ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

NEURO NETWORK TECHNIQUES OF TELEMETRY MULTIVARIATE TIME SERIES PROCESSING AND THEIR APPLICATIONS IN INDUSTRY

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ABSTRACT

The main innovations proposed for development and implementation within the framework of the project, assessment of their fundamental novelty and competitiveness, compliance with environmental and other indicators, as well as the requirements of international standards. The main innovation of the project is to create more accurate methods and algorithms for identifying and predicting abnormal situations in the subsystems of remote technical objects (spacecraft, UAVs) using ensembles of artificial neural networks. The practical significance lies in the fact that the use of the developed methods and algorithms for the implementation of high-performance software and hardware systems will significantly reduce the time spent on processing incoming telemetry data, and especially on training classifiers of spacecraft states. An effective solution can be the development of a neural network software system for identifying the state of onboard objects and spacecraft subsystems based on modeling their behavior and intelligent processing of telemetric data.

Keywords: *ANN, Telemetry, Multivariate Time Series*

1. INTRODUCTION

Spacecraft operate in extremely challenging and unforgiving environments [1]. This calls for careful planning of their operations and close monitoring of their status and health [2]. The spacecraft's monitoring includes analysing housekeeping telemetry data that measure and describe the spacecraft's status, its activities, and its environment [3]. These include temperature values at different locations, radiation values, power consumption estimates, status/command execution of active onboard equipment, performed computational activities [4]–[10].

Analysing telemetry data is complex and nontrivial since typically such data is: high dimensional (the number of features easily reaches the thousands); multimodal (data measured from different onboard components at different times); heterogeneous (the variables describing the status can be of different data types); with temporal dependence (the housekeeping data are typically multidimensional time series); has missing values (different sampling periods and timings, not always all values of all variables are retrieved); and contains obvious outliers (extreme abnormal values caused by errors in data conversion or transmission) [4].

Based on the analysis of these telemetry data, the spacecraft mission-planning and operations teams make decisions about the spacecraft's next operations - what activities it will perform (in terms of its mission) and when it will perform them [11]. The space telemetry is a set of technics allowing us to collect distantly information about the state of on-board subsystems of a spacecraft [12]. They inspect their functioning by means of analysis of readings of monitors distributed over the subsystems [12]. Thus, the telemetry data is a multidimensional time series. One of the problems of the analysis is to forecast the given series.

Journal of Theoretical and Applied Information Technology
15th May 2022. Vol.100. No 9

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

In the general form, a forecasting problem for a multidimensional time series is formulated as follows [13]: using the known value of the sequence $y(k)$ and its history $y(k-1)$, $y(k-2)$, …, $y(k-m)$ it is necessary to estimate the next value of the sequence $y(k+1)$. In the instant k each sequence member is a set of numbers. The length of the history m we use for forecasting is called a time-window.

Since neural network (NN) approaches allow on to simulate dependences between variables by means of training by examples, they are widely used now when solving forecasting problems [14]. At that, their efficiency depends on architectural solutions and training methods. Consequently, the experiments have to be repeatedly performed. There are examples of neural networks use in on-board intellectual decision support systems [15].

2. MATERIAL AND METHOD

The main innovations proposed for development and implementation within the framework of the project, assessment of their fundamental novelty and competitiveness, compliance with environmental and other indicators, as well as the requirements of international standards. The main innovation of the project is to create more accurate methods and algorithms for identifying and predicting abnormal situations in the subsystems of remote technical objects (spacecraft, UAVs) using ensembles of artificial neural networks. The practical significance lies in the fact that the use of the developed methods and algorithms for the implementation of high-performance software and hardware systems will significantly reduce the time spent on processing incoming telemetry data, and especially on training classifiers of spacecraft states. An effective solution can be the development of a neural network software system for identifying the state of onboard objects and spacecraft subsystems based on modeling their behavior and intelligent processing of telemetric data.

