Control of a Technological Cycle of Production Process Based on a Neuro-Controller Model

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***Abstract*—In this paper a method for constructing a model of a neuro-controller for implementation of control in the presence of external disturbances for the optimal trajectory finding on the phase plane of system states for technological cycle of a production process is proposed. A type of a neuro-controller based on recurrent neural network architecture with long short-term memory blocks as a knowledge base on the external environment, previous states of the controller and control actions is being used.**

***Keywords*—neuro-controller, recurrent neural network, LSTM, adaptive control, technological cycle of production process**

I. Introduction

Recently, artificial intelligence theory is being widely applied to solving such classes of problems as classification, clustering, prediction, approximation, data compression and other tasks [1][2][3][4]. However latest research in this area shows, that the application of artificial neural networks (ANNs), which are currently being considered one of the most important research directions in the area, is not limited only to the listed classes of problems. Researchers and practitioners are being interested in solving problems of complex process control in the areas of activity which are difficult to formalize [5][6][7].

It should be noted that despite the high level of complexity of the practical problems in this area that can be solved by application of the artificial intelligence methods, ANNs are a fairly effective and convenient tool for finding solutions to these problems based on construction of a finite set of mathematical models, which is being considered as a single model of the object under study as a complex technical system [8].

For this reason application of neural networks training for complex technological objects analysis provides an important advantage over the traditional research methods, including the simulation modeling [9], because during the training process neural network is able to extract complex dependencies between input and output data, as well as provide necessary generalizations.

When analyzing the operation of complex technical systems the existing methods of analysis often provide insufficient effectiveness, especially in cases of project modeling when the structure of such objects can be altered in the process of their evolution. The reason of this is in diversity and complexity of the practical tasks arising at the stage of project modeling, and also when estimating the operation reliability and safety for potentially hazardous technical systems.

Therefore development of a new approach to analyze complex systems at the stage of their project modeling automation, which would allow to take into account the changes in structural connectivity of the controlling system when changes of technological cycle structure occur due to failures, is a task of great importance.

Such an approach can be developed using the procedure of project modeling of the object under study, which is based upon an adaptable structure of the control system using the neuro-controller model, which takes into account all the changes in the technological cycle of production operation process.

It is known that the main task of the effective control of the technological cycle of production consists in implementing the sequence of universal control actions that would allow to optimize the output parameters of the technological system when possible changes in the structure of the technological cycle occur. Such changes can be the result of having the elements of potentially hazardous production in the multicriterial control problem under consideration.

The recent research in the area shows that high-quality analysis of the control systems operation requires taking into account a great amount of factors, which undergo changes during the process of operation of the object under study. It can be achieved through implementing adaptive control algorithms for the systems under study.

The recent trends in the use of some system-wide principles and methods of research in various fields of knowledge, open semantic technologies for intelligent systems, lead to the unification of the system approach when considering specific scientific and practical problems.

Such trends allow to hope for the future creation of the necessary knowledge base and the software capable of logical inference as part of the task under consideration, which would allow the researcher to interact with systems of varying degrees of complexity, disregarding their physical nature or the limitations of some specific formalization.

One of the most important tasks in this area is the task of constructing an adaptive control system for technological cycle, which is capable of providing a rational structure of the control loop at the given moment of time [5]. The latter is directly related to the loop's restructuring during its operation and constructing the adaptive control algorithms to optimize the technological cycle resource consumption in real time in the presence of external control actions.

The neural network controller modeling is effective when a high-quality controller of the controlled system is available [11]. In this case the neural network acts as an approximator of its function and is trained to simulate the effects of the controller on the controlled system. In some situations it may be the case that the use of the neuro-controller constructed in that way is more practical because of the common properties of ANNs.

Results in the area of research of controlled technological systems based on constructing the models of ANNs for providing effective control of the technological production cycle [10][12] are given in this paper. A method for constructing a model of neuro-controller for technological production cycle control in the presence of external disturbances is being proposed.

