

**HIERARCHICAL ADAPTIVE CONTROL SYSTEM
OF A MANIPULATOR BASED ON THE SYNTHESIS
OF A NEURAL NETWORK OF FUZZY INFERENCE
AND AN ITERATIVE REFINEMENT ALGORITHM**

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Abstract

The main aim of this work is to develop an adaptive control system for a kinematically redundant multilink industrial manipulator. Proposed solution allows to construct a unified real-time control system with the ability to control the accuracy of calculations. In order to achieve the required accuracy of the calculations and the performance of the control system, we propose an algorithm that is based on the so-called hybrid method for finding the solution of the inverse kinematics (IK) problem, including the adaptive neural network and fuzzy inference system with subsequent iterative refinement of numerical solution by the Newton — Raphson method. The influence of the training sample size on the quality of the obtained initial approximation for the neural network part of the algorithm is described in the paper. The results of experimental studies of the developed hybrid algorithm are presented in comparison with the iterative and neural network methods for three-, five- and eight-link manipulator structures. Paper presents the main steps of the control system synthesis for kinematically redundant industrial manipulator, including the description for developed algorithms for finding an IK solution of multilink structures. The structure of a multi-level hierarchical manipulator control system, based on a programmable logic controller and electric stepping motors with the possibility of integration into the production system at various levels, is presented

Keywords

Robot manipulator, adaptive control, neural network, fuzzy inference system, iterative refinement, programmable logic controller, electric stepper drive

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Introduction. In the mid-1990s in the market of industrial robots adaptive robots appeared, which were equipped with sensor devices. The adaptation process was added to a computer model-based control system for robotic

manipulators (“applying the calculated torque” [1]) without changing the controller structure. The model of the reference adaptive control using signal synthesis was developed with the estimated nominal coefficients [1, 2]. Such approach made it possible to increase the dynamic accuracy of the industrial manipulator control, taking into account the deviation of the actual parameters during solving the forward kinematics. This has greatly increased the dynamic accuracy of the manipulator and facilitated the solution of problems associated with the solution of kinematic tasks. The synthesis of the control system of the industrial manipulator during the active movement of the working body is associated with the solution of a whole complex of tasks: the choice of robot control methods, the construction of the working body trajectory, the control of actuators. The solution of the problems of construction systems for dynamic control of manipulators was considered in detail [3]. Such features of the control object as nonlinearity, multi-connectedness, nonstationarity, uncertainty of the dynamic model, and the effect of external disturbances have to be taken into account during developing a control system. Therefore, it is not always possible to apply traditional methods based on solving the inverse dynamic problem. A new direction is associated with the use of neural networks that are able to assess the dynamics of the system in real time [4, 5].

The proposed paper considers a control system that can be attributed to a group of robotic systems — hierarchical learning systems with intellectual capabilities at each level of the hierarchy. The separation into separate functional blocks (modular principle [6]) and the presence of several control levels with the ability to make decisions is characteristic for this group. The key advantages of such systems are high adaptive qualities and ease of scalability of the control system. The proposed control system is similar in structure to the systems [6–8], however, it has significant differences in solving kinematic tasks.

The algorithms for finding a solution to the IK problem meet high requirements for accuracy and performance. From there it is necessary to develop new methods for solving kinematic problems. The main problem is to determine the parameters of the manipulator (angles of rotation of links) for a given, but variable position of its working body. The desired rotation angles can be obtained in the form of an analytical dependence of the parameters of the manipulator kinematic scheme when using rigorous methods. In this case, the process of determining the desired angles is reduced to calculation of the values of previously obtained analytical dependencies. Unfortunately, the precise solution cannot be obtained for every manipulator kinematics. The approximate methods, in particular, methods of numerical solution, taking into account the constraint equations are usually used to solve this problem. They allow to find

solutions for any kinematic schemes, however, these methods have a number of drawbacks, due to the application of an iterative approach, which consists in the sequential computation and specification of the desired solution, that slows down the process. The problem of finding an iterative solution can be formulated as the problem of finding the vector of the difference between the current and the desired position of the links [9, 10]. As a rule, iterative methods are resource-intensive and converge slowly; therefore, there is a large number of different optimization algorithms: the Levenberg — Marquadt method [11], the Newton — Raphson method [12], the Newton — Gauss method [13].