Belarusian scientists Acad. S.V. Ablameiko, Corresponding Member A. V. Tuzikov, professors, doctor of technical sciences. V. A. Golovko, V.V. Krasnoproshin, A.M. Nedzvedem, A.A. Dudkin, M.M.Tatur and others have so far developed neural network models for identifying and classifying objects in the form of a neocognitron, self-organizing Kohonen maps and their combinations, ensembles of neural networks, a method for choosing optimal neural networks, as well as methods for their training, which allow to increase the stability and reduce the computational complexity of the learning process with fuzzy information about objects. In the open press, various options for constructing effective on-board and ground-based means of monitoring and diagnosing the state of subsystems of remote objects are described, both the general principles of constructing such systems and the possibility of expanding the intelligent functions of the on-board control complex (BCC) are considered. At the same time, researchers are particularly interested in the possibility of using artificial neural networks (ANNs).

For the successful implementation of this project, it is advisable to involve Pembangunan Pancabudi University, which specialists in the development of neural systems, systems using elements of artificial intelligence and hardware and software data collection in various technical applications, in order to jointly develop methods and algorithms and processing tools information, as well as for the development of the concept of building technical diagnostic systems based on them. Pembangunan Pancabudi University are specialists in the development of models, expert systems, distributed intelligent systems and neural network training methods. The results of preliminary studies from researcher of Pembangunan Pancabudi University show that the proposed approaches are promising and will help achieve the goal of the project. It is necessary to use the experience of Indonesian scientists in terms of PCA and original forecasting methods.

2.1 General Architecture

The main objective of the project are creating a neural network model, methods and algorithms using ensembles of neural networks that allow automating the process of solving problems of forecasting and classifying telemetric information represented by multidimensional time series received from remote technical objects. The research project will be carried out by the following breakdown scheme below:

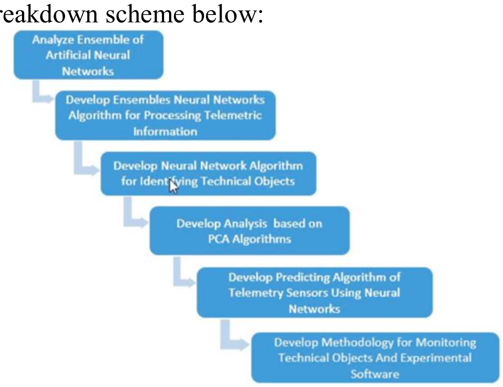

Figure 1: General Architecture

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The steps from Figure 1 are explained based on the following steps:

1. Analyze ensembles of Artificial Neural Networks for processing multidimensional time series
2. Develop algorithms for the formation of ensembles of Neural Networks for processing telemetric information
3. Develop Neural Network algorithms for identifying the states of technical objects
4. Develop analysis algorithms based on the Principal Component Analysis
5. Develop algorithms for predicting the values of telemetry sensors using neural networks
6. Develop methodology for monitoring the states of subsystems of technical objects and experimental software that implements it.

3. RELATED WORK

The ensemble learning method combines decisions from multiple sub-models to a new model and then to make the final output to improve the prediction accuracy or the overall performance in Figure 2. There are many different ensemble learning models: MaxVoting, Averaging, WeightedAverage, Stacking, Blending, Bagging, Boosting, Adaptive Boosting (AdaBoost), Gradient Boosting Machine (GBM), eXtreme Gradient Boosting (XGB), etc. [16]. Different ensemble models have different characteristics and can be used to solve different problems in various domains. A simple example to describe the ensemble learning method is that compared with an individual's decision, a diverse group of people are more likely to make a better decision. The same principle applies to machine learning and deep learning models; a different set of models are more likely to perform a better comparison to a single model [17] since each model has their own strength and they can complement each other to overcome their individual shortcomings.

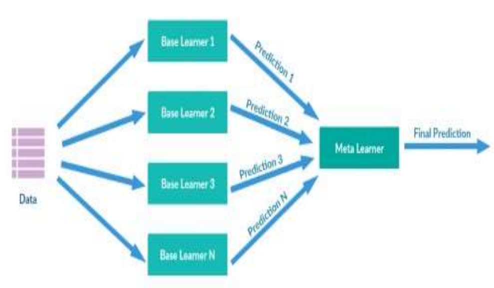

Figure 2: Advanced Ensemble techniques [18]

