MODELING OF NEURAL NETWORK MONITORING AGENT TO PREDICT TRAFFIC SPIKES AND AGENT TRAINING

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Abstract: The article completes the study of solutions to the problem of creating distributed QoS monitoring control in IoT and IIoT telecommunications. A multi-agent architecture is used. For the proposed structure of the LSTM network, approaches to the process of its training (configuring the network configuration) are considered, based on the representation of this process in the form of a Markov decision-making process, which made it possible to solve the problem of determining the training times of the network within one epoch, as well as its retraining using a variant of the dynamic programming method – the iteration algorithm by values, which In the future, it allows you to proceed to the synthesis of an iterative algorithm for dynamically configuring the parameters of the developed LSTM network.

Key words: QoS monitoring, multi-agent architecture, Markov decision-making process, training times of the network, dynamic programming method.

1. INTRODUCTION

The article concludes the research [1, 2] devoted to modeling neural network monitoring of agents for predicting traffic surges and agent training in IoT and IIoT telecommunication structures.

2. DESIGNING THE STRUCTURE OF A NEURAL NETWORK MONITORING OF AGENTS

The prediction of time series values at time t using a LSTM [1, 2] is performed for a time point t+1 using the previous values of the time series (t-1, t-2, …, t-τ), where the value t+1 determines the depth of the retrospective "immersion" - the number of LSTM layers. Vector values are received at the inputs of the LSTM layer $x(t)=(x_{t-\tau+1}+1, x_{t-\tau+2},\ldots, x_t)$, and the output value is the predicted value x_{t+1}. The training sample for such an LSTM network is formed not only on the basis of the time series of parameters of monitoring nodes MN_k controlled by intelligent monitoring agents (IMA) IMA_k, but also the parameters MN_{k-1} and MN_k which characterize the delta interval h of their distribution time. This means that $\{Mm_{k-1}, Mm_{k+1}\}$ generates prior data and MNk generates prior data for multiple sources of retrospective parameters for other roommate nodes (Figure 1). Thus, the values of the analyzed parameters from the set of all MN are in spatial-temporal correlation.

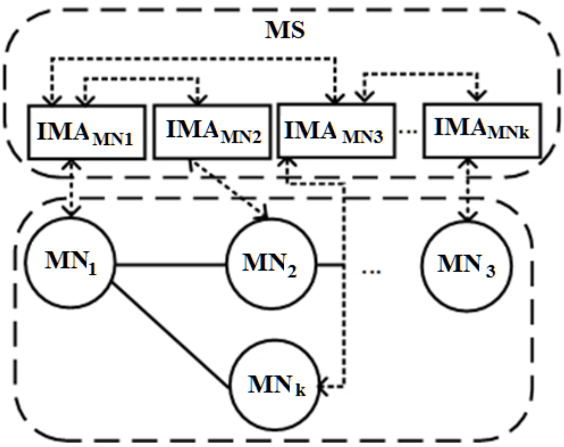

Figure 1. {Mmk-1, Mmk+1} generates prior data and MNk generates prior data for multiple sources of retrospective parameters for other roommate nodes; MS - monitoring system; IMA - intelligent monitoring agents MN – monitoring node

It is proposed to take into account such a correlation in the element $Cell_{LSTM}$. To determine the correlation between the values of the parameters in different MN_k, $Cell_{LSTM}$ can be represented by a correlation matrix A_t. So, in the general case, for an management object (MO) consisting of a set of nodes $MN_{MO}=\{MN_1, MN_2, \ldots, MN_m\}$, the matrix A_t is defined as A_t: $MN_{MO}\times MN_{MO}$. At the same time, the states of the elements MN_{MO} of the set are both in temporal correlation (current parameter values MN_m and parameter values at the previous moment of monitoring) and in spatial correlation (the MN elements that are neighboring are a subset $\{MN_{m-1}, MN_m, MN_{m+1},\}$) to the current node along the peak load propagation vector. That is, the values of the matrix elements are the A-vectors, the characteristics of which are related both to the time of the moment of monitoring t and the interval S_m determining the duration of the monitoring cycle.

$$A_{t,S_M} = Cr\left(A_{t+1,S_M}, A_{t+2,S_M}, \ldots, A_{t+N,S_M}\right) \tag{1}$$

where Cr is the cross–correlation function, $A_{t,S_M} = [x_1, x_2, ..., x_m]^T$ is the vector of the parameters x_j (j=1,2,…,m) of the MN for the i-th time interval S_m.