Nowadays, the most promising areas for the synthesis of control systems for industrial robots are those based on the application of artificial intelligence methods. In particular, a method based on a multilayer perceptron using reference tables has been proposed [14]. In the case of the mechanical scheme complication, when the construction of both the network itself and the training set is significantly hampered, neural networks based on radial basis functions are used [15]. However, this approach is limited in use due to the need to adjust the parameters of the radial functions in the case of multi-link tasks with a large amount of training sets. At the present time various “hybrid methods” that combine the advantages of certain approaches appear more than ever; the solutions based on the use of neural networks in conjunction with an expert correction system [16] and the method of applying neural networks in conjunction with genetic algorithms [17] can be examples of such methods. Artificial neuro-fuzzy networks are successfully used for solving tasks in which the source data are unreliable and poorly formalized. For example, in [18], the use of a position control system for a mechanical model of a human foot, which is based on an adaptive neuro-fuzzy inference system, is considered. As a result, the required joint angles were obtained for a given position in a planar task successfully.

Mechanical structure. In this paper, the structure of a manipulator with series-connected links is considered. The control system is built for a group of mechanical structures, the kinematics of which can be represented as

$$\begin{aligned} x &= \left[\sum_m \left(L_m \sin \left(\sum_p Q_p \right) \right) \right] \cos Q_0; \\ y &= \left[\sum_m \left(L_m \sin \left(\sum_p Q_p \right) \right) \right] \sin Q_0; \\ z &= L_0 + \sum_m \left(L_m \cos \left(\sum_p Q_p \right) \right), \end{aligned} \quad (1)$$

where $m = 1, \dots, k$, $p = 1, \dots, m$; L_k is link lengths (constant parameters); k is number of links involved in relative movement; Q_k is rotation angles of the links; x, y, z are coordinates of the working body.

The methods described in this paper have been applied to three-, five-, and eight-link manipulators. To simplify the description of the structure, a manipulator consisting of three links, the first of which is connected to the support post (base), and the latter is provided with a working body (gripper) is considered as an example. Each link has connections to no more than two others so that no closed circuits are formed. The connection of two links is a joint that has only one degree of freedom (rotation in one plane). Fig. 1 shows the kinematic scheme of the n -link manipulator.

The principle of constructing the hybrid algorithm for solving IK problem based on neural networks.

The proposed hybrid method combines elements of an adaptive neural network based on a fuzzy inference system with an iterative refinement procedure based on the Newton — Raphson method. A multilayer perceptron is chosen as the network structure — a four-layer feedforward neural network. For a selected number of links, the construction of the manipulator is described, the equations are used to find attainability domains (working areas). The databases for training neural networks are formed on the basis of the generated work areas.

The scheme of the algorithm of the developed hybrid solution search method is shown at Fig. 2. For a given desired position of the manipulator working body in the space $(x, y, z)_T$, first of all, the accessibility check (entry into the working area) is performed. Next, the required coordinates in space proceed at the trained neural networks (NN_1-NN_k) , corresponding to the number of required angles. As a result of the initiation of the network operation, the angles of rotation of the links $(Q_0-Q_k)_{NN}$ are obtained. On the direct

