Prediction of EIGRP traffic parameters by 3D approximation using neural networks

Vorhersage von EIGRP-Parametern durch 3D-Approximation mittels neuronaler Netze

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Abstract — In the dynamic development of modern communication technologies, the use of intelligent methods for automatic adaptation of communication traffic parameters is increasingly necessary. The problems of self-decision and predictable adaptation of traffic parameters have to be solved within the autonomous system. The article presents a study of the ability of neural networks of type Multi-Layer-Perceptron and Kohonen, to adaptively predict the necessary change of the bandwidth, depending on the dynamic changes in other parameters of the dynamic routing protocol metric. The experiment was conducted for the Enhanced Interior Gateway Routing Protocol, observing different ratios between two of its basic metrics parameters - load and reliability. The input and output vectors of the neural networks are represented by a 3D approximation surface, where different approaches to approximation were used and compared. The precision of the prediction is tested when the metric parameters change. The accuracy of the proposed method is analyzed. The achieved results are represented and discussed, as well feature work is proposed.

Zusammenfassung — Bei der dynamischen Entwicklung moderner Kommunikationstechnologien wird zunehmend der Einsatz intelligenter Verfahren zur automatischen Anpassung von Kommunikationsverkehrsparametern notwendig. Die Probleme der Selbstentscheidung und der vorhersehbaren Anpassung von Verkehrsparametern müssen innerhalb des autonomen Systems gelöst werden. Der Artikel präsentiert eine Studie über die Fähigkeit neuronaler Netze vom Typ Multi-Layer-Perceptron und Kohonen, die notwendige Änderung der Bandbreite abhängig von den dynamischen Änderungen anderer Parameter der dynamischen Routing-Protokoll-Metrik adaptiv vorherzusagen. Das Experiment wurde für das Enhanced Interior Gateway Routing Protocol durchgeführt, wobei unterschiedliche Verhältnisse zwischen zwei seiner grundlegenden Parameter - Last und Zuverlässigkeit - beobachtet wurden. Die Eingangs- und Ausgangsvektoren der neuronalen Netze werden durch eine 3D-Approximationsfläche dargestellt, wobei verschiedene Approximationsansätze verwendet und verglichen wurden. Die Genauigkeit der Vorhersage wird getestet, wenn sich die metrischen Parameter ändern. Die Genauigkeit der vorgeschlagenen Methode wird analysiert. Die erzielten Ergebnisse werden dargestellt und diskutiert, sowie zukünftige Arbeit wurde vorgeschlagen.

I. Introduction

In the dynamic development of modern communication technologies, the use of intelligent methods for automatic adaptation of communication traffic parameters is increasingly necessary. The problems of self-decision and predictable adaptation of traffic parameters have to be solved within the autonomous system. At present, there are various studies and attempts for practical realizations of dynamic adjustment of the parameters of the routing protocols as well as of the routes themselves. In most modern studies, this is accomplished by applying adaptive decision-making methods such as applying different types of neural networks. This article presents a study of the ability of neural networks of type Multi-Layer-Perceptron (MLP) and Kohonen, to adaptively predict the necessary change of the bandwidth, depending on the dynamic changes in other parameters of the EIGRP (Enhanced Interior Gateway Routing Protocol) dynamic routing protocol metric. The experiment was conducted, observing different ratios between two of its basic metrics parameters - load and reliability. The input and output vectors of the neural networks are represented by a 3D approximation surface, where different approaches to approximation were used and compared. The precision of the prediction is tested when the metric parameters change and the accuracy of the proposed method is analyzed. The next section II presents some related works, the next one section III explores the proposed method. Section IV shows the experiment and the obtained 3D surface results. Section V includes the conclusion.

II. Related Works

Many modern researchers are trying to find effective adaptive methods to optimize the parameters of IP/TCP traffic in terms of predicting the best route, by providing the appropriate bandwidth. Methods using neural networks are increasingly being used, due to their good adaptive capabilities.