Implementation of control for the optimal trajectory finding task in an arbitrary region of complex structure requires a high-quality controller, which is able to adapt its actions according to the local environmental data available at the given moment of time. To implement successfully pathfinding strategies it is also required to store and take into account the data received by the controller at the previous moments of time. Exploration of applicability of ANNs for solving the tasks of this class is an important research direction because of the advantages that these models have.

In this paper a method for constructing a model of a neuro-controller for implementation of control for the optimal trajectory finding in the case of a dynamically changing region of arbitrary configuration is being proposed. Recurrent neural network architecture with LSTM-blocks, which allows to store information about the states of the system at the past moments of time that may be significantly distant from the current moment of time [13][14], is being used as a mathematical model.

II. Related Work

ANNs have proven to be an effective instrument to solve a set of various problems from different areas of human action. The properties of the ANNs made researchers to consider ANNs as a suitable model to solve control tasks. Different approaches were developed to implement neural networks in the control tasks [24][26][27] and many examples of successful applications exist [5][6][7][28]. Applications in the area of production process control and optimization were also developed, typically using feedforward types of neural networks in order to solve specific tasks related to the production operation or its aspects [25][29][31]. Some adaptive control approaches based upon neural network modeling were proposed for plant control and dynamic systems control [30][26].

Recurrent neural networks research shows that it may be useful to apply such architecture to the tasks where processes evolving over time take place. The recurrent neural network architecture is capable of capturing time dependencies therefore allowing to solve various real-world tasks [3][4]. However while having interesting potential capabilities [3][15] that can be achieved with different variations of the recurrent architecture [7][16][17][18][19], it also has a known problem when the task requires taking into account the long-term dependencies [14]. LSTM blocks allow the long-term storage of data [13] and can be applied to the tasks where long-term time dependencies must be taken into account [20][21][22][23].

III. Formalization of the Task

In the considered task of trajectory finding on the phase plane of system states, the controlled object moves across a two-dimensional region which is divided into nonintersecting subregions (cells) that may be passable or impassable. Cells beyond the edge of the region are considered to be impassable. A passable subregion is assigned a value of 0, while the impassable one is assigned a value of 1. In the given region, a target subregion is designated. It is guaranteed that a path from the starting position of the controlled object to the target subregion exists in the region at any stage of its evolution. At each moment of time, the controller receives a vector of seven elements: data on four cells adjacent to the current position of the controlled object, the distance to the target subregion and the direction to the target subregion.

The result produced by the neuro-controller at a given moment of time is a four-element vector that determines the direction of the next move of the controlled object in the region. The controlled object continues to move until the target subregion is reached.

IV. Architecture of the Neuro-Controller

The set of specific features of the control tasks, which require controller to make decision within some long-term strategy in the case of a dynamically changing environment and availability of the local environmental data of arbitrary nature at the given moment of time, requires the controller to have a specific structure. A structure of the controller, that includes encoder module for encoding and pre-processing of the environmental data, memory module for the long-term storage of data and decision-making module, which determines the output signals of the the controller at the given moment of time, is being proposed. The proposed general scheme of the controller is shown in Figure 1.

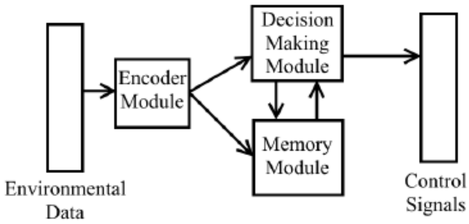

Figure 1. General scheme of the controller

This implies from the point of view of the ANNs architecture that the network will have structural elements with the functions that can be interpreted as functions of the listed modules. The input layers of a given neural network can be considered as the encoder module which preprocesses and encodes input signals. (For example, in the case when the controller has image as input data, a sequence of convolutional and subsampling layers that gradually reduces dimensionality of the data and converts it into a vector, can be considered as encoder module.) A subnet that consists of LSTM modules can be considered as the structural element for long-term data storage. A subnet of arbitrary structure that is connected to the structural elements for encoding and storing data and includes the output layer of the network, that produces the control signals, can be considered as the decision-making module.