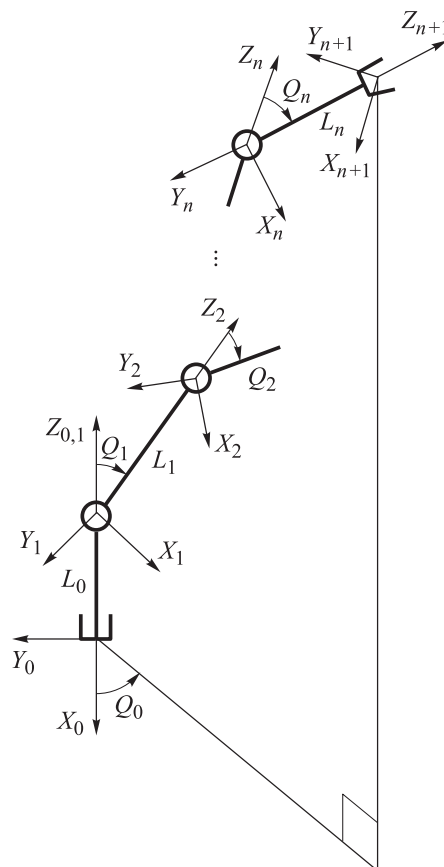


Fig. 1. Mechanical structure of the n -link manipulator

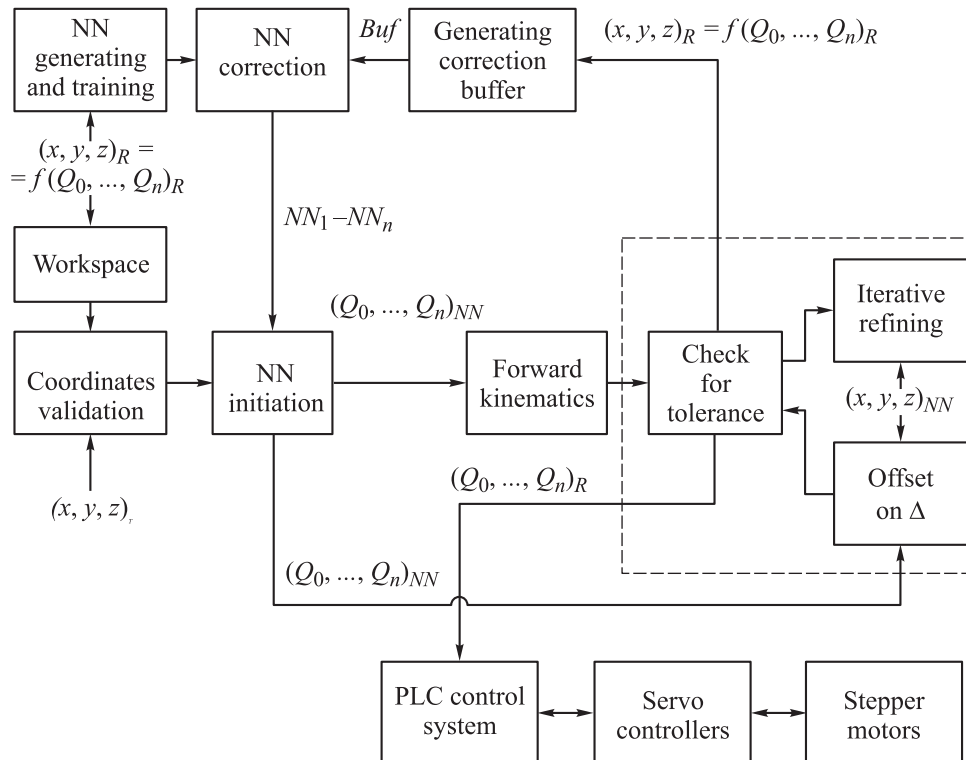


Fig. 2. The scheme of the hybrid algorithm for IK problem computation

forward kinematics, the control system carries out an accuracy check and, in case of its insufficiency, proceeds to numerical iterations in the vicinity of the obtained coordinates (rotation angles of the links). When the required accuracy is achieved, the data is transmitted to the coordinate regulator, which tracks the execution of the movements. After that, the control signal is supplied to the electric stepper motors through the servo controller. During the operation of the manipulator, a correction buffer is generated (corrected data from the iterative refinement algorithm) for neural networks and later it is used to correct the training set and further training of neural networks. The advantages of this hybrid method in comparison with the iterative approach are in increasing the computational speed of the algorithm with controlled accuracy. The search for a solution is much faster and does not depend on the complexity of the design (systems of equations describing it) in comparison with iterative methods using neural networks for inverse kinematic problems, but its accuracy is not very high.

