integral terminal sliding-mode-based adaptive integral backstepping control for precision motion of a piezoelectric ultrasonic motor", *Mechanical Systems and Signal Processing, 144, (*2020), 106856, doi:10.1016/j.ymssp.2020.106856.

[15] A.Ounissi. A.Kaddouri,R.Abdessmed, "Hybrid Approach Control of Micro positioning stage Piezoelectric Actuator (PEA)", *J. Intelli Syst. Control,* 1,(2022) no. 1, 35-45. doi:10.56578/jisc010104.

[16] Yung-Yue Chen, Yu-Jen Lan and Yi-Qing Zhang., Robust Control Design Based on Perturbation Cancellation for Micro-Positioning Design with Hysteresis, *Actuators,10, (2021),* No. 278, doi:10.3390/act10110278.

[17] Tong Yang, Ning Sun, He Chen and Yongchun Fan., Observer-Based Nonlinear Control for Tower Cranes Suffering From Uncertain Friction and Actuator Constraints With Experimental Verification, *IEEE Transactions on Industrial Electronics,* 68,(2021) No. 07, 6192-6204, doi: 10.1109/TIE.2020.2992972.

[18] Anuradha M. Annaswamy and Alexander L.Fradkov.,A Historical Perspective of Adaptive Control and Learning, *Annual Reviews in Control,* 52,(2021) , 18-41. doi: 10.1016/j.acontrol.2021.10.014.

[19] Caihao Sun, Zong cheng Liu, Yong Chen, Yang Zhou and Qingyang Qu., Global Adaptive Control for Uncertain Nonlinear Systems under Non-Lipschitz Condition with Quantized States, *Electronics,11 (2022),* 3160. doi:10.3390/electronics11193160.

[20] Pil Rip Jeon, Moo Sun Hong and Richard D.Braatz., Compact neural network modeling of nonlinear dynamical systems via the standard nonlinear operator form, *Computers and Chemical.Engineering* 159 (2022) 107674, doi:10.1016/j.compchemeng.2022.107674.

[21 Christian Legaard, Gerald Schweiger,Jan Dragona, Claudio Gomes, Alexandros Iosifidis and Mahdi Abkar., Constructing Neural Network Based Models for Simulating Dynamical Systems, *ACM Computing Surveys,* 55, (2023)No. 11, 1–34.doi:org/10.1145/3567591.

[22] Christian Legaard,Pedram Agrand and Mahdi Aliyari Shoorehdeli., Adaptive Model Learning of Neural Networks with UUB Stability for Robot Dynamic Estimation, *arXiv:2210.15055v1 [cs.RO]* 26 Oct 2022.

[23] S.Piche and J.Grimm, "Gain confidence of a neural network used for model based control", *International Joint Conference on Neural Networks (IJCNN). IEEE, (2017),* 4244–4251, doi:10.1109/IJCNN.2017.7966393.

[24] P.Agand, M..Shoorehdeli, and Khaki-Sedigh., Adaptive recurrent neural network with lyapunostability learning rules for robot dynamic terms identification, *Engineering applications of artificial intelligence,(*2017). doi:10.1049/cth2.12137.

[25] Hui Ma, Hongyi Li, Renquan Lu and Tingwen Huang., Adaptive event-triggered control for a class of nonlinear systems with periodic disturbances, *Part of Springer Nature 2.* vol. 63, doi:10.1007/s11432-019-2680-1.

[26] A. Lamb, A. Goyal, Y. Zhang, S. Zhang, A. Courville and Y. Bengio.,Professor forcing: A new algorithm for training recurrent networks, *ArXiv preprint arXiv:1610.09038,* 2016, doi:10.48550/arXiv1610.09038.

[27] H. Hamedi, Ch. ben Regaya and A. Zaafouri., Real-time study of a photovoltaic system with boost converter using the PSO-RBF neural network algorithms in a MyRio controller, *Solar Energy*, 183,(2019), 1-16. doi:10.1016/j.solener.2019.02.064.

[28] Zh. Zhao, Weitian . He, Fu. Zhang, C. Wang and Keum-Shik . H., Deterministic Learning from Adaptive Neural Network Control for a 2-DOF Helicopter System With Unknown Backlash and Model Uncertainty, *.IEEE Transactions on Industrial Electronics,(2022)*, 1-10.doi:10.1109/TIE.2022.3213916.

[29] A. Ounissi, M. Landry, A. Kaddouri, R. Abdessmed., PSO Based Parameter Identification of Colman-Hodgdon Model of a Piezoelectric Actuator and PID Feedback Controller, 7*, (*2014), No. 4, 179-192. doi:10.12988/ces.2014.3953.

[30] Habib Khan, Q. Khan, L. Khan, W. Alam, Nihad . A, I. Khan, Kottakkaran . So and R. A. Khan .,MPPT Control Paradigms for PMSG-WECS:A synergistic Control Strategy With Gain-Scheduled Sliding Mode Observe, *IEEE Access,* 9,(2021), 139876-139887, 2021.
doi: 10.1109/ACCESS.2021.3119213.

[31] A. Ounissi, A. Kaddouri, R. Abdessmed., Synergetic control of micro positioning stage piezoelectric actuator, *Intenational Journal of applied Power Engineering (IJAPE)*. 11, (2022), No. 4, 264-270. doi: 10.11591/ijape. v11i4.

[32] Slotine and W. Li .,Applied nonlinear control, *Prentice Hall, Englewood, Cliffs, NJ, 1991*.