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COMPARISON OF DIFFERENT TYPES OF NEURONAL NETS FOR FAILURES LOCATION WITHIN WATER-SUPPLY NETWORKS

PORÓWNANIE RÓŻNYCH TYPÓW SIECI NEURONOWYCH DO LOKALIZACJI AWARII W SIECIACH WODOCIĄGOWYCH*

The different types of neuronal nets for failures location within a water-supply network are presented in the paper. The present utilization of the monitoring systems does not exhaust their possibilities. The monitoring systems operated as autonomic programs gather the information about flows and pressures of water in the source pumping stations, in the zones of hydrophore stations and also in some selected pipes of water network, giving general knowledge about state of its work, when simultaneously they could and should be used as elements of IT systems for network management, and particularly regarding detection and location of hidden water leaks. The models of network failures location are created by means of neuronal nets in the form of MLP and Kohonen nets.

***Keywords**: water-supply networks, network hydraulic models, detection and location of water leaks, MLP and Kohonen neuronal nets.*

W artykule prezentowane są różne typy sieci neuronowych do lokalizacji awarii w sieci wodociągowej. Obecne wykorzystanie systemów monitorowania nie odpowiada ich możliwościom. Współcześnie systemy monitoringu służą jako autonomiczne programy do zbierania informacji o przepływach i ciśnieniach wody w pompowniach źródłowych, hydroforniach strefowych i końcówkach sieci wodociągowej, dając ogólną wiedzę o stanie jej pracy, gdy jednocześnie mogą i powinny być wykorzystane jako elementy IT systemów zarządzania siecią, w tym w szczególności w zakresie wykrywania i lokalizacji wycieków wody. Modele lokalizacji awarii sieci zostały utworzone przy wykorzystaniu jednokierunkowych sieci neuronowych ze wsteczną propagacją błędu typu MLP i sieci Kohonena.

***Słowa kluczowe**: sieci wodociągowe, modele hydrauliczne sieci, wykrywanie i lokalizacja wycieków wody, sieci neuronowe MLP i Kohonena.*

1. Introduction

At the Systems Research Institute of Polish Academy of Sciences (IBS PAN) an IT system for computer aided management of communal water networks has been developed and one of its tasks is the water net failures localization [9]. To do it the water net hydraulic model and a SCADA system installed on the water net are used. In the paper a new algorithms for the water net failures localization using the water net hydraulic model, a SCADA system and the MLP (multilayer network with error back propagation) or Kohonen neuronal nets is described.

The waterworks enterprise regarding the water network management deals with the water distribution of appropriate quality and in quantity guaranteeing satisfaction of the recipient's needs, with correct exploitation of water-supply network assuring the proper pressure in receiving units, with the efficient removing of failures and with planning and executing the works connected with conservation, modernization and extension of the network [2]. One can say that there are generally 3 main tasks of water net management: water supply in desired amounts to the water net end users [6], production of water of desired quality [6, 14] and reduction of water net operational costs; in the latter case the reduction of water losses resulted through the water net failures is one of the most essential management problems [3, 4, 8, 13, 15]. The water leaks can cause the losses of water in pipelines coming sometimes even to 30% of the whole water production what influences negatively the financial results of waterworks enterprises. Therefore the fast location and elimination of hidden leaks of water from leaky pipelines brings the measurable economic advantages both for the supplier, that is the water-supply enterprise, and for the users of the water network.

2. Algorithms of failure location in water-supply networks

Different approaches and the computational algorithms to aid detection and location of water leaks in water networks have been already described by many authors. In each case the measurements of water flow and pressures in the water net and sometimes also the water network hydraulic model are the basis of investigation. An appropriate computer infrastructure installed and exploited in the waterworks is needed for practical realization of these algorithms. Different stages of the water net failures localization can be presented in the following way:

- failure detection – a failure state on a water net is determined through observation of a higher water reception, but its location is not known,
- failure location – failure state and its exact or approximate location are determined by means of some suitably worked algorithms, with the use of a monitoring system, hydraulic models of water network and potentially of neural networks,
- failure counteraction – prognoses of coming failures basing on historical data concerning the previous failure cases are calcu-

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl*** lated and using them the development of plans of water net revitalization is occurred.