The iterative refinement algorithm (blocks in a dashed line in Fig. 2) includes the following steps.

1. The initial approximation is set (data obtained by the neural network method).

2. Until the stop condition is satisfied, a new approximation is calculated. The estimation is chosen as a stop condition

$$|Q_{k,(n+1)} - Q_{k,n}| < \varepsilon, \quad (2)$$

where ε is permissible error (determined from the requirements for the accuracy of positioning the manipulator working body).

3. When a specified number of iterations $N_{i \max}$ is exceeded, the initial coordinates are displaced

$$\Delta = (\varepsilon - \text{rand}(0, \dots, \varepsilon)) Q_k, \quad (3)$$

where rand is pseudorandom variable within the given limits $(0, \dots, \varepsilon)$.

4. The continuation of the algorithm from point 2, as long as the number of performed displacements is no more than $N_{c \max}$.

5. If the solution was not refined (based on the inequality of the estimation (2)), the obtained initial approximation from neural networks is used. If the refinement has been completed successfully, then the results are recorded in the "neural network refinement buffer". The spooling capacity and the conditions for its use are determined on the basis of the operating conditions and the operating mode of the manipulator.

The maximum allowable values of the number of iterations $N_{i \max}$ and displacements $N_{c \max}$ are determined from the requirements for the allowable accuracy of computation and the performance of the control system.

In general terms, the solution refinement is clarified by the following formula:

$$Q_{k,(n+1)} = Q_{k,n} - \frac{f_{FK}(Q_{k,n})}{f'_{FK}(Q_{k,n})}, \quad (4)$$

where $k = 1, \dots, 3$ is angle number, n is iteration number, f'_{FK} is the first derivative of the function of the direct kinematic problem (analytic dependence) $f_{FK}(Q)$.

The deviation D of the manipulator working body from a given desired position is determined by the following formula:

$$D = \sqrt{(x_T - x)^2 + (y_T - y)^2 + (z_T - z)^2}, \quad (5)$$

where x_T, y_T, z_T are given desired position of the working body of the manipulator are space; x, y, z are current calculated position of working body.

The developed algorithm combines the advantages of iterative and neural network methods: high accuracy and performance. The required coordinates

(angles of rotation of links) for the inverse kinematic problem are calculated using neural networks at first, and then specified by the iteration method of Newton — Raphson. In this case, the number of iterations of the numerical method and the execution time of the algorithm are reduced greatly.

To obtain a qualitative initial approximation from neural networks, it is necessary to perform network training on a sufficient number of examples. This procedure includes the passage through all nodes of the layer in the forward direction (from the input to the output), after which all nodes of the neural networks are adjusted using the least-squares method. After the forward pass, a reverse pass is performed and the mismatch factor (the difference between the obtained solution and the specified value) is propagated through the nodes of the neural networks and adjusts the parameters of the membership function at the nodes using the gradient descent method. As a training set, a set of data obtained from solving a direct kinematics problem by sequentially iterating over the coordinates of the working area has been used. Subsequently, the invalid manipulator configurations have been excluded from the training set. A series of experiments have been conducted to analyze the effect of the size of the training sample on the quality of the obtained solution and the duration of neural networks training. Table 1 shows the results of the research and the calculated deviation of the working body of an industrial manipulator from a given trajectory with the use of neural networks.

It follows from these experiments (Table 1) that with an increase in the size of the training set, an exponential increase in time costs is observed. The deviation of the working body of the manipulator also exponentially tends to a certain value.