The coefficient of participation $l_{j,k}$ of the parameters of the j-th MN at the k-th monitoring point over a time interval S_m, as $|j-k| \times S_M$. Then the interval cross-correlation function can be defined as:

$$l_{j,m}(S_M) = CR\left(X(t), X'(t+S_M)\right) \quad (2)$$

Where X(t) is the time series of the j-th MN, and $X'(t+S_M)$ is the time series of the m-th MN. Thus, at time t, a vector of parameters is fed to the input of the $Cell_{LSTM}$ element, which is closely related to the state of MN at time t-1, and the dynamics of changes in the values of the matrix A_t elements will depend both on the current value of the monitoring moment t and on the time interval S_m. The values stored in $Cell_{LSTM}$ are used as input parameters of the LSTM network layers L_t, both at the stage of its training and when solving the problem of predicting parameters MN_i at a time t+1.

In a generalized form, the structure of the proposed neural network model for predicting i+q monitoring parameters of MN_j and forecast depth t+p is shown in Figure 2 [3].

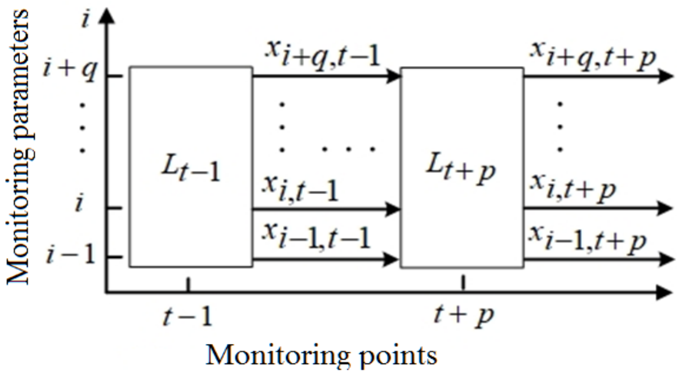

Figure 2. Generalized view of the proposed neural network model of IAM

The number L_t of layers determines the depth of forecasting T_{fo}, and the values Δt_i determine the duration of the monitoring moments S_M:

$$T_{f0} = \sum_{i=1}^{p} \Delta t_i \quad (3)$$

It can be seen from Figure 2 that the horizontal measurement indicates monitoring moments, and the vertical measurement indicates the vector of parameters of observation points ($\overline{X} = \left(t_{cl}^{j}\right)$ – monitoring parameters). Thus, we have established that our version of LSTM in the proposed form is a network in time and space

In this case, the values Δt_i should be adjusted by minimizing the sum of the quadratic errors of the output values of the layer. Based on the analysis [3, 4], it is proposed to use three criteria to evaluate the target indicator: the average absolute error

(MAE), the average quadratic error (MSE) and the average relative error (MRE) (expression (4)). Each of which is defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\tilde{\varphi}_i - \varphi_i\right|,$$
$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\tilde{\varphi}_i - \varphi_i\right)^2, \quad (4)$$
$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\tilde{\varphi}_i - \varphi_i}{\varphi_i}\right|,$$

where $\tilde{\varphi}_i$ is the forecast data, and φ_i is the measurement data.

We have established that MRE is preferable as an evaluation criterion. The fact is that MAE and MSE, defined in (4), react more acutely to raw data.

The expanded elements of the layer structure L_t at the time of monitoring from t-2 are shown in Figure 3 [2].