4. TIME SERIES FORECASTING UNIVARIATE FORECASTING

A purely univariate forecasting problem refers to predicting future values of a time series based on its own past values. That is, there is only one time dependent variable. Given the target series:

$$X = (x_1, x_2, \dots, x_t, \dots, x_T) \quad (1)$$

the problem of univariate forecasting can be formulated as follows:

$$\{x_{T+1}, \dots, x_{T+h}\} = F(x_1, \dots, x_T) + \varepsilon \quad (2)$$

Here, F is the function approximated by the model developed for the problem with the variable X. The function predicts the values of the series for the future time steps from T +1 to T +H, where H is the intended forecasting horizon. _denotes the error associated with the function approximation F. Time series forecasting has been traditionally a research topic in Statistics and Econometrics, from simple methods such as Seasonal Naïve and Simple Exponential Smoothing, to more complex ones such as ETS [19] and ARIMA [20]. In general, traditional univariate methods were on top in comparison to other computational intelligence methods at many forecasting competitions including NN3, NN5 and M3 [21], [22]. The bene_t of the traditional univariate methods is that they work well when the volume of the data is minimal [23]. The number of parameters to be determined in these techniques is quite low compared to other complex machine learning techniques. However, such traditional univariate techniques introduced thus far lack few key requirements involved with complex forecasting tasks. Since one model is built per each series, a frequent retraining is required which is compute intensive especially in the case of massive time series databases. Also, these univariate techniques are not meant for exploiting cross-series information using global models since they take into account only the features and patterns inherent in a single time series at a time. This is not an issue if the individual time series are long enough having many data points so that the models become capable of capturing the sequential patterns. However in practice this is usually not the case. On the other hand, learning from many time series can be e_ectively used to address such problems of limited data availability in the single series.

A recurrent neural network (RNN) is a deep learning model archetype first introduced by Rumelhart et al. in 1986. It contains connections between hidden layers, allowing the model to retain information about past inputs, enabling time-series modeling. The original model suffers from the vanishing gradient problem, making it unable to learn from long sequences [24]. Two modified RNN architectures have since risen in popularity: (1) Long-Short Term Memory (LSTM) models, proposed in [25] and (2) Gated Recurrent Units (GRUs), proposed in [26]. Both approaches utilize gates to filter what information is kept and what is discarded, allowing learning on longer time-series sequences. Many modern sequence-based processes utilize one of these neural networks.

Time series forecasting is a highly common data modeling problem since temporal data is generated in many different contexts [27]. Classical forecasting approaches autoregression (VAR) [28]. Here, a forecast estimate is dependent on a linear combination of the past values and errors. Autoregressive models work well if the assumption of stationarity is true and the series is generated by a linear process [29]. On the other hand, these hard assumptions limit the effectiveness of autoregressive models if one deals with non linear series, as it is the case with the majority of practical time series problems. LSTM, a particular variant of artificial recurrent neural networks (RNN), overcomes these shortcomings as it makes no assumptions about the prior distribution of the data. One can think of RNNs as regular feed-forward networks with loops in them. This enables RNNs to model data with interdependencies such as autoregression. It has been shown that artificial neural networks with one hidden layer can, in theory, approximate a continuous function arbitrarily well [30]. As the RNN gets deeper, vanishing or exploding gradients often lead to poor model performance. Long Short Term Memory (LSTM) solves this problem with a gating mechanism that controls the information ow in the neurons. LSTMs show superior performance in a variety of sequence learning tasks such as machine translation [30].

5. CONSTRUCTION OF ENSEMBLES FOR TELEMETRY DATA PROCESSING

We solved the forecasting problem of telemetry data for three subsystems, such as, the power system (PS), the corrective propulsion system (CPS) and the target equipment (TE). Consequently, we generated three ENN for the telemetric data (TD) processing. Preprocessed TD and the identifier of the subsystem in question are fed to the ENN input, which is delivered to the supervisor of the ensembles with the aid of the communication block. The supervisor generates a signal for choosing of ENN for the given subsystem and initiates the procedure of its additional training. The incremental block of additional training is responsible for preparation of the training data set and training of new elements of ENN.

We use a multilayer perceptron with one hidden layer and the nonlinear activation function in the form of *the hyperbolic tangent* as the basic element of ENN. We define the size of the input layer *N*I for NN of single ENN as the product of the number of the monitors of the subsystem for which we generate this ENN and the time-window we use in the forecast. We define the size of the hidden layer *N*I for NN of single ENN during the experiment using the procedure of searching of the suboptimal size of the hidden layer of single NN. The size of the output layer *N*O for NN of single ENN is defined by the number of monitors of subsystem for which this ENN is generated.

