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NEURAL NETWORK COMPENSATION OF DYNAMIC ERRORS IN A POSITION CONTROL SYSTEM OF A ROBOT MANIPULATOR

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This paper considers a position control system of a 3-link robot manipulator. The authors reviewed publications on nonlinear compensation of dynamic errors with the use of neural networks in robot manipulator control systems. The paper presents mathematical description of the control system with the compensation of nonlinear dynamics of the robot mechanism. We carried out training of multivariable neural network compensators of dynamic errors occurring because of the influence of inertia, Coriolis and gravity load torques. We developed computer models of the control system with different types of neural network compensators which are included in feedforward and feedback of the system and carried out a computer simulation of control systems with prototype and different kinds of neural network compensators. We also conducted a comparative analysis of dynamic errors in the system with different combinations of neural network compensators and gave recommendations on program realization of neural network compensators for real robot manipulator position control systems.

Keywords: robot manipulator, position control system, neural networks, nonlinear multivariable compensators, simulation, dynamic errors.

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НЕЙРОСЕТЕВАЯ КОМПЕНСАЦИЯ ДИНАМИЧЕСКИХ ОШИБОК В ПОЗИЦИОННОЙ СИСТЕМЕ УПРАВЛЕНИЯ МАНИПУЛЯЦИОННЫМ РОБОТОМ

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Рассмотрена система позиционного управления трёхзвенным манипуляционным роботом. Проведен обзор публикаций по вопросам нелинейной компенсации динамических ошибок в системах программного управления манипуляционными роботами с использованием нейронных сетей. Представлено математическое описание системы управления с нелинейной компенсацией динамики исполнительного механизма робота. Проведено обучение многомерных нелинейных нейросетевых компенсаторов динамических ошибок, обусловленных действием инерционных, кориолисовых и гравитационных нагрузочных моментов в приводах робота. Разработаны компьютерные модели системы управления с различными вариантами многомерных нейросетевых компенсаторов, включаемые в разомкнутый канал управления и замкнутый контур системы управления. Проведено компьютерное моделирование систем с прототипными и нейросетевыми компенсаторами рассматриваемых типов. Сделан сравнительный анализ динамических ошибок в системах управления с различными комбинациями нейросетевых компенсаторов. Даны рекомендации по программной реализации нейросетевых компенсаторов для реальных позиционных систем управления манипуляционными роботами.

Ключевые слова: робот-манипулятор, позиционная система управления, нейронные сети, нелинейные многомерные компенсаторы, моделирование, динамические ошибки.

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Introduction

These days the new problems of robot manipulator (RM) motion control are given significant consideration. One of such problems is increasing the precision characteristics of robots executing various technological operations. When the motion of robot links along program trajectories is performed, substantial dynamic errors occur mainly because of considerable nonlinearity of RM dynamics and because of robot links' interaction [1–4].

The design of RM motion control systems (CS) requires a very precise description of system dynamics and knowing technical parameters of a RM. Existing control methods, including the control based on the calculation of torques in link joints and other control methods based on the direct solving of the inverse dynamics problem, require the use of precise RM dynamics models [5–7]. However, mathematical models of real control systems contain some parameter uncertainties. Therefore, RM control requires taking into account not only the links' interaction but also the influence of various load torques.

Lately, algorithms based on fuzzy logic and neural networks have been implemented for the purpose of increasing robot precision characteristics [8–10]. In particular, neural network calculators can be used in robot drives as nonlinear quasi time-optimal regulators [11]. Neural network interpolators of robot link trajectories can be implemented instead of traditional spline interpolators in computer numerical control (CNC) systems [12, 13]. Also, neural network can be used for solving inverse kinematics of a robot [14, 15].

In this paper, we explore robot manipulator motion control systems with neural network (NN) compensators of dynamic errors occurring when robot drives execute program trajectories of the robot links. These errors are caused by torque loads resulting from nonlinear robot dynamics. Similar investigations were carried out in [16, 17].

The purpose of this work is the choice of structures and the training of multivariable nonlinear NN compensators of dynamic errors occurring on program gripper trajectories of a 3-link robot that operates in an angular coordinate system.

The main problems we approach in this paper are listed below:

1) mathematical modeling of control systems with prototype compensators of dynamic errors;
2) training of NN compensators which occur on given program trajectories of RM links;
3) computer simulation of control systems with prototype and NN compensators;
4) evaluation and comparative analysis of dynamic errors in the systems under consideration.

Mathematical models of prototype nonlinear compensators

Multivariable compensators of dynamic errors are described by expressions corresponding to the nonlinear dynamic model of a robot, which is presented in the form of Lagrange equations [1–4]:

$$A(q)\ddot{q}+B(q,\dot{q})\dot{q}+C(q)=Q_d-Q_L, \tag{1}$$

where (q, $\dot{q}$, $\ddot{q}$) – N×1 vectors of position, speed and acceleration coordinates of the robot links; N – the number of robot links.