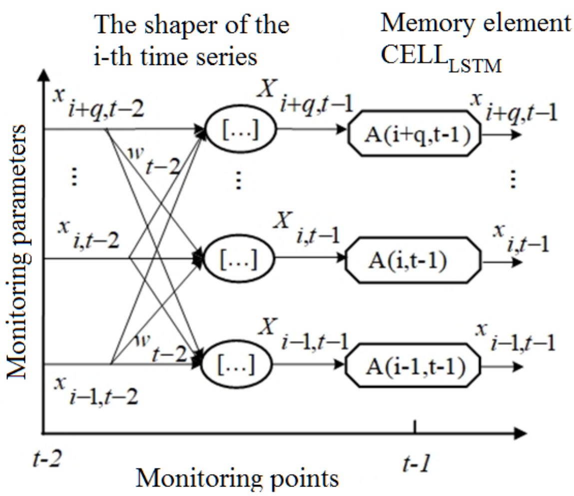

Figure 3. Layer structure of the proposed L_{t-1} LSTM network

3. MODELING OF THE LEARNING PROCESS

Since data on the required number of layers for the developed LSTM network is a priori unknown, however, the result of its functioning has an effect on the controlled MN, the use of a class of Reinforcement Learning methods was proposed as a basic learning method (setting the parameters of its layers). Since a distinctive feature of the IMA, according to the theory of multi-agent systems, is its autonomy, it is proposed to use an algorithm for configuring the structure of the LSTM network, which is implemented as part of the IMA software, to solve the problem of such configuration.

Let's define the learning process with reinforcement of the LSTM network [5] as an episode described by the finite Markov decision-making process (MDMP), represented by a tuple $<S,A_S,P_S,\pi>$ (states, actions, probabilities of transition from state to state), where π is a strategy, some function of matching actions to states [6], since it is a repetitive interaction and interaction IMA with the "environment" is controlled by the MN.

Since the configuration of the LSTM network is configured for two hyperparameters: the number of layers and the number of training epochs, we determine that the current configuration contains $n \geq 1$ layers, and k training epochs are required to obtain this current configuration. Then any of the $s \in S$ states, excluding the initial one, is associated with these hyperparameters. The current configuration of the LSTM network is defined as a set $\{l,j \cdot e\}$, where $l \subset n$ is the number of layers, e is the number of training epochs required for this number of layers. $j \cdot e$ – the product of the elements of a numerical series $j = \left\{1, 2, ..., \frac{k}{e}\right\}$ by an integer e, which determines the value of the number of epochs needed for training. Then we define the set of states S for it as $s \in S_{l,j \cdot e}$. For $s \in S_{l,j \cdot e}$ let's define a set of actions:

$$A_{s_{l,j \cdot e}} = \left\{a_{s_{l,j \cdot e} \& s_{l,(j+1) \cdot e}}, a_{s_{l,j \cdot e} \& s_{l,(l+1) \cdot e}}\right\} \tag{5}$$

The action $a_{s_{l,j \cdot e} \& s_{l,(j+1) \cdot e}}$ is a comparison of configurations $\{l,j \cdot e\}$ and $\{l,(j+1) \cdot e\}$. If the prediction accuracy in the configuration $\{l,(j+1) \cdot e\}$ is higher than in the previous one, then the transition to the state $s' = s_{l,(j+1) \cdot e}$ is performed, otherwise the state $s' = s_{l,j \cdot e}$ remains unchanged.

Action $a_{s_{l,j \cdot e} \& s_{l+1, \cdot e}}$ - determining the fact of increasing the accuracy of forecasting when adding a new layer (changing the configuration $\{l,j \cdot e\}$ to $\{s+1,e\}$). The transition to the state $s' = s_{l+1,e}$ occurs when the prediction accuracy increases with a new layer. Otherwise, the state $s' = s_{l,j \cdot e}$ remains unchanged.

