DESIGNING THE ARCHITECTURE OF A DISTRIBUTED SYSTEM FOR INFORMATION MONITORING OF IoT AND IIoT INFRASTRUCTURES TRAFFIC

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Abstract: The article considers an approach to designing the architecture of a distributed information monitoring and quality management system for communication services provided by the Internet of Things and Industrial Internet of Things infrastructures based on solutions supporting machine-to-machine and human-machine interaction. The choice of a neural network with long Short-Term memory (LSTM) is justified as a theoretical basis for modeling the active node of an information monitoring system. The developed structure of the LSTM network is presented, taking into account the spatial and temporal correlation of the obtained indicators at various observation points of the distributed information monitoring system. The criteria for evaluating the effectiveness of the proposed model for the conditions of information monitoring of non-stationary load in a mode close to real time are substantiated.

Key words: distributed information monitoring system, quality management of communication services, network traffic forecasting, neural networks, decentralized control.

1. INTRODUCTION

Modern distributed information monitoring systems (IMS) in packet-switched transport networks (PSTN), as a rule, have a centralized architecture based on the "manager-agent" model. Probes are usually considered as agents of such systems - passive measuring devices that collect key performance indicators (KPI) of the node and channel components of the PSTN. The manager is the IMS data processing center, a specialized computing system for processing the flow of incoming KPI values on a near-real-time scale.

Such an architecture is focused on general-purpose infocommunication services and does not take into account the features of network traffic generated by the solutions of the Internet of Things (IoT) and the Industrial Internet of Things (IIoT) [1], based on business logic models of machine-to-machine (M2M) and human-machine (people-to-machine, P2M) interactions. Existing centralized distributed IMS solutions implement centralized collection and statistical processing of KPIs from a variety of probes to obtain parameters of the packet transmission time distribution law in order to identify idle and/or overload modes.

The article is devoted to the development of new solutions in the field of distributed IMS architecture that carry out information monitoring of traffic generated by IoT and IIoT infrastructures.

2. PREVIOUS RESEARCH

Unlike the traffic models of traditional multiservice telecommunications services [2], the traffic of IoT and IIoT infrastructures has a stochastic character. In [3], the model of traffic generated by such solutions is substantiated. The values of its KPI significantly depend on both local territorial events, temporal factors [4], and dynamically generated within the framework of M2M and P2M models of computing infrastructures [5], which have hidden correlations, the identification of which manifests itself only in long time intervals of information monitoring [6]. These features do not allow us to determine with a given accuracy the type and parameters of the distribution law and determine the moments of operational traffic control. Thus, the development of new solutions in the field of distributed IMS architecture that carry out information monitoring of traffic generated by IoT and IIoT infrastructures is an urgent research task.

An analysis of the features of publications shows that at the moment it is not possible to determine the type and parameters of the distribution law with a given accuracy and to determine the moments of operational control of data movement in a distributed system. Thus, the development of new solutions in the field of distributed IMS architecture that carry out information monitoring of traffic generated by IoT and IIoT infrastructures is an urgent research task. It is necessary to: (1) Transform the existing centralized monitoring system into a decentralized one; (2) Create a neural network model with long-term short-term memory to predict time series with parameters of key performance indicators of structural components of the transport layer of packet management in the network.

3. MODIFICATION OF THE EXISTING CENTRALIZED INFORMATION MONITORING SYSTEM SCHEME FOR A DECENTRALIZED STRUCTURE

The manager-agent model used in centralized IMS is implemented in a decentralized IMS as part of an active monitoring node (AMN) that performs the functions of collecting and processing KPIs, as well as managing the parameters of the network component assigned to it. The interaction of multiple AMNS in such an IMS is implemented on the basis of a reasonably selected decentralized control protocol. A hypothesis is put forward about the use of a neural network structure with long Short-Term memory (LSTM) as a model for predicting KPI deviations.

In order to predict the KPI values of the structural components of the PSTN (routing nodes, access nodes (AN), subscriber terminals (UT)), which provides proactive control of their state, it is proposed to modify the existing centralized IMS scheme, replacing it with a variant with a decentralized structure.