The algorithm RPROP trains individual neural networks. We use a number of different approaches when generating the output value ENN. They are [31]:

(1) The output value of ENN is generated as a sum of outputs of individual NNs. In the case of one output neuron we calculate it according the formula

$$y = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{3}$$

where n is the number of models of NN, and yi – is the output of the i-th NN;

(2) The output value of ENN has the form of the weighted sum of outputs of individual NNs. In the case of one output neuron it is calculated by the formula

$$y = \sum_{i=1}^{n} y_i w_i \tag{4}$$

where n is the number of models, yi is the output of the i-th NN, wi is the weight of the i-th NN calculated as

$$w_i = \frac{mse_i}{\sum_{i=1}^{n} mse_i} \tag{5}$$

And $msei$ is the MSE-error of the i-th NN on the validation set.

(3) The output value of ENN is the weighted sum of outputs of individual NNs (Eqs. (2) and (3)). At that, we repeat the weighting after specified intervals of the processed

sets (time readings) with an estimate on this set (dynamically weighted ENN).

The concept of *drift of values* refers to changes of the defined value with time and, consequently, to changes in the distribution of the given value. The medium from which these values were obtained is not stationary. A shift of the probability may indicate that definitions of the events may also change. An ensemble of experts trained step-by-step on the input data (without access to the previous data) combined with a form of weighted voting for obtaining the final solution is the common of the algorithms of the drift detecting (Elwell, 2009; Parikh, 2007).

Incremental training of ENN means estimating of accuracy of all models and their ranging by accuracy at each forecasting iteration. When the error of ENN increases, the drift of the target variable is detected and a new element trained at the relevant data is added the ensemble. In this approach, we retain the model put in during the initial training and add new parameters without the problem of "forgetting". This is the way of additional training of ENN.

The algorithm of the incremental training of ENN includes the following steps:

1. The algorithm estimates the accuracy of ENN comparing the errors in the previous and the current steps of its functioning.
2. If the error does not change or the change is in a predetermined range the work stops.
3. Otherwise the training data set including all the stored data after the last additional training is formed.
4. Generation and training of new NN takes place.
5. Generated NN is added to the ensemble.
6. For all NN in the ensemble recalculation of the weight coefficients according Eq. (3) takes place.

Consequently, shown in Fig. 1 the two-level model of ENN forecasting data of subsystems of the spacecraft is generated and works according the following algorithm.

1. Introduction of the sizes *N*PS ENNPS for processing of TD of PS, *N*CPS ENNCPS for processing of TD of CPS, and *N*TE ENNTE for processing of TD of TE
2. Training of *N*PS individual NN using the set of TD of PS.
3. Training *N*CPS individual NN using the set of TD of CPS.
4. Training of *N*TE individual NN using the set of TD of TE.
5. Calculation of the weighted coefficients for individual NNs for each of the ensembles ENNPS, ENNCPS, and ENNTE.
6. Receiving of TD for processing.
7. Defining of the processed subsystem (PS, CPS, or TE).
8. Transmission of TD to the corresponding ENN.
9. Generation of the result according Eqs. (1) or (2).
10. Incremental additional training of the chosen ENN.
11. If there are data for processing, repeat item 6.

6. CONCLUSION

Multivariate Time Series based forecasting allows forecasting by considering all variables that affect the forecasting objective variable so that it is expected that the level of accuracy will be higher. The development of forecasting models must involve the concept of deep learning which emphasizes the exploration of the many types of algorithm models used in the construction of forecasting models. In addition to the many models used, the exploration of the number of neurons and epochs is also considered in the implementation process. This paper also proves that the large number of epochs and neurons does not guarantee an increase in the level of accuracy. For future research development, it is hoped that the test source data used can be increased to more. In addition, it is necessary to evaluate the architecture and more in-depth testing in terms of batch size values, and optimization of the algorithms used. It would be better if we added more comparisons of other deep learning models such as CNN or hybrid combinations between methods such as the CNN-LSTM algorithm.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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