The routing algorithm proposed in [1], is based on link state routing protocols, considering the number of hops, bandwidth, load and delay. The authors have created a new metric, that uses artificial neural network logic, in order to optimize route selection, optimize network resources and reduce link occupancy. They use two different Hopfield neural networks: the first - in order to ensure that every change of network topology (or network parameters) is distributed to the network as fast as possible and the second one is dedicated to the route selection problem, based on previously collected information. The authors investigate the relation between bandwidth and load, but instead for the EIGRP - for the OSPF, because EIGRP is a proprietary Cisco routing protocol. Search for the shortest path with a Genetic algorithm (GA) is used for routing in packet switched data networks in [2]. The authors explore solution space in multiple directions at once. They claim that GA is well suited for routing problem as it explores solution space in multiple routing directions at once. But to improve the results, the authors are looking for other options for applying intelligent approaches for populating the routing table and using mutation probabilities, enhancing it to support for load balancing. The authors of [3], determine the final route through two phases. First, a Kohonen [4] neural network creates link clusters, with formulating the Cost parameter (based on Bandwidth, Density, Delay and Reliability, in the same manner as metric within EIGRP protocol, and added it to every link. With costs reduced in such a manner, the second phase of the algorithm is entered. This phase demands the use of Hopfield's neural network, which has exhibited good results while searching for the optimal route. Further, on all four parameters are being analyzed, but only the links with higher reliability are stimulated. The second phase demands the use of Hopfield's neural network, which has exhibited good results while searching for the optimal route. All of the above-mentioned methods aim to optimize routing parameters but are based on complex algorithms and calculations without examining the achieved accuracy and performance of the result.

The simple method proposed in this work presents a study of the ability of neural networks of type MLP [5] and Kohonen, to adaptively predict the necessary change of the bandwidth, depending on the dynamic changes in other parameters of the EIGRP dynamic routing protocol metric. The experiment was conducted, observing different ratios between two of its basic metrics parameters - load and reliability. The output vectors of the neural networks are represented by two different 3D approximation surface approaches when applying Kohonen SOM (Self Organized Map), compared with the results when MLP neural network is used.

III. The Proposed Method

The proposed approach for dynamically tuning one of the parameters forming the EIGRP metric, namely the bandwidth, is based on defining a relative factor. This factor adapts dynamically, according to the neural network decision, which is taught by the other two main parameters defining the EIGRP metric - load and reliability.

A. Selecting the parameters

The parameters load, reliability and bandwidth are represented by relative units whose high values (maximum = 1) represent a strong participation in the EIGRP metric of the relevant parameter, reciprocal to the low values. They serve as recommendation about giving relatively high, low or middle bandwidth values for the selected route, depending on the combination and the ratio between load and reliability. That is the reason to train the neural network with these two parameters and teach it to give appropriate output bandwidth. The corresponding values are given in Table I.

TABLE I. Relative Parameter Values

reliability	load	bandwidth requirements
0.5	0.5	0
1	0	1
1	1	1
0	1	1
0	0	1
0.5	0	1
1	0.5	1
0.5	1	1
0	0.5	1
0.5	0.25	0.5
0.75	0.5	0.5
0.5	0.75	0.5
0.25	0.5	0.5
0.25	0	1
0.75	0	1
1	0.25	1
1	0.75	1
0.75	1	1
0.25	1	1
0	0.75	1
0	0.25	1