The node of such an IMS is an active monitoring node (AMN), combining the functions of a probe and an IMS manager with a centralized structure. In general, AMN is represented by an autonomous computing system that implements functions:

- collecting a set of KPIs, the structural component of the PSTN assigned to it;
- formation of a set of control actions (CI) to adjust the parameters of the structural component of the PSTN assigned to it;
- implementation of a protocol for decentralized interaction with a subset of AMN in order to receive/transmit KPI values in the spatiotemporal monitoring.

The scheme of organization of a distributed IMS with decentralized control and the features of its interaction with the structural components of the PSTN are shown in Figure 1.

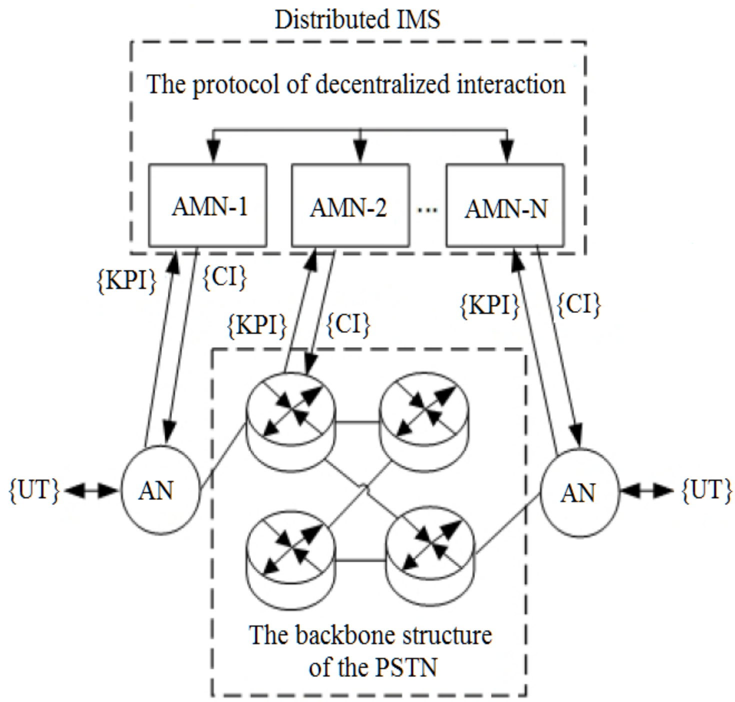

Figure 1. Block diagram of a distributed IMS with decentralized control

Obviously, the development of such an IMS requires solving two types of interrelated tasks:

1. Selection and justification of the AMN decentralized interaction protocol.
2. Development of the AMN structure, in particular, the module for processing a set of KPIs and forming a set of CI.

The article considers an approach to solving the second problem.

4. FEATURES OF THE MODULE FOR PROCESSING A SET OF KPIS AND GENERATING A SET OF CI

A feature of the proposed IMS structure (Figure 1) is to increase the accuracy of {CI} to adjust the parameters of a set of structural components of the PSTN by organizing mutual exchange of KPI parameters and the results of their processing between neighboring AMN nodes (a subset of {AMN_{n-1}, AMN_n, AMN_{n+1}}. Thus, each AMN forms a {CI} based not only on data on the functioning of the structural component of the PSTN assigned to it, but also on data on the functioning of the closest components. At the same time, structurally specified PSTN components can be represented not only in spatial, but also in temporal domains due to the streaming nature of the packet distribution model. A generalized structure of the AMN_n node, which supports the implementation of these features of IMS with decentralized management, is shown in Figure 2.