The main loads of the robot drives are the elements of the vectors in the left part of the equations (1), where: $Q_{iner} = A(q)\ddot{q}$ – N×1 vector of inertia torques caused by accelerated links' motion; $A(q)$ – N×N matrix of the robot's kinetic energy; $Q_{cor} = B(q,\dot{q})\dot{q}$ – N×1 vector of Coriolis and centrifugal torques; $B(q,\dot{q})$ – N×N matrix; $Q_{grav} = C(q)$ – N×1 vector of gravity torques and other potential forces.

In the right part of equations (1) Q_d – N×1 vector of torques generated by the robot drives; Q_L – N×1 vector of additional loads occurring in the drives because of frictions in the joints and the influence of external forces on the robot gripper:

$$Q_L = J^T(q)F_L, \tag{2}$$

where $J^T(q)$ – N×N matrix transposed to the robot's Jacobi matrix; $F_L = (F_x, F_y, F_z, M_x, M_y, M_z)^T$ – 6×1 vector of coordinates of an external force and an external torque that influence the gripper.

In motion control systems, trajectories of robot links are calculated by solving the inverse kinematics problem in the base points of a robot gripper trajectory. After that, the link trajectories are interpolated using spline or other polynomials. Thus, the torques which the drives must overcome can be calculated with the program values of position, speed and acceleration vectors of the links (q_p, $\dot{q}_p$, $\ddot{q}_p$):

$$Q_{iner}=A(q_p)\ddot{q}_p, \quad Q_{cor}=B(q_p,\dot{q}_p)\dot{q}_p, \quad Q_{grav}=C(q_p), \tag{3}$$

$$Q_{ff} = Q_{iner} + Q_{cor} + Q_{grav}. \tag{4}$$

Expressions (3) and (4) can be used directly for compensation of dynamic errors in CS with torque drives.

Fig. 1 shows the functional diagram of a system with compensators included in a feedforward (FF) circuit of the system, where PCU is a program control unit.

In case there are additional torques of loads Q_L, there might be significant errors in a system with FF compensation. These errors can be reduced by adding a linear compensator into the position PID regulator:

$$U_{pid}=(K_p e+K_i\int edt-K_d\dot{q})+K_{com}\dot{q}_p, \tag{5}$$

where $K_{com} = diag\{K_{(com,i)}\}$ – the diagonal matrix of linear compensator coefficients.

Nonlinear compensators can be also included into a closed loop of a system with position and speed feedback (FB), in a combination with a PID regulator or a more complex nonlinear regulator. In this case the FB compensator uses signals of real links' positions and speeds that are measured by sensors:

$$Q_{iner}=A(q)U_{pid}, \quad Q_{cor}=B(q,\dot{q})\dot{q}, \quad Q_{grav}=C(q), \tag{6}$$

$$Q_{fb} = Q_{iner} + Q_{cor} + Q_{grav}, \tag{7}$$

where the output vector of the PID regulator U_{pid} is interpreted as a vector of program accelerations.

A functional diagram of a system with a nonlinear FB compensator is shown in Fig. 2.

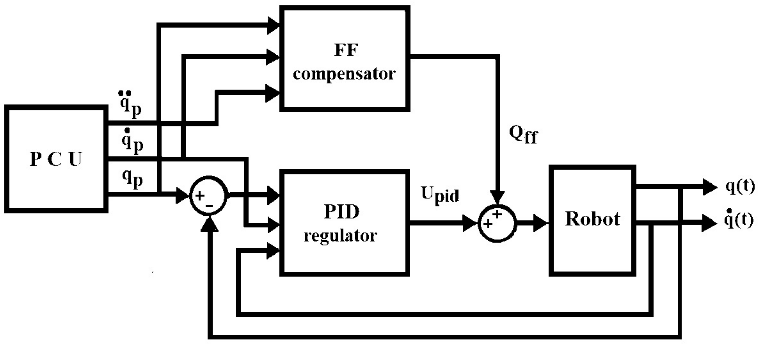

Fig. 1. A control system with feedforward compensation

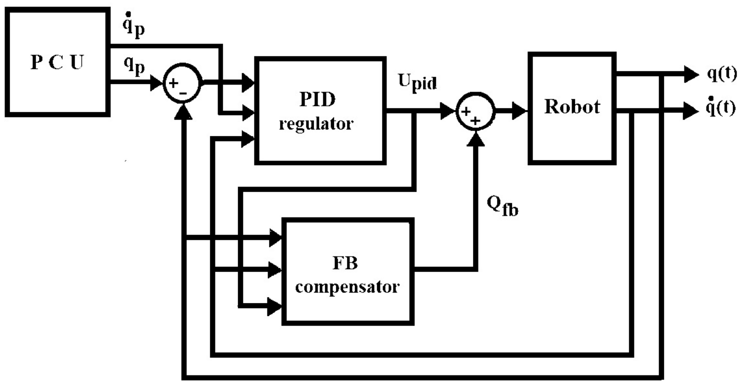

Fig. 2. A control system with feedback compensation

Multivariable compensators (6) and (7) perform the functional linearization of the robot's nonlinear dynamics described by equations (1), and thus, help make the robot drives work more accurately.