B. Maintaining the neural network types

To examine the accuracy of the approximation, two types of neural networks - of the MLP type and the self-organizing Kohonen Map – SOM, were trained, aiming to compare the results and recommend the better method. First two different topologies of SOM were trained with structure 3-inputs and 21 outputs in the feature map. Then, the number of neurons in the map was incrementally increased to allow for greater accuracy in structures 3-inputs and 36 outputs in the map – shown in Fig. 1. The two parameters *load (L)* and *reliability(R)* were given also to the input of a MLP neural network with structure 2-5-1. The idea of the combination of the set relative values of the parameters in Table 1 consists of the following: when at least one of the two L or R parameters has a very low or very high value - the *bandwidth (B)* parameter can be defined by the network as a prescription/need for dynamic increase of the bandwidth. Accordingly, in all other cases where the same two parameters have average values, the requirements for bandwidth should not be changed, the process is considered to be constant and stable. The difference between the MLP and the SOM neural network is that the MLP approximates its output (B) depending on the values of L and P, while SOM simultaneously adapts the three variables L, R and B, assigning to each winner-neuron, three approximated values. However, in both cases, the three variables will approximate a 3D surface that will set B on its Z axis.

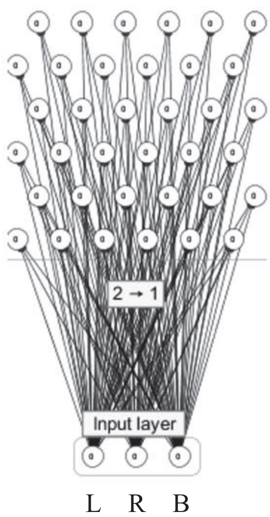

Fig. 1. Trained SOM structure with 3 inputs and 36 neurons in the map

IV. Experimental Results

To determine the structure of the SOM that provides a good ratio between the number of neurons in the map and accuracy, two different methods to create/ approximate a 3D surface of the weight values resulting in the "winning" neurons were applied. These are the methods *Inverse Distance to a Power (IDP)* and *Minimum Curvature (MC)*.

A. IDP Method

The IDP method is fast but has the tendency to generate "bull's-eye" patterns of concentric contours around the data points. Inverse Distance to a Power does not extrapolate Z values beyond the range of data [6]. It uses the approximation calculations given in (1), where

$$\widehat{Z}_j = \frac{\sum_{i=1}^{n} \frac{Z_i}{h_{ij}^b}}{\sum_{i=1}^{n} \frac{1}{h_{ij}^b}} \tag{1}$$

$$h_{ij} = \sqrt{d_{ij}^2 + \delta^2}$$

is the effective separation distance between grid node *j* and the neighboring point *i*;
$\widehat{Z}_j$ is the interpolated value for grid node *j*; Z_i are the neighboring points; d_{ij} is the distance between the grid node *j* and the neighboring point *i*; *b* is the weighting power parameter; δ is the smoothing parameter.

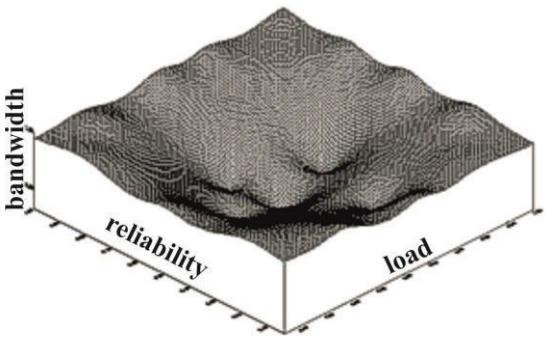

Fig.2 3D approximation results with IDP approximation method and SOM 3-inputs and 21 neurons in the map

Fig. 2 represents the obtained surface when the SOM network with 21 neurons in the map, is trained with all combinations of 3 values shown in Table 1 and fed to the three input neurons. Fig. 3 represents the obtained surface when the SOM network with 36 neurons in the map, is trained with all combinations of 3 values shown in Table 1 and fed to the three input neurons.