In the framework of the described approach a neuro-controller with a recurrent architecture that contains LSTM blocks is being considered in this paper. The recurrent architecture with LSTM block includes three fully-connected layers consisting of five, sixteen and four neurons, respectively. The LSTM block has a state of size 16 and is connected to the second layer of the neural network through the elements of a time delay. Its current state is passed to the input of the third layer. There is also a feedback connection through a time delay elements between the second layer and the first layer. The architecture was selected experimentally as the one that would have the minimal number of neurons in all layers and be able to train and perform pathfinding on the testing set. In Figure 2 the scheme of this architecture is shown.

The choice of the recurrent architecture is based upon the necessity to take into account time dependencies in the environmental data available to the controller. LSTM blocks allow the long-term storage of data. In case of the pathfinding task it is necessary for the implementation of the pathfinding strategies stretched upon relatively long periods of time, required by the task.

The neuro-controller model, the training and testing environments, and data generation process were implemented in Python programming language using Tensorflow machine learning framework.

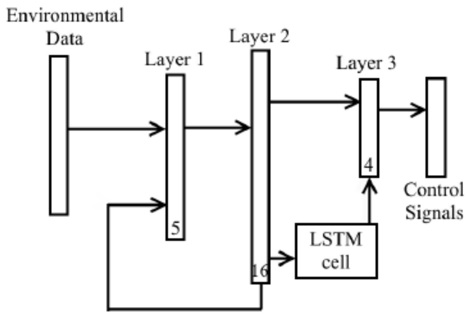

Figure 2. Scheme of the recurrent neural network architecture with LSTM block.

V. Generating Training Data

In order to train a neural network successfully it is important to use a large sample of data that adequately represents a variety of real-world situations that can be encountered by the neural network.

The neuro-controller described in this paper is used to solve the task of pathfinding in a complex environment of arbitrary structure that can change dynamically over time. Therefore examples of such environments need to be generated for training and testing.

30x30 regions with random placements of impassable subregions were generated for the training procedure. Cellular automaton has proven to be a suitable model which allows implementing a gradual evolution of the structure of the region. Parameterizing the automata in different ways it is possible to achieve various patterns of structural change, which will result in increase or decrease of the amount of impassable cells in the region over time, or have circular nature. The evolving regions can be randomized further by selecting the lengths of time periods (steps) in which the next change to the region will happen.

100,000 sequences of regions of 30x30 cells with impassable areas changing over time were generated to be used in the training and testing process of the neuro-controller. In Figure 3 example of a region evolving through time is shown.

In this paper supervised learning was used to train the neuro-controller. A recurrent neural network is trained on sequences of input and output signals. In order to train the neuro-controller to implement pathfinding strategies the sequences have to be of significant length. Sequences of 40 movements were used for the training procedure. A sequence consists of a list of vectors of the local data for the current cell in the path (network inputs, including data on the adjacent cells, calculated distance and direction to the target cell) and a list of corresponding vectors of required movement to achieve the next cell in the path (desired network outputs).

Such sequences in the task considered can be obtained by generating example paths in the regions. For this purpose in each region a starting cell and a target cell were selected randomly. In order to be able to obtain the training sequences of the required length of 40 movements it was checked that throughout the region's evolution the path between the cells existed and that the shortest path between them was at least 40 movements long. The described procedure of cells selection was repeated several times in each region. Sometimes the configuration of the region and evolution in its structure made it impossible to select suitable cells. 10% of the regions with suitable cells were used for testing after the training was complete.

The best-first search was used to generate the paths between the selected cells pairs in the evolving regions. Considering the non-static nature of the regions and the fact that only local data is available at each moment of time to the neuro-controller, the paths were generated dynamically. A path was regenerated started with each point where a change in local data was triggered by the region's structure dynamic changes. Based on the length of the paths generated by the described procedure one or more training sequences were prepared based on each of them.

60,000 training sequences of 40 movements were obtained based on the generated paths and used for training.