Simulation of a system with prototype nonlinear compensators

Certain Simulink models were built for the investigation of control systems with prototype FF and FB compensators. Parameters of a 3-link RM model corresponded to the parameters of the first three links of the 6-link PUMA-560 robot. Frictions in the robot joints were not taken into consideration [18–20].

A helical (spiral-shaped) trajectory was chosen as a standard program trajectory of a robot gripper. Fig. 3 illustrates the animation of the robot gripper movement along a helical trajectory made with functions from Robotics Toolbox 10.3.1 [20].

The dynamic errors on the gripper trajectory were calculated using the expression below:

$$E = \sqrt{(X_p - X_r)^2 + (Y_p - Y_r)^2 + (Z_p - Z_r)^2}, \tag{8}$$

where $(X_p, Y_p, Z_p)^T$ – the program coordinates of gripper positions; $(X_r, Y_r, Z_r)^T$ – the real coordinates of gripper positions.

Fig. 4 shows dynamic errors obtained in the process of simulation for the two types of systems: 1 – for the system with a PID regulator only, without a linear compensator (dash line); 2 – for the system with a PID regulator and an additional linear FF compensator (solid line).

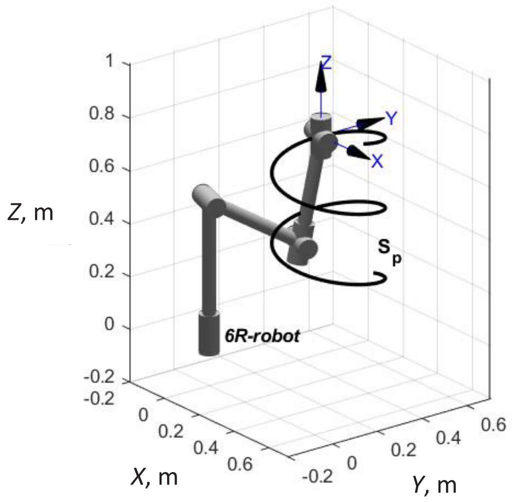

Fig. 3. The helical program trajectory of the robot gripper

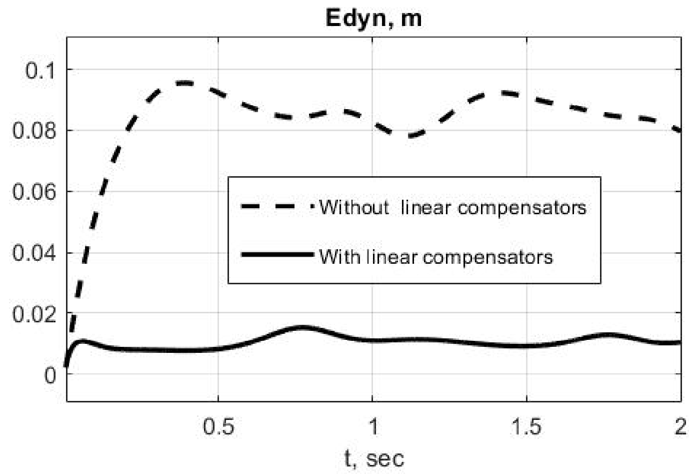

Fig. 4. Errors in the systems without nonlinear compensators

Fig. 5 shows dynamic errors in the systems with a linear compensator and additional nonlinear FF compensators of different types:

1 – FF compensation of gravity torques;

2 – FF compensation of Coriolis and centrifugal torques;

3 – FF compensation of inertia torques;

4 – full FF compensation of load torques.

Fig. 6 shows dynamic errors in the systems with a linear compensator and different combinations of nonlinear FF compensators:

1 – FF compensation of gravity torques only;

2 – FF compensation of gravity and Coriolis torques;

3 – FF compensation of gravity, Coriolis and inertia torques.

From what we can see in Fig. 5 and 6, the minimal dynamic errors are achieved with the use of a linear compensator together with all types of nonlinear FF compensators.