Table 1

Study of the effect of the training set size

Characteristics of the manipulator working body	The size of the training set, points						
	64	512	4096	32 768	64 000	125 000	248 000
Network training time, s	0.142	0.714	6.574	120.649	381.453	1314.55	9951.19
Network response time, ms	0.832	1.121	0.811	0.912	0.954	0.983	0.992
Maximum deviation $\max(D)$, mm	52.155	27.348	24.617	23.183	22.868	21.921	21.244
Mean deviation $\text{med}(D)$, mm	19.085	11.959	11.261	10.888	10.686	10.531	10.499

The process of refinement of solution with the use of the developed algorithm is shown at Fig. 3. The dashed and solid lines are the positions of the manipulator at the initial value (before refinement) and at the refined solution, respectively. The figure also shows the search (refinement) path of the solution, each of the points of the iteration cycle.

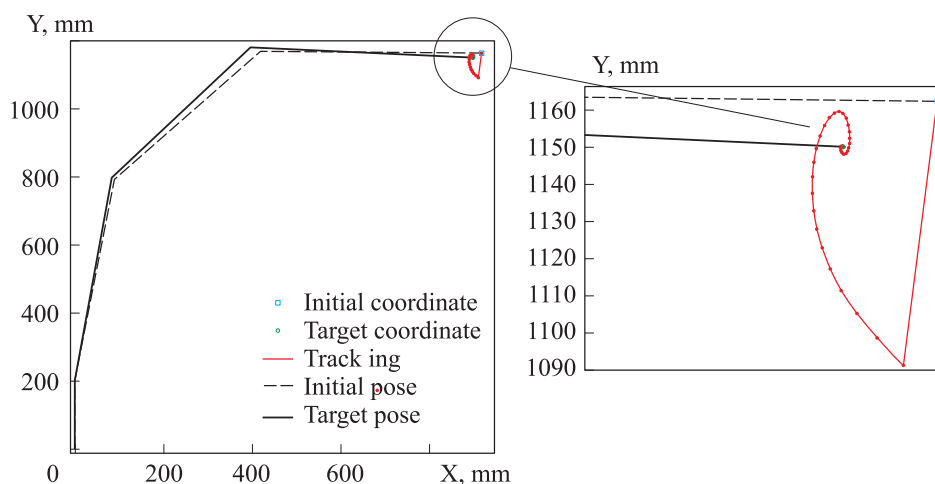


Fig. 3. The refinement of solution

A comparative analysis of the hybrid method and its component parts, the method based on the neuro-fuzzy network and the iterative method has been carried out using the developed algorithms (Table 2). The initial (previously calculated) value of the coordinates was used as the initial approximation of the iterative method, and zero value was used for the first coordinate. This made it possible to find all the required variable values at a sufficiently small displacement (due to the large number of steps on the trajectory) successfully. A comparative analysis was carried out for the three-, five-, and eight-link construction of the manipulator, in accordance with the selected type of mechanical structure.

Experimental studies have been carried out in the computation of a given trajectory consisting of 4000 points. To calculate the allowable displacement of the manipulator working body, the accuracy has been set equal to 1 mm.

It can be concluded from the presented data that the iterative approach depends on the duration of the search for a solution on the complexity of the structure. The impact of design complexity is negligible using a neural network. The use of the neural network component in the hybrid algorithm has greatly reduced the number of required iterations of the refinement algorithm, as a result of which the performance has increased significantly with controlled accuracy.

A graph of the change of the angle Q_3 value in the joint of the five-link manipulator during working out a given path following, consisting of 200 points, is presented at Fig. 4. The computation was performed by iterative, neural network and hybrid methods. As can be seen from the graph, the uniformity of the coordinates distribution increases and, accordingly, the smoothness of the angle change in the joint of the manipulator increases when a neural network is used.