VI. Training the Neuro-Controller

During the training process such values of the network parameters (connection weights and bias values of neurons) are found that the network produces desired outputs for the given inputs. Training can be considered a nonlinear optimization task of minimizing some loss function specified on the training set with respect to all of the network parameters. In this paper the supervised learning was used, which corresponds to the situation when a large dataset with examples of the control sequences is available.

The neuro-controller was trained using the RMSProp optimization algorithm to minimize the loss function. The cross entropy function was used as the loss function. The training set of example sequences was divided into batches and the parameters of the neural network (all weights and neuron biases) were corrected after presenting a batch of 50 sequences. Figure 4 shows the minimization of the loss function during first 20 epochs of training.

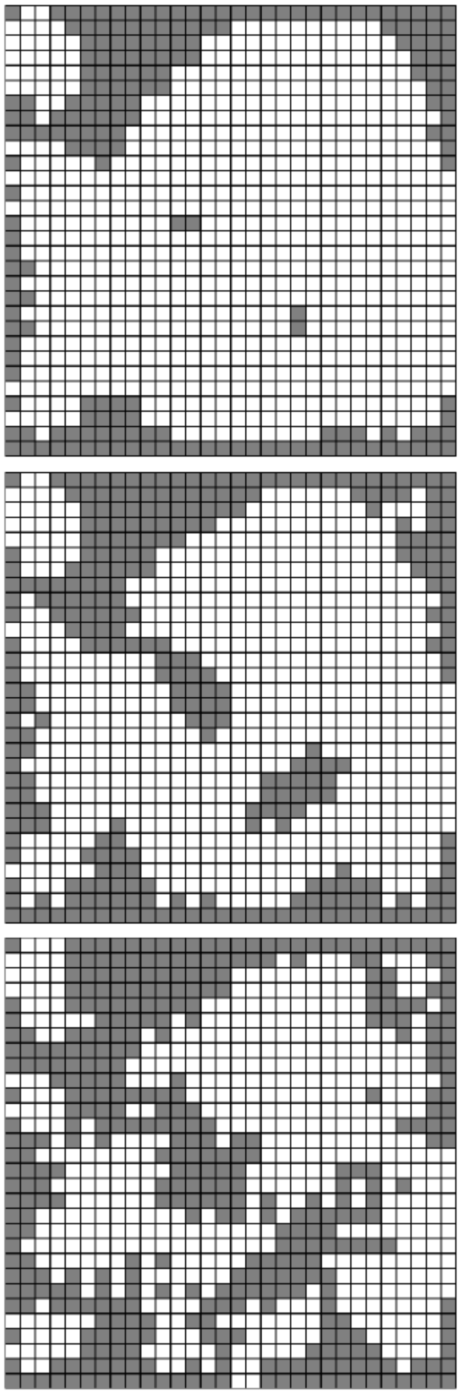

Figure 3. Example of a dynamically changing over time region generated for the neural network training.

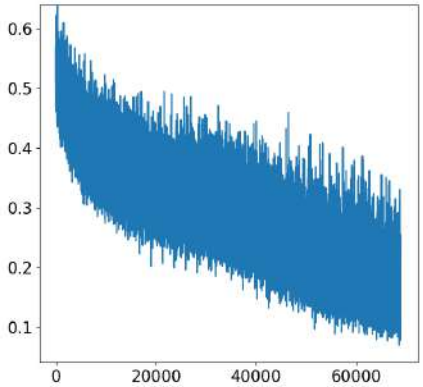

Figure 4. The loss function values during first 20 epochs of training of the neuro-controller.

VII. Testing the Trained Neuro-Controller

After the training the neuro-controller was able to find trajectory successfully on the phase plane of the controlled system states with dynamically changing configuration of the allowed states subregion. 10% of the generated region sequences were used to perform the testing and assess the performance of the trained neural network. A test was considered to be successful if the neuro-controller did not perform any forbidden actions (moving on impassable cell) and was able to reach the target cell in less than 60 movements. The controller was able to generate path to the target subregion in a reasonable time in approximately 70% of the regions in the test set. Figure 5 shows an example of pathfinding by the neuro-controller.