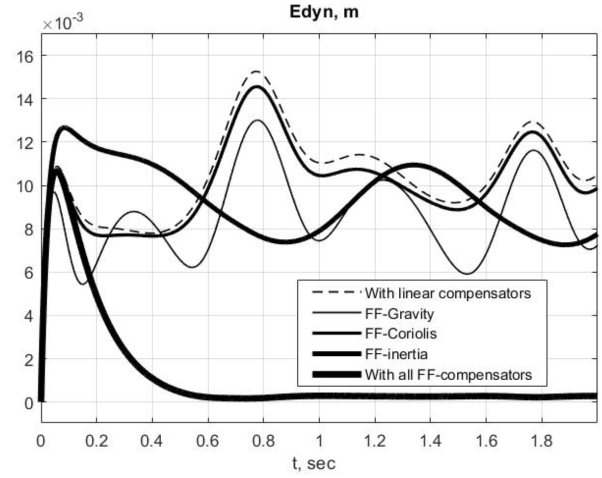

Fig. 5. Errors in the systems with nonlinear FF compensators

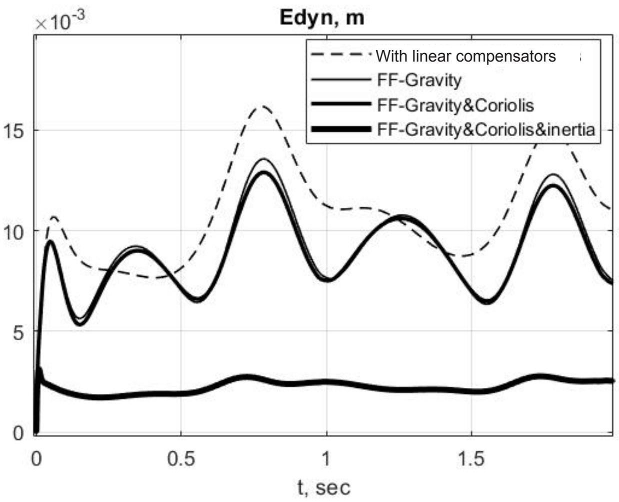

Fig. 6. Errors in the systems with a combination of FF compensators

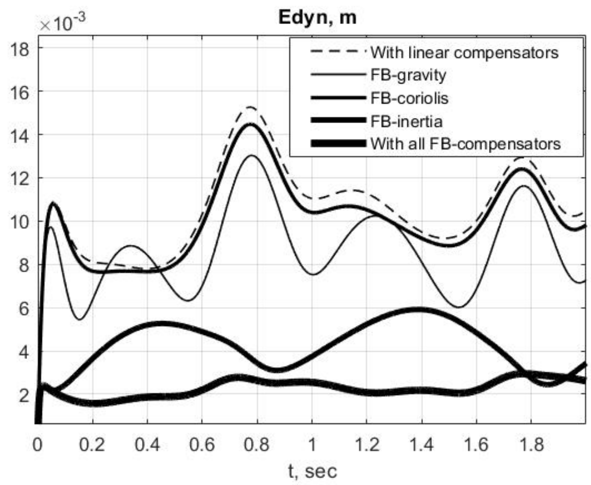

Fig. 7. Errors in the systems with nonlinear FB compensators

Fig. 7 illustrates dynamic errors in the systems with a linear compensator and additional nonlinear FB compensators of different types:

1 – FB compensation of gravity torques;
2 – FB compensation of Coriolis and centrifugal torques;
3 – FB compensation of inertia torques;
4 – full FB compensation of load torques.

Training of nonlinear neural network compensators

Neural network compensators can be realized with the use of different types of neural networks [21–26]. In this work, models of prototype compensators were used for the training of NN compensators. Program links' coordinates $(q_p, \dot{q}_p, \ddot{q}_p)$ on a given helical gripper trajectory were chosen as input data for the training of NN compensators. Calculated load torques $(Q_{iner}, Q_{cor}, Q_{grav})$ were used as output data. Radial basis neural networks were chosen as NN compensators. The training was performed using functions from Neural Network Toolbox in MATLAB.

Simulation of a system with nonlinear neural network compensators

Simulink models shown in Fig. 8, 9 and 10 were developed for the analysis of processes in systems with neural network FF and FB compensators.

Dynamic errors obtained during the simulation of the system shown in Fig. 8 are close to the errors shown in Fig. 5.