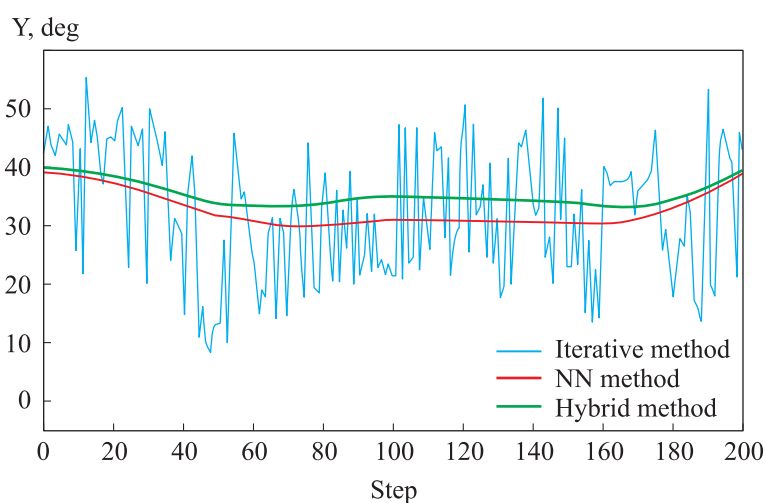


Fig. 4. The variation of angle Q_3

Synthesis of the manipulator control system. The control system for the kinematically redundant multi-link manipulator was built taking into account the possibility of integration into production systems and the specifics of industrial equipment. There was a necessity for a multi-level hierarchical control structure. The construction of the system was performed on the basis of stepping electric motors.

Fig. 5 shows the hierarchical structure of the control system, which ensures the interrelated functioning of all elements of the system. This architecture is decentralized and has the ability to be integrated into the production system at various levels using modern industrial communication standards.

The control system architecture has four levels.

The first is the level of the executive mechanisms: the working body — the gripper 10 and the stepping electric motors 9, equipped with built-in optical incremental encoders.

The second level — controllers of low level: servo-controllers (7 is for motors, 8 is for gripper), which directly control the current in the motor windings and monitor their condition. There is the possibility to organize direct