VIII. Conclusion

The theoretical research results described in this paper provide a basis for the future development of new effective methods of analysis and synthesis of optimal structure of the technical systems with adaptive control. The approach proposed by authors is applicable within its framework to a whole variety of problems of the optimal control structure synthesis and complex technological systems synthesis. The research results can be used in the development of intelligent decision support systems designed for the corresponding tasks, automation of the technological production processes by artificial intelligence systems, development and automation of the designing process of new technological objects, and also quality assessment of the production technological cycle control in real time.

In the course of this work an approach to application of the neuro-controller to implementation of the adaptive control of the technological cycle was developed and tested. The experimentation on models has shown that

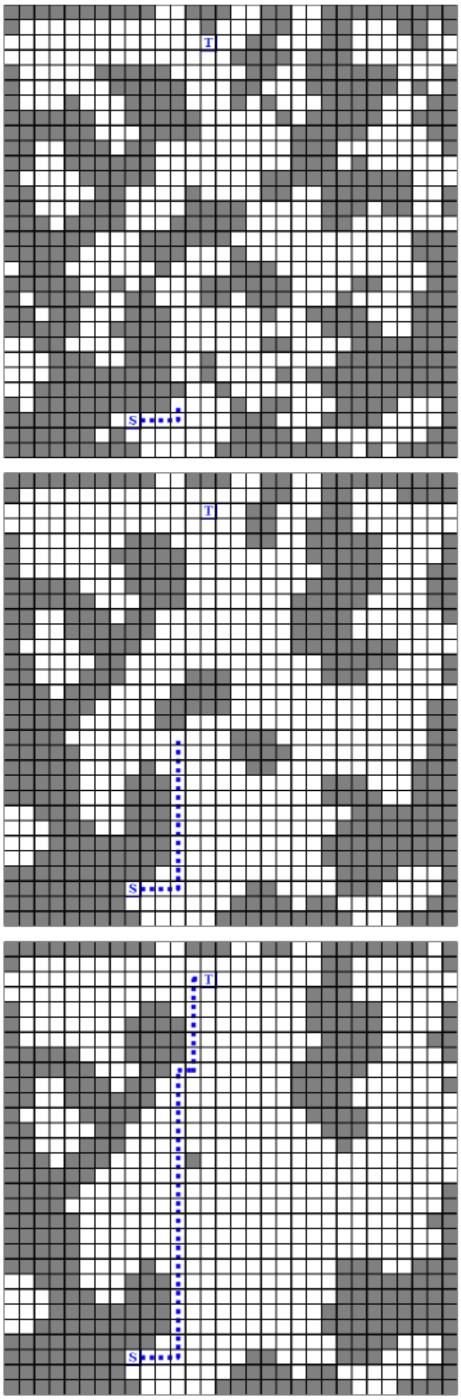

Figure 5. Example of successful pathfinding by the trained neuro-controller in a dynamically changing region.

neuro-controller based on a recurrent neural network with LSTM blocks can be successfully used for the adaptive control tasks. LSTM blocks allow the neural network to store information about the states of the system from the past moments of time that may be significantly distant from the current moment of time, which allows the neural network to learn long-term dependencies and to reproduce long sequences of reactions to random disturbances and external influences. The possibility of increasing the efficiency of the existing architecture by adding additional memory modules and training on longer data sequences depends on the specific parameters of the modeling object operation.

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УПРАВЛЕНИЕ ТЕХНОЛОГИЧЕСКИМ ЦИКЛОМ ПРОИЗВОДСТВА НА ОСНОВЕ МОДЕЛИ НЕЙРОКОНТРОЛЛЕРА

Смородин В.С., Прохоренко В.А.

Предложен способ построения модели нейроконтроллера для реализации управления технологическим циклом производства при решении задачи поиска оптимальной траектории на фазовой плоскости состояний технологической системы в условиях наличия внешних возмущений. Использован тип нейроконтроллера на базе рекуррентной нейросетевой архитектуры с модулями долгой краткосрочной памяти в качестве базы знаний о внешней среде, предыдущих состояниях контроллера и управляющих воздействиях на систему.

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