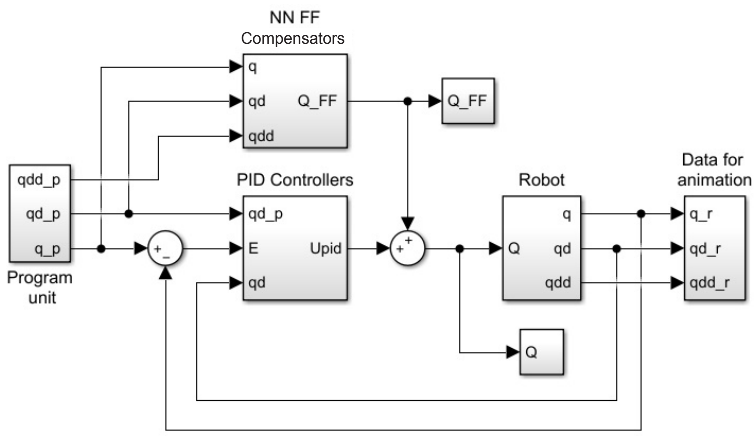

Fig. 8. The model of a control system with neural network FF compensators

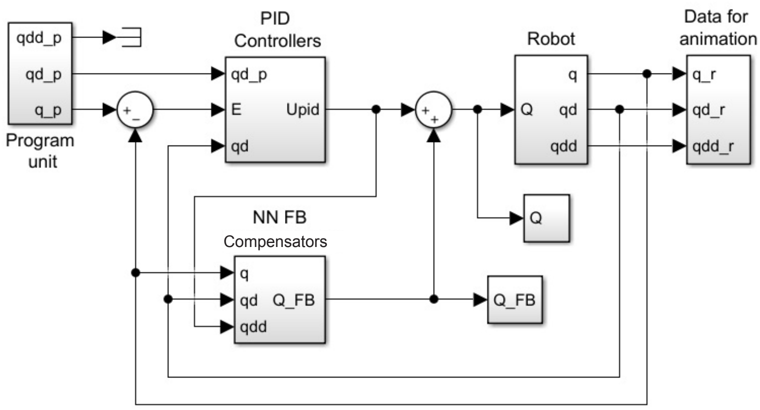

Fig. 9. The model of a control system with neural network FB compensators

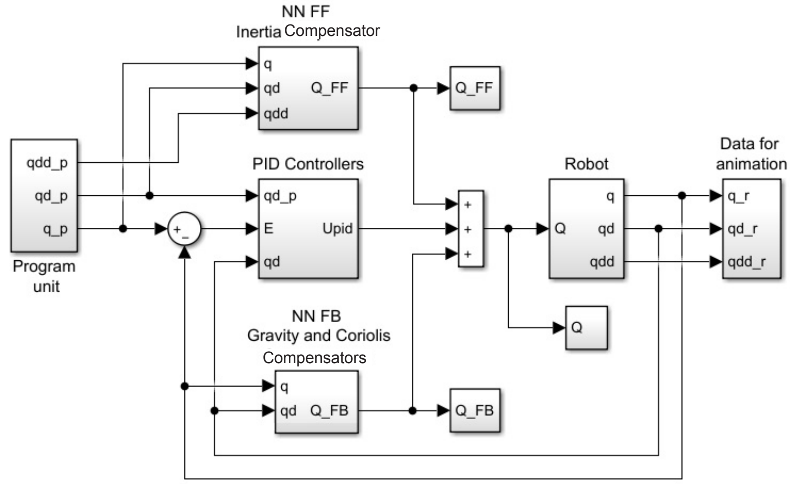

Fig. 10. The model of a control system with two neural network FB compensators and one FF inertia compensator

Dynamic errors obtained during the simulation of the system shown in Fig. 9 are different from the errors shown in Fig. 7.

The model in Fig. 10 includes two neural network FB compensators (of gravity and Coriolis torques) and one neural network FF inertia torques compensator.

Fig. 11 shows dynamic errors in three systems with a linear compensator and different combinations of neural network FF compensators:

1 – full neural network FF compensation;

2 – neural network FB compensation of gravity and Coriolis torques;

3 – neural network FF compensation of inertia torques and FB compensation of gravity and Coriolis torques.

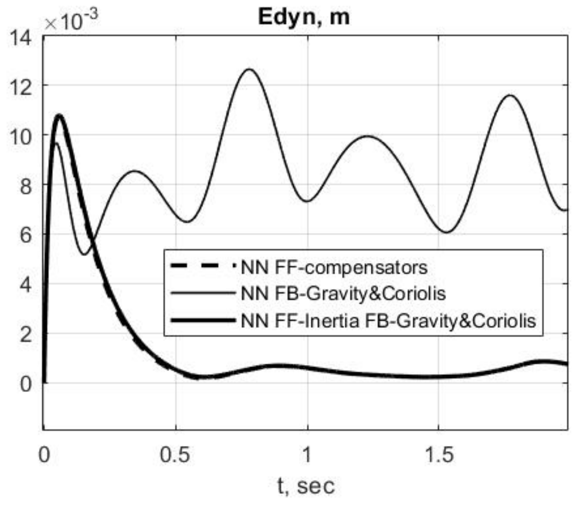

Fig.11. Errors in the systems with neural network FF and FB compensators

The evaluation of errors in Fig. 11 leads to the conclusion that the minimal dynamic errors are achieved in the system with two neural network FB compensators of gravity and Coriolis torques and one additional neural network FF compensator of inertia torques, just as in the system with full neural network FF compensation.

