«Forecasting technique of radio information system characteristics for optimal technical condition of the space control system components»

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Problem statement

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• Nowadays, the outer space security is an urgent issue for any country in the world. Today, there are only two systems that can provide such security: missile warning system in USA and Space Monitoring System in Russia. SMS involves: the space defense system and control of outer space, the radio-optical complex Krona, the optical-electronic complex Okno, the radio-technical complex Moment; the radar system Krona-N and Russian Space Surveillance System. Various components interact with SMS, such as radio detection and ranging (Radar) and optical-electronic stations (OES).

• In order to effectively interact with these components, it is necessary to optimize their technical condition. Therefore, there is an urgent need to forecast the radio information complex characteristics (sensor) of space objects parameters by information resources (sensors) from the group of Radar and OES when determining the optimal-technical condition of the components of the space monitoring system (SMS). Each group element has a set of sensors for measuring space objects parameters, which we will consider as univariate time series.
Solution methods

- By univariate time series values $X(t) = \{x_1, x_2, ..., x_{n-1}, x_n\}$ which characterizes the states (normalized measurements) of the sensor at discrete equidistant points in time $T = \{1, 2, ..., n-1, n\}$ we need to define the values of the following «m» elements of the time series that make up the vector $Y(t) = \{x_{n+1}, x_{n+2}, ..., x_{m-1}, x_m\}$ for the corresponding time points $T = \{n+1, n+2, ..., m-1, m\}$. Parameters «n» and «m» are set manually before starting model training. The interval between taking sensor readings is 30 seconds.

- We need to define the following functional dependency to solve the task:

  $$f(X) = Y$$

- where $X$ – the vector which is used for forecasting ($|X| = n$); $Y$ – the vector of forecasted values ($|Y| = m$); $f$ – the function of dependence between time series elements which is set by the RNN internal structure.
The function «f» is determined by pre-training the RNN model on the sample U consisting of 1080 normalized sensor measurements with 30 seconds interval, i.e. time series U = \{u_1, u_2, ..., u_{1080}\}. During the training process pairs of vectors are iteratively selected from the sample \((X', Y')\) according to the algorithm, meanwhile |X'| = n, |Y'| = m:

\[
X' = \{u_i, u_{i+1}, ..., u_{i+n-2}, u_{i+n-1}\} \\
Y' = \{u_{i+n}, u_{i+n+1}, ..., u_{i+n+m-2}, u_{i+n+m-1}\} \\
i = [1, |U| - n - m]
\]

Each pair of vectors \((X', Y')\) is substituted in (2) instead of X and Y, therefore, there is a change in the internal RNN structure, depending on the given data, i.e. training the model and defining «f».
Conclusions

The paper proposes the forecasting technique of the radio information complex of space objects parameters, using a recurrent neural network and information tools from an early-warning radar stations group and Russian Aerospace Forces optical-electronic stations when determining the optimal technical condition of the SMS components.

There is proposed the algorithm for forecasting radio information complex characteristics by analyzing values of time series by a recurrent neural network model based on LSTM with different parameters.

The example shows the method of experimental determination of optimal values of the forecasting model important parameters – the forecast horizon and the volume of input data.

If we increase the number of input data, the prediction error decreases starting from the value of 22.5 minutes. The lowest value of the average error for any forecast horizon is achieved when analyzing the values for the previous 30 minutes.

It seems that a further increase of the period of analyzed values may lead to an even smaller value of the forecast error. Using the optimal set of parameters \((n = 30, m = 9)\) gives the average forecast error \(\sim 0.5\%\) with a forecast horizon of 9 minutes, which is a good result.

On this basis, further experimental work on optimizing the RNN model parameters can improve this solution.
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