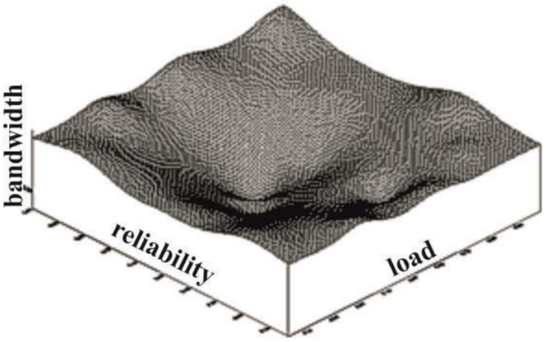

Fig.3 3D approximation results with IDP approximation method and SOM 3-inputs and 36 neurons in the map

B. MC Method

Minimum Curvature generates smooth surfaces and is fast for most data sets. The internal tension and boundary tension allow controlling over the amount of smoothing. Minimum Curvature can extrapolate values beyond data's Z range [6].
Fig. 4 and Fig. 5 represent the obtained surface, applying MC method, when the SOM network with respectively 21 and 36 neurons in the map, is trained with all combinations of the 3 values shown in Table 1 and fed to the three input neurons.

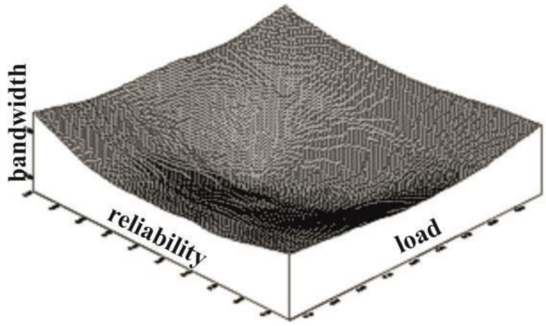

Fig.4 3D approximation results with MC approximation method and SOM 3-inputs and 21 neurons in the map

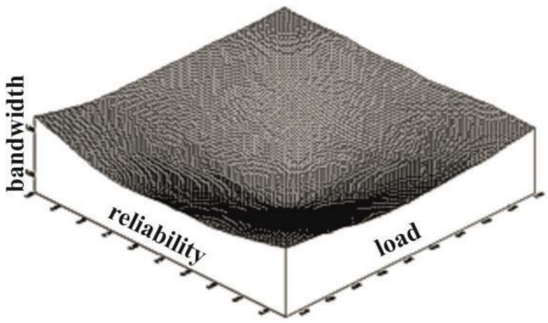

Fig.5 3D approximation results with MC approximation method and SOM 3-inputs and 36 neurons in the map

C. MLP Method

The next experiment was conducted by training the MLP neural network of structure 2-5-1. It has been trained with the input data *load* and *reliability* of Table 1, with a set output neuron value corresponding to the *bandwidth* column. Both networks SOM and MLP were trained with the same number of 1250 iterations and train error of 0.01. In this case, the graph of the 3D surface shows steeper slopes, which would reflect in more dynamic changes of the Z-Axis, i.e of the bandwidth parameter.

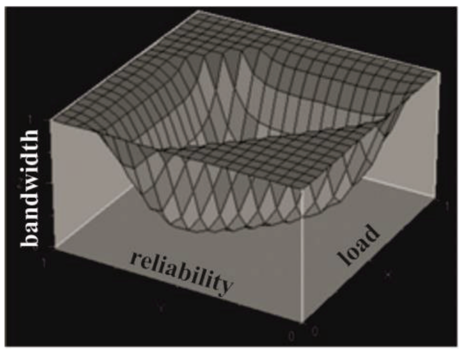

Fig.6 3D approximation results with MLP approximation method and structure 2-5-1

D. *Methods comparison*

To compare the accuracy of approximation using SOM and MLP for the same parameter training, the obtained graphics are shown in Fig. 7 and Fig. 8.