Conclusion

The dynamical precision of traditional CNC systems is achieved with combined control of the robot drives that includes regulation with feedbacks and one-variable linear compensation of errors caused by derivatives of drives' inputs. But in case of robot manipulators decreasing dynamical errors requires nonlinear multivariable compensation of the influences of inertia, Coriolis, centrifugal and gravity torques in the robot link drives when moving along complex program trajectories.

In this work, the authors explore robot manipulator control systems when the robot operates in determined conditions. In this case construction parameters and the robot's dynamic model are known. This allows to calculate torques of load that occur on given trajectories of the robot gripper beforehand in order to compensate for the influence of torques during the operation.

NN compensators of dynamic errors are an alternative to prototype nonlinear compensators, which have specific structures and parameters described with complex nonlinear equations. Training of NN compensators should be performed in the autonomous (offline) mode based on the results of computer simulation of prototype compensators for certain program trajectories of the robot gripper. The minimal time of training is achieved when using NN compensators with RBF neurons.

NN compensators are effective for increasing the robot's precision in modern CNC systems. Also, the functional linearization of complex and nonlinear multivariable robot dynamics that they give ensures more stable work of robot link drives. In systems without nonlinear compensation, the robustness of high-precision drives can be obtained only with the use of adaptive regulators, which are rather complicated to implement.

The necessary condition for NN compensators use is that the computer model used for their training corresponds to the real robot dynamics. In this case compensators trained for certain program trajectories of the robot links will not cause instability of closed-loop drive systems. In situations with some parameter uncertainty of real robot dynamics, NN compensation will be incomplete, and the drives robustness can be improved with adaptive regulators. However, the problems of synthesis of such kind of regulators require special consideration.

The estimates of dynamic errors on the gripper helical trajectory obtained by computer simulation show that errors in systems with multivariable RBF NN compensators and standard PID position regulators are much smaller compared to systems with linear compensators. The results of simulation show that the highest precision is achieved in the control system with two NN FB compensators and one NN FF inertia compensator (Fig. 10). Such structure can be recommended for implementation in real systems.

For NN approximation of different torques of load with necessary precision, the number of RBF neurons and training time depend on the type of trajectories, operation time and singularity points on the continuous-path gripper trajectory. Program realization of nonlinear NN compensators requires high-speed microprocessors, such as digital signal processors (DSP). However, the problems of implementation of NN compensators require more detailed consideration that is beyond the scope of this paper.

REFERENCES

1. **Zenkevich S.L., Yuschenko A.S.** *The basis of robot manipulator control*. Moscow: MGTU named by N.E. Bauman Publ., 2004. (rus)

2. **Jurevich E.I.** *The basis of robotics*. St. Petersburg: BHV–Petersburg Publ., 2018. (rus)

3. **Ignatova E.I., Lopota A.V., Rostov N.V.** *Robot motion control systems: computer-aided design*. St. Petersburg: Polytechnic University Publ., 2014. 301 p. (rus)

4. **Lewis F.L., Abdallah C.T., Dawson D.M.** *Control of robot manipulators*. New York: Macmillan, 1993.

5. **Santibañez V., Camarillo K., Moreno-Valenzuela J., Campa R.** A practical PID regulator with bounded torques for robot manipulator. *Int. J. Control Autom. Syst.*, 2010, Vol. 8, No. 3, Pp. 544–555.

6. **Lee G., Wand Cheng F.T.** Robust control of manipulators using the computed torque plus H∞ compensation method. *IEEE Proc. Control Theory Appl.*, 1996, Vol. 143, No. 1, Pp. 64–72.

7. **Islam S., Liu X.P.** Robust sliding mode control for robot manipulators. *Proceedings of IEEE Trans Ind Electron.*, 2011, Pp. 2444–2453.

8. **Zabihifar S., Markazi A., Yuschenko A.** Control of a two link manipulator with the use of fuzzy logic sliding mode control. *Vestnik MGTU named by N.E.Bauman*, 2015, No. 6 (105), Pp. 30–45. (rus). DOI: 10.18698/0236-3933-2015-6-30-45

9. **Lewis F.L., Jaganathan S., Yesildirek A.** *Neural network control of robot manipulators and nonlinear systems*. London: Taylor & Francis, 1999.

10. **Kim Y.H., Lewis F.L.** Neural network output feedback control of robot manipulators. *Proceedings of IEEE Trans Robot Autom.*, 1999, Pp. 301–309.

11. **Ishmuratov V.N., Rostov N.V.** Computer training of neural network quasi time-optimal digital regulators. *Proceedings of International Scientific and Practical Conference*, 2007, Pp. 134–136.