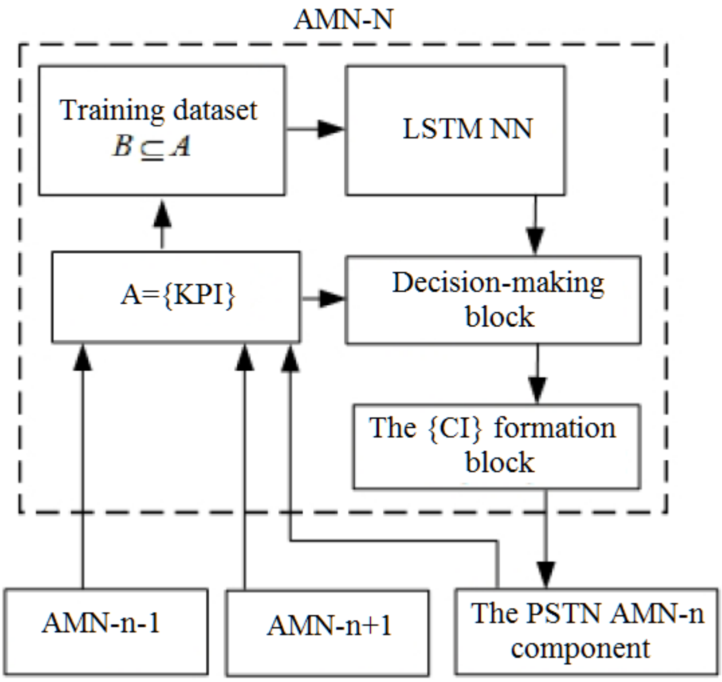

Figure 2. Generalized structure of the AMN_n node of a distributed IMS with decentralized management

Figure 2 shows that the set A is formed from a set of KPI parameter values coming not only from the controlled PSTN component, but also from neighboring AMN_{n-1} and AMN_{n+1}. From the set A, a subset B is selected, which acts as a training sample (dataset) for a neural network (NN). The decision block generates a predictive overload value based on the analysis of the parameter values of set A and the forecast of the time series of KPI parameters of the subset {AMN_{n-1}, AMN_n, AMN_{n+1}} generated by NN.

5. LSTM NEURAL NETWORK MODEL FOR PREDICTING TIME SERIES OF KPI PARAMETERS OF PSTN STRUCTURAL COMPONENTS

The task of long-term forecasting of the overload mode on a time scale close to real time cannot be solved by direct analysis of the values of the KPI parameters at the current time, since the characteristics of traffic have correlations depending on a number of temporal labels. Because such temporal labels are periodic in nature and can act as predictive variables. At the same time, classical time series analysis models based on autoregression (AR), can only reveal a linear time dependence and are not always applicable for predicting processes in which the data model is nonlinear, as in the case of the stochastic nature of traffic generated by IoT and IIoT terminals.

It can be assumed that the results of observations of KPI parameter values obtained in the specified temporal labels can act as precedents, which allows the use of machine learning methods based on precedents.

In this case, the prediction of the values of the time series is performed one countdown ahead, using some of the previous values. The input parameter is the vector $x(t)=(x_{t-\tau+1}, x_{t-\tau+2}, \ldots, x_t)$, and the output parameter is the value of x_{t+1}, where x is the value of some KPI indicator. Usually, the parameter τ indicates the width of the observation window or, in the case of NN using, the depth of immersion.

In general, the process of using NN to predict the values of a time series is represented by the following stages:

1. Selecting the value of the parameter τ.

2. The formation of a training sample (subset B, Figure 2) by dividing the time series is divided into a set of training examples. In this case, the i-th training example represents a pair:

$$(x(\tau+i-1), x(\tau+i)) \tag{1}$$

where $x(\tau+i-1)=(x_i, x_{i+1}, \ldots x_{i+t-1})$.

3. Formation of the NN structure with the number of inputs equal to τ.

4. NN training on the generated training sample.

Since the values of the elements of the time series can exceed the modulo value of 1, the following solutions are applied:

- preliminary normalization of data in order to obtain values falling within the ranges [-1;1] or [0;1];
- replacing the values of the time series with the differences of neighboring elements;
- the use of NN neurons with a linear activation function in the output layer.

Additionally, in the NN structure, it is necessary to take into account the correlation in the spatial (location of neighboring AMN) and temporal regions of the parameters of the set of incoming KPIs. To account for these types of correlation, it is proposed to use the correlation matrix M. Then, for m structural components of PSTN, a matrix of size m×m is formed, which is given as

$$M_{t,\Delta t}=Cr(S_{t+\Delta t}, S_{t+2\Delta t}, \ldots, S_{t+i\Delta t}, \ldots, S_{t+N\Delta t}) \tag{2}$$

where Cr is a correlation function, and $S_{t+i\Delta t}$ is a vector denoting the observed state of the load at a given monitoring point in the i-th time interval, which can be represented as (3):

$$S_{t+i\Delta t} = \left[x_1, x_2, \ldots, x_m\right]^T \tag{3}$$

where x_j are traffic data at the j-th monitoring point in the time interval $t+i\Delta t$.