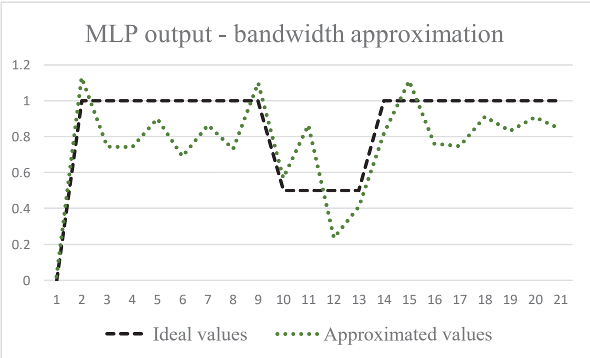

Fig.7 Approximation of MLP 2-5-1 output "bandwidth" with ideal (desired) and the obtained values

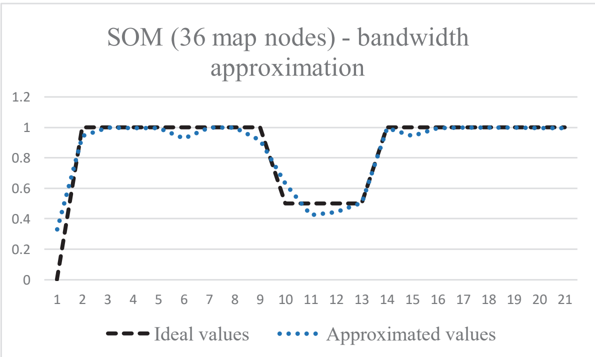

Fig.8 Approximation of MLP 2-5-1 output "bandwidth" with ideal (desired) and the obtained values

The error $Approx_{err}$ of approximating the output neuron of the MLP and *B* neuron of the SOM networks is calculated using the equation given in (2),

$$Approx_{err} = \sqrt{\frac{\sum_{i=1}^{N}(BW_{ideal} - BW_{appr})^2}{N}} \tag{2}$$

where BW_{ideal} is the desired bandwidth and BW_{appr} represents the approximated value. Fig. 9 shows the obtained results for $Approx_{err}$ for SOM-map-21; SOM-map-25; SOM-map-36 and MLP 2-5-1. It is obvious, that with increasing the number of neurons in the SOM map, the accuracy of approximation

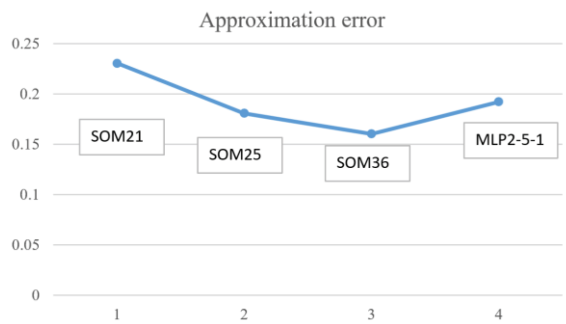

Fig.9 $Approx_{err}$ for different SOM maps and for MLP 2-5-1

improves. The calculation according to equation (2) is done for the 3D approximation, according to the MC method, since according to the graphs of Fig.2-5 it produces better results.

V. Conclusion

The represented paper is a study of the ability of neural networks of type Multi-Layer-Perceptron (MLP) and Kohonen, to adaptively predict the necessary change of the bandwidth, depending on the dynamic changes in other parameters of the EIGRP dynamic routing protocol metric. The experiment was conducted, observing different ratios between two of its basic metrics parameters - load and reliability. The 3D approximation surface was obtained, where different approaches to approximation were used and compared. The precision of the prediction is tested when the metric parameters change and the accuracy of the proposed method is analysed.

The results obtained show, that compared to the MLP, the better method is that with the application of the SOM neural network, which according to Fig. 9 gives the lowest value of the error of approximation. In MLP case, the graph of the 3D surface shows steeper slopes, which would reflect in more sharp changes of the Z-Axis - of the bandwidth parameter. It is obvious, that with increasing the number of neurons in the SOM map, the accuracy of approximation improves. Furthermore, it is evident that the MC method is superior to the IDP method for 3D approximation, as the comparison of the graphs of Figs. 2-5 shows a more uniform surface representation, which would result in a smoother change of the bandwidth parameter.

This pre-comparative study is necessary to precede the implementation of the real-time method in communication in topology working with the specified routing protocol, which is also the subject of further research development.

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