12. **Terpukhov S.Yu., Rostov N.V.** Neural network interpolation of program trajectories of links of a robot manipulator. *Proceedings of International Scientific and Practical Conference*, 2010, Pp. 70–72.

13. **Yan Z., Rostov N.V.** Error analysis of neural network interpolators of program trajectories of links of a robot manipulator. *Proceedings of ComCon-2018*, 2018, Pp. 114–119.

14. **Bhattacharjee T., Bhattacharjee A.** A study of neural network based inverse kinematics solution for a planar three joint robot with obstacle avoidance. *Assam University Journal of Science & Technology: Physical Sciences and Technology*, 2010, Vol. 5, No. 2, Pp. 1–7.

15. **Chiddarwar S.S., Babu N.R.** Comparison of RBF and MLP neural networks to solve inverse kinematic problem for 6R serial robot by a fusion approach. *Engineering Applications of Artificial Intelligence*, 2010, Vol. 23, Pp. 1083–1092.

16. **Duc M.N, Trong T.N.** Neural network structures for identification of nonlinear dynamic robotic manipulator. *Proceedings of IEEE International Conference on Mechatronics and Automation*, 2014, Pp. 1575–1580.

17. **Singh H.P., Sukavanam N., Panwar V.** Neural network based compensator for robustness to the robot manipulators with uncertainties. *International Conference on Mech. Electr. Technol. Proc.*, 2010, Pp. 444–448.

18. **Dixon W.E., Moses D., Walker L.D., Dawson D.M.** A Simulink-based robotic toolkit for simulation and control of the PUMA 560 robot manipulator. *Intelligent Robots and Systems. Proceedings of IEEE/RSJ International Conference*, 2001, Vol. A, Pp. 2202–2207.

19. **Corke P.I.** *Robotics, vision and control. fundamental algorithms in MATLAB*. Berlin: Springer-Verlag Berlin Heidelberg, 2017. DOI: 10.1007/978-3-319-54413-7

20. **Corke P.I.** Robotics toolbox for MATLAB. Release 10. 2017. Available: *http://www.petercorke.com/robot*

21. **Seshagiri S., Khalil H.K.** Output feedback control of nonlinear systems using RBF neural networks. *Proceedings of IEEE Trans Neural Networks*, 2000, Pp. 69–79.

22. **Tai N.T., Ahn K.K.** A RBF neural network sliding mode controller for SMA actuator. *Proceedings of International J. Control Autom. Syst.*, 2010, Pp. 1296–1305.

23. **Kumar N., Panwar V., Borm J.H., Chai J.** Enhancing precision performance of trajectory tracking controller for robot manipulators using RBFNN and adaptive bound. *Appl. Math. Comput.*, 2014, Vol. 231, Pp. 320–328. DOI: 10.1016/j.amc.2013.12.082

24. **Yan Z., Rostova E.N., Rostov N.V.** Neural network compensation of dynamic errors in a robot manipulator programmed control system. *Lecture Notes in Networks and Systems. Cyber-Physical Systems and Control*, 2020, Vol 95, Pp. 554–563. DOI: 10.1007/978-3-030-34983-7_543

25. **Farzam T., Nafise F.R.** Robust control of a 3-DOF parallel cable robot using an adaptive neuro-fuzzy inference system. *Artificial Intelligence and Robotics (IRANOPEN)*, 2017, Pp. 97–101. DOI: 10.1109/RIOS.2017.7956450

26. **Zabihifar S., Yuschenko A.** Hybrid force/position control of a collaborative parallel robot using adaptive neural network. *Lecture Notes in Computer Science. Interactive Collaborative Robotics*, 2018, Vol. 11097, Pp. 280–290. DOI: 10.1007/978-3-319-99582-3_29

Received 10.01.2020.

СПИСОК ЛИТЕРАТУРЫ

1. **Зенкевич С.Л., Ющенко А.С.** Основы управления манипуляционными роботами. М.: Изд-во МГТУ им. Н.Э. Баумана, 2004.

2. **Юревич Е.И.** Основы робототехники. СПб.: BHV–Петербург, 2018.

3. **Игнатова Е.И., Лопота А.В., Ростов Н.В.** Системы управления движением роботов. Компьютерное проектирование. СПб.: Изд-во Политехн. ун-та, 2014. 301 с.

4. **Lewis F.L., Abdallah C.T., Dawson D.M.** Control of robot manipulators. New York: Macmillan, 1993.

5. **Santibañez V., Camarillo K., Moreno-Valenzuela J., Campa R.** A practical PID regulator with bounded torques for robot manipulator // Int. J. Control Autom. Syst. 2010. Vol. 8. No. 3. Pp. 544–555.

6. **Lee G., Wand Cheng F.T.** Robust control of manipulators using the computed torque plus H∞ compensation method // IEEE Proc. Control Theory Appl. 1996. Vol. 143. No. 1. Pp. 64–72.