On the first stage of investigation only appropriate densely monitoring and diagnostic systems (SCADA) installed on the water nets can be used whose tasks are to find out and to localize the arisen leaks. The diagnostic methods implemented in these systems exploit in their calculations the measurements of water flows in the water net pipes like pressure, velocity, flow rate and temperature [1, 3, 13] and the only disadvantage of them is the necessity of installation of many measurement devices on the pipelines. This induces high costs of the whole installation which mostly are not to cover by the waterworks. On the second stage beside the technical infrastructure as SCADA also several software applications are in use for failure location in the water networks what makes the problem more sophisticated. In a more simple version of investigation the additional items being the complement of the monitoring system are mathematical models of the water network and these models are mostly a water net hydraulic model to simulate the network and a parametrical model for modeling the hydraulic one [15, 16]; in the latter case often neuronal nets or fuzzy sets or time series models are used. By more complex versions of investigation integrated IT systems are used that consist not only of SCADA and water net mathematical models but also of a GIS system and of different algorithms of optimization. Such the technical and information infrastructure permits not only to detect and locate the water net failures but also to manage the network, executing such the tasks like the water net control, analysis of water quality, optimization and design of the network etc. [8, 11]. This marks that the high developed computer technologies can become in future an useful and indispensable tool for the water net operators and the waterworks decision makers helping the rational operation and exploitation of the network and the whole enterprise. So far such the complex and integrated IT systems because of their very high costs are under development mostly in academic units but not in use in Polish waterworks [10]. On the third stage of investigation the problem to be solved concerns not the finding out the water net failures that have been already occurred but it consists in recognition of the potential failure risk and in eliminating it by appropriate technical counteractions.

The analysis presented in the paper belongs to the second stage of investigation and it consists on detection and localization of water net failures by means of an IT system consisting of GIS, SCADA, a water net hydraulic model and of neuronal nets simulating the network by means of its hydraulic model. The goal of the investigation is to confirm the usefulness of neuronal nets by modeling the water networks and detecting their failures. A positive result will allow to include this modeling tool into the IT system developed as an integral system module. The exemplary calculations have been made with the real data coming from the communal waterworks in Rzeszow [5] and the neuronal nets applied were MLP and Kohonen ones [12]. The investigation has been made using the following algorithm:

1. Planning the monitoring system to be installed on the water net investigated. The system shall consist of specially selected measurement points which are most sensitive against the flow and pressure changes arisen in the water net.
2. Calibration of the water net hydraulic model by using the monitoring system planed.
3. Hydraulic calculations of the water networks by its standard load to determine the standard distributions of flows and pressures in the selected monitoring points.
4. Successive simulation of water leaks in all nodes of the water net by use of the hydraulic model to determine the distributions of flows and pressures in the monitoring points resulted from the failures simulated.
5. Creation of the neuronal classifier locating the failures in form of different type of neural nets and choice of the best classifier according to criterion of the largest sensibility.

2.1. Planning the monitoring system regarding the most sensitive water net points

While planning a monitoring system the number and location of the measurement points must be defined carefully. It means that regarding the high installation costs the number of points shall be minimized and their location shall be chosen in the way assuring the winning of possibly most information concerning the water flow changes in the water net. Such the sensitive points reacting on the flow changes not only in their closest neighborhood but also in farther surroundings are called characteristic points and their choice is not a trivial problem. Usually while planning monitoring systems for water nets the goal to maximize recorded information will be achieved by maximizing the number of monitoring points what raises the monitoring costs and discourages the decision makers to develop the sufficient densely systems. As a result the systems installed are not suited to calibrate the water net hydraulic models neither to find out the water leaks. To solve this problem properly an algorithm of multi-criterion optimization can be used with 2 criteria regarding the number of measuring points and the quantity of gaining information [8]. The minimized number of measuring points concerns the water net characteristic points and the choice of them can be performed for example by means of the algorithm proposed by Straubel and Holznagel in [7]. In our investigation the rang list of sensitive points of the water network in Rzeszow has been made using the algorithm of Straubel and Holznagel and for the farther calculations two sets of points were choosen for the planed monitoring system: one set with 10 most sensitive points and the second set with 20 measuring points.