In general, the element $r_{i,j}$ of the matrix M determines the coefficient of participation of data from the i-th monitoring point in the j-th monitoring point with a time interval $|i-j|*\Delta t$. The correlation function can be represented as (4):

$$r_{i,j}(\Delta T)=corr(X(t), Y(t+\Delta T)),\ t=1, 2, \ldots, N \tag{4}$$

where X(t) is a time series defining traffic data at the i-th monitoring point, $Y(t+\Delta T)$ is traffic data at the j-th monitoring point, $r_{i,j}(\Delta T)$ is the correlation coefficient of the specified monitoring points.

Obviously, the matrix M is dynamic, and the values of its elements depend on both the observation time t and the time interval ΔT. These elements are the input parameters of the developed NN LSTM. Its structure is shown in Figure 3.

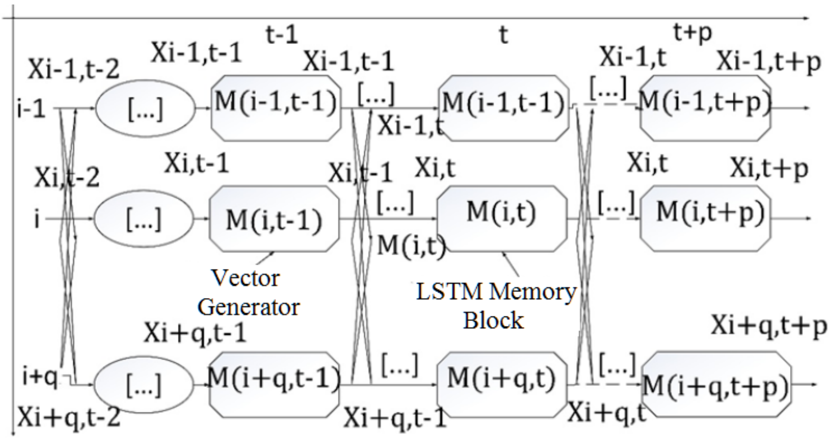

Figure 3. The structure of the LSTM neural network of an active monitoring node of a distributed IMS with decentralized management

The developed NN is structurally two-dimensional and takes into account measurements both in the time domain and in the spatial domain. The reference intervals $\Delta_{t_1}, \Delta_{t_2}, \ldots, \Delta_{t_m}$ are indicated as and correspond to the restriction (5):

$$T_f = \sum_{i=1}^{m} \Delta t_i \tag{5}$$

where T_f is the forecast generation time on m NN layers.

The values $\Delta_{t_1}, \Delta_{t_2}, \ldots, \Delta_{t_m}$ are adjusted using the minimum criterion of the integral quadratic error. The output data of the memory modules developed by NN for time t is also a matrix, which is formed by the repmat function from MATLAB based on traffic data S_{t-1} (6):

$$I_t=M(t,\Delta t)*repmat(S_{t-1},m) \tag{6}$$

An important task is to evaluate the effectiveness of the developed NN model, which, in general, is determined by the value of the prediction error. As part of the study, the use of the average absolute forecasting error, the average quadratic forecasting error and the average relative forecasting error. In [7, 8] it is indicated that, in general, these indicators are the inverse values of Forecast Accuracy. A generalized criterion for the effectiveness of NN LSTM functioning can be the minimization of prediction error values.

6. CONCLUSION

The development of infocommunication infrastructures supporting the paradigms of the IoT and IIoT raises the problem of managing traffic parameters generated by a set of terminal computers of these infrastructures. The quality of service management models known for the functioning of multiservice systems, focused on service level indicators and based on centralized information monitoring systems, in such cases turn out to be insufficiently effective, since they do not take into account the complex nature of traffic generated by these nodes and aggregates from these nodes on a time scale close to real time. Obtaining predictive values of the characteristics of such traffic is possible only through its multidimensional (spatial and temporal) analysis over long periods of time. The article discusses the implementation of a variant of an information monitoring system that provides such an analysis. Unlike traditional monitoring systems, it uses decentralized management of data collection and processing of key performance indicators. Its basic component is a specialized computing node - an active monitoring agent, which, using a dynamically retrained neural network of the LSTM type and interacting with similar neighboring nodes, receives predictive estimates of traffic parameters that allow proactive management of the network infrastructure component assigned to it.

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