7. **Islam S., Liu X.P.** Robust sliding mode control for robot manipulators // Proc. of IEEE Trans Ind Electron. 2011. Pp. 2444–2453.

8. **Забихифар С., Маркази А., Ющенко А.** Управление двухзвенным манипулятором с использованием нечеткого управления скользящего типа // Вестник МГТУ им. Н.Э. Баумана. 2015. № 6 (105). С. 30–45. DOI: 10.18698/0236-3933-2015-6-30-45.

9. **Lewis F.L., Jaganathan S., Yesildirek A.** Neural network control of robot manipulators and nonlinear systems. London: Taylor & Francis, 1999.

10. **Kim Y.H., Lewis F.L.** Neural network output feedback control of robot manipulators // Proc. of IEEE Trans Robot Autom. 1999. Pp. 301–309.

11. **Ishmuratov V.N., Rostov N.V.** Computer training of neural network quasi time-optimal digital regulators // Proc. of Internat. Scientific and Practical Conf. 2007. Pp. 134–136.

12. **Terpukhov S.Yu., Rostov N.V.** Neural network interpolation of program trajectories of links of a robot manipulator // Proc. of Internat. Scientific and Practical Conf. 2010. Pp. 70–72.

13. **Yan Z., Rostov N.V.** Error analysis of neural network interpolators of program trajectories of links of a robot manipulator // Proc. of ComCon-2018. 2018. Pp. 114–119.

14. **Bhattacharjee T., Bhattacharjee A.** A study of neural network based inverse kinematics solution for a planar three joint robot with obstacle avoidance // Assam University J. of Science & Technology: Physical Sciences and Technology. 2010. Vol. 5. No. 2. Pp. 1–7.

15. **Chiddarwar S.S., Babu N.R.** Comparison of RBF and MLP neural networks to solve inverse kinematic problem for 6R serial robot by a fusion approach // Engineering Applications of Artificial Intelligence. 2010. Vol. 23. Pp. 1083–1092.

16. **Duc M.N, Trong T.N.** Neural network structures for identification of nonlinear dynamic robotic manipulator // Proceedings of IEEE Internat. Conf. on Mechatronics and Automation. 2014. Pp. 1575–1580.

17. **Singh H.P., Sukavanam N., Panwar V.** Neural network based compensator for robustness to the robot manipulators with uncertainties // Internat. Conf. on Mech. Electr. Technol. Proc. 2010. Pp. 444–448.

18. **Dixon W.E., Moses D., Walker L.D., Dawson D.M.** A Simulink-based robotic toolkit for simulation and control of the PUMA 560 robot manipulator // Intelligent Robots and Systems. Proc. of IEEE/RSJ Internat. Conf. 2001. Vol. A. Pp. 2202–2207.

19. **Corke P.I.** Robotics, vision and control. fundamental algorithms in MATLAB. Berlin: Springer-Verlag Berlin Heidelberg, 2017. DOI: 10.1007/978-3-319-54413-7

20. **Corke P.I.** Robotics toolbox for MATLAB. Release 10. 2017 // URL: http://www.petercorke.com/robot

21. **Seshagiri S., Khalil H.K.** Output feedback control of nonlinear systems using RBF neural networks // Proc. of IEEE Trans Neural Networks. 2000. Pp. 69–79.

22. **Tai N.T., Ahn K.K.** A RBF neural network sliding mode controller for SMA actuator // Proc. of Internat. J. Control Autom. Syst. 2010. Pp. 1296–1305.

23. **Kumar N., Panwar V., Borm J.H., Chai J.** Enhancing precision performance of trajectory tracking controller for robot manipulators using RBFNN and adaptive bound // Appl. Math. Comput. 2014. Vol. 231. Pp. 320–328. DOI: 10.1016/j.amc.2013.12.082

24. **Yan Z., Rostova E.N., Rostov N.V.** Neural network compensation of dynamic errors in a robot manipulator programmed control system // Lecture Notes in Networks and Systems. Cyber-Physical Systems and Control. 2020. Vol. 95. Pp. 554–563. DOI: 10.1007/978-3-030-34983-7_543

25. **Farzam T., Nafise F.R.** Robust control of a 3-DOF parallel cable robot using an adaptive neuro-fuzzy inference system // Artificial Intelligence and Robotics (IRANOPEN). 2017. Pp. 97–101. DOI:10.1109/RIOS.2017.7956450

26. **Zabihifar S., Yuschenko A.** Hybrid force/position control of a collaborative parallel robot using adaptive neural network // Lecture Notes in Computer Science. Interactive Collaborative Robotics. 2018. Vol. 11097. Pp. 280–290. DOI: 10.1007/978-3-319-99582-3_29

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