It is necessary to establish the probability with which the system moves between states s and s', if a_s works - $P(s'|s, a_s)$, and the time spent on performing this action as $T(s'|s, a_s)$. Then, when performing an action $a_{s_{l,j \cdot e} \& s_{l+1, \cdot e}}$ with a transition to a state $s' = s_{l,(j+1) \cdot e}$ (that is, iterations of network training with l layers and the number of training epochs $(j+1) \cdot e$) it takes time:

$$T_l \; (s' \mid s, a_{s_{l,j \cdot e} \& s_{l,(j+1)e}}) = t_l \bullet (j+1) \bullet e, \tag{6}$$

where t_l is the execution time of one training epoch for a network with l layers.

When performing an action $a_{s_{l,j \cdot e} \& s_{l+1, \cdot e}}$, a network with a configuration $\{l+1,e\}$ requires additional training on e epochs, which takes time:

$$T_2(s' \mid s, a_{s_{l,j \cdot e} \& s_{l+1,e}}) = e \bullet t_l + 1 \tag{7}$$

The transition diagram of the considered decision-making method is shown in Figure 4.

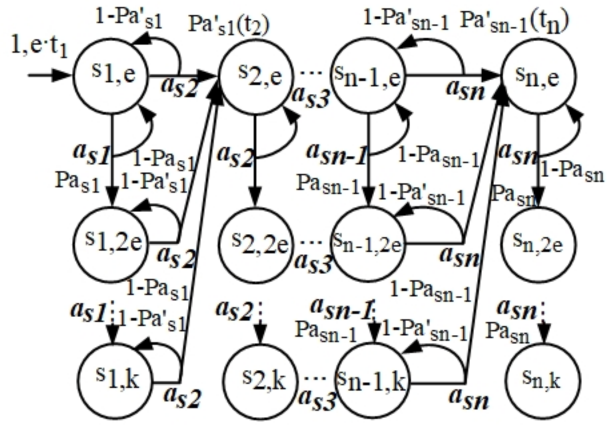

Figure 4. Transition diagram of the Markov decision-making process describing an episode of LSTM network training

Based on expressions (5)-(7), the optimal strategy will be one in which the selected configuration of the LSTM network maximizes the prediction accuracy (output of the LSTM network) while minimizing the time values T_1 or T_2. As a method of solving this problem, the use of dynamic programming methods is proposed, in particular, modification of the algorithm of iteration by values (ValueIteration), the basis of which is the Bellman equation [7].

In accordance with this, we introduce the quality of action function (Q-function) $q_i^{\pi}(s,a_s)$:

$$q_i^{\pi}(s,a_s) = \sum_{s'} P(s' \mid s,a_s) \bullet (T(s' \mid s,a_s)) + \gamma \bullet \upsilon_{i-1}(s')), \tag{8}$$

where $\upsilon_{i-1}(s')$ is the value function of the state s' for the strategy π at the i-1 iteration, and $0<\gamma<1$ is the depreciation coefficient (discount rate). Since for the considered IMA all the costs and expenses associated with network training accumulate, the condition $\gamma=1$ is accepted. Based on the Bellman optimality principle, the value function of the state s in the current iteration i is defined as the minimum of the function $q_i^{\pi}(s,a_s)$:

$$\upsilon_i(s) = \min\, q_i^{\pi}(s,a_s) \tag{9}$$

Using the proposed approach to modeling the learning process [8] of the IMA neural network model allows us to proceed to the synthesis of an iterative algorithm for dynamically configuring the parameters of the LSTM network, which will form its optimal configuration in terms of accuracy in predicting the moments of occurrence of non-stationary load on the controlled MN.

4. CONCLUSION

We have justified the choice of a neural network model for the class of LSTM networks. A cell memory matrix has been developed for such networks. The elements of the matrix are the LSTM network consistency components and archived traffic data of monitoring components near the node under study, while taking into account the time behavior of the burst moments.

For the proposed structure of the LSTM network, approaches to the process of its training (configuring the network configuration) are considered, based on the representation of this process in the form of a Markov decision-making process, which made it possible to solve the problem of determining the training times of the network within one epoch, as well as its retraining using a variant of the dynamic programming method – the iteration algorithm by values, which In the future, it allows you to proceed to the synthesis of an iterative algorithm for dynamically configuring the parameters of the developed LSTM network.

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