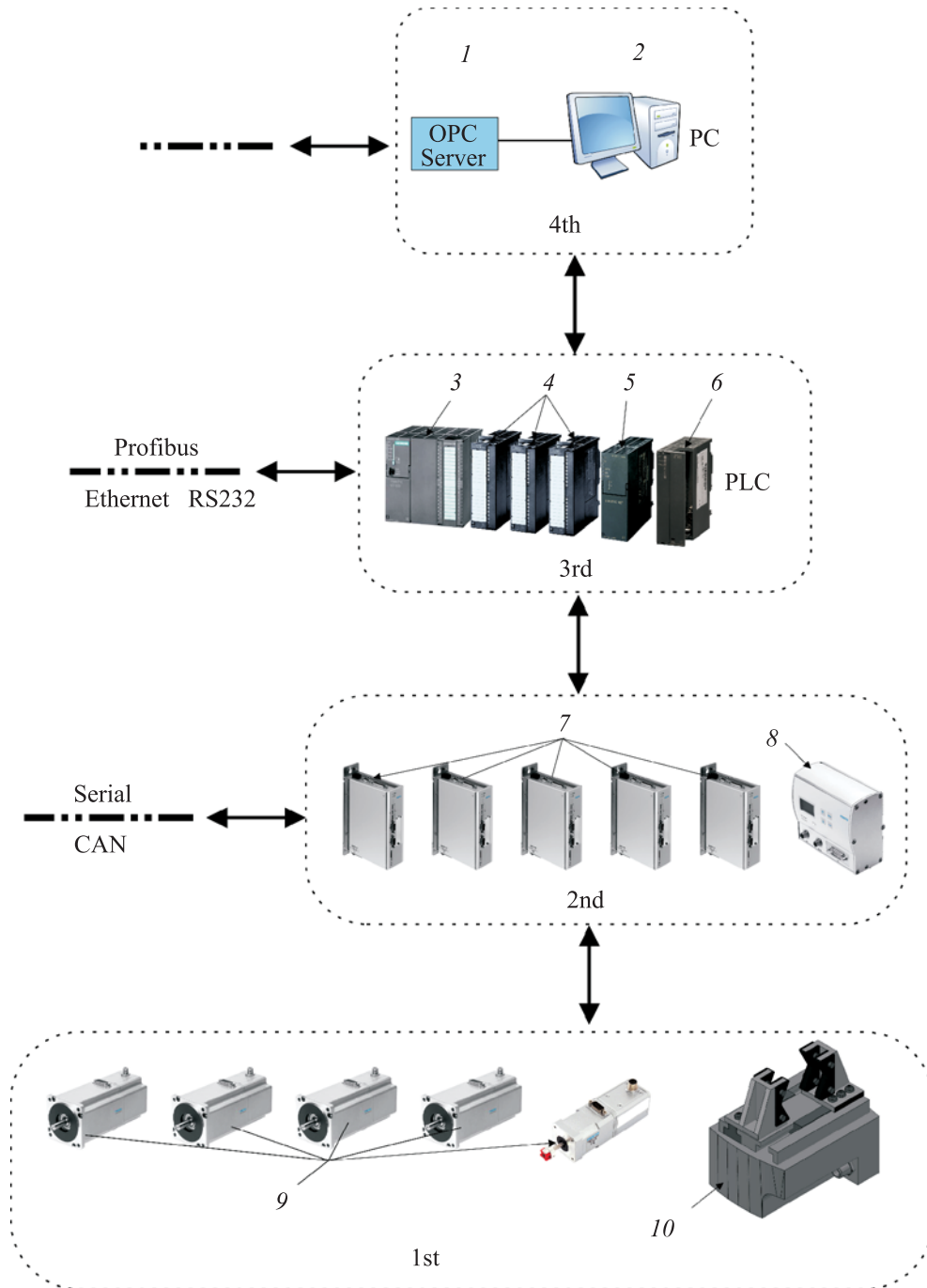


Fig. 5. The control system structure

control of actuators through the appropriate serial communication interfaces (Serial), omitting the upper levels, or through an organized industrial network based on the CAN interface.

The third level is the high level controller (programmable logic controller (PLC)) acts as a control device for the actuators, contains the required control laws. It is a node that integrates an industrial Profibus network, Ethernet, or network using an RS 232 interface (for example, a Modbus network) into the production system; PLC has a modular structure and is equipped with a main processor module 3 with a set of discrete inputs/outputs, the necessary number of analog modules 4 for controlling actuators, communication modules Ethernet 5 and RS 232 — 6.

The fourth level is a personal computer (PC) 2 with an OPC-server 1: it performs the functions of calculating coordinates, including trajectory planning, also the OPC-server serves as a link for integration into a common industrial system; the PC is equipped with various communication interfaces.

The calculated and refined coordinates (the required angles of rotation of the links) have been transmitted to the PLC level, which in its turn monitors the modification of displacements, receiving data from the servo controllers. The servo controller of the drive has feedback from the actuator and allows to monitor the status of the drive (position, moment, speed, acceleration, etc.) in dynamics. Servo controllers also provide the ability to control the actuators directly, eliminating the high-level controller (PLC) and PC from the control.

Conclusion. A method has been developed for solving kinematic problems for multilink industrial manipulators, based on the use of neuro-fuzzy networks and the subsequent iterative refinement of the numerical solution. The adaptation of neural networks is provided for solving typical tasks in order to increase performance. The combination of neural networks and iterative refinement allows to achieve the required accuracy of the solution while reducing the number of iterations and, consequently, time-consuming. A decentralized hierarchical control system for an industrial manipulator based on stepping drives and programmable logic has been designed for the developed kinematic algorithms. This control system has powerful capabilities for integration into production systems and a unified structure, which allows it to be used for various manipulator designs. The efficiency of the control system was confirmed on the basis of an experimental facility at the Department of Management and Informatics of Moscow Power Engineering Institute (National Research University). The conducted experimental studies demonstrate the possibility of using the developed methods for solving the inverse kinematics problem of multilink kinematically redundant industrial manipulators based on neuro-fuzzy networks in real-time control systems.

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