2.2. Hydraulic calculation of the water network by use of the calibrated hydraulic model

After the monitoring system has been already planed the calibration of the water net hydraulic model can be automatically executed. To do this a multi-criterion optimization can be also used with two criteria regarding the differences between the measured and calculated values of water flows and pressures in the monitoring points [8]. With the hydraulic model calibrated the simulation runs for the water net with its standard load (normal state) and with the simulated water leaks in different net nodes (failure states) can be performed. The recorded values of flows and pressures in the monitoring points for normal and failure states of the water net can be used for the preparation of learning files for the neural networks that will serve in turn as models to detect and locate the failures in the water network. In our investigation for its simplification only the water flow values have been regarded and recorded.

The simulation of water leaks in the water net has been made as follows:

– the values of water flow in chosen network nodes have been enlarged for several times,
– each time the hydraulics of the water net has been calculated using the hydraulic model,
– the differences in flow values between the normal and failure states of the water net observed in the monitoring points have been recorded,
– the monitoring point with strongest reaction on the simulated failure has been registered.

2.3. Creation of the neuronal classifier locating the failures using the MLP networks

The models for failure detection and location are created by use of neural networks of MLP type [12]. These networks are currently most widespread and used in the practice. In a multi-layer network with error backpropagation (MLP) the selection of number of neurons in input layer is conditioned by the dimension of data vector x. The neural model consists of the sum of input signals $x_1, x_2, ..., x_N$ multiplied by weight coefficients $w_{i1}, w_{i2}, ..., w_{iN}$ and of an additional value w_{i0}. The output signal of the model marked u_i has got the form:

$$u_i = \sum w_{ij} x_j + w_{i0} \tag{1}$$

and it is subsequently given to a non-linear activation sigmoidal function $f(u_i)$:

$$f_u(u_i) = \frac{1}{1 + \exp(-\beta u_i)} \tag{2}$$

In the calculations performed the experiments with neuronal networks of different structure and with 1 hidden layer have been executed. The water net investigated consists of 390 nodes. On the first step of calculations 10 monitoring points have been considered and in 36 selected nodes the water leaks have been simulated. On the second step the number of monitoring points raised to 20 and the number of nodes with water leaks raised to 44. The neuronal classifier was created according to the methodology described in [4]. While calculating the MLP models 2 parameters were changed in the network structure: the number of neurons in the hidden layer that changed from 5 to 25 and the number of learning epochs that has taken the values 200, 500 and 1000. The inputs of the neural nets calculated are the flow values in the water net nodes with simulated leaks and the output of the neural nets shows the monitoring point with strongest reaction on the water leak (Fig. 1).

27	28	29	30	31	32	33	34	35	36	37
2740	2779	3028	6144	3587	3596	4138	4181	4250	4411	Monitoring point
-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	0
-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	4
-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	6
-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	6
-25,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	7
-5,04	-470,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	10
-5,04	-94,46	-10,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	4

Fig. 1. The structure of teaching set for MLP nets; columns 27 till 36 are the inputs and column 37 is the output

Table 1. The parameters of MLP nets for 10 monitoring points

No	Network name	Teaching quality	Testing quality	Validation quality
1	MLP 36-8-11	88,31776	95,55556	88,88889
2	MLP 36-15-11	97,66355	97,77778	95,55556
3	MLP 36-22-11	94,39252	97,77778	93,33333
4	MLP 36-19-11	97,66355	97,77778	95,55556
5	MLP 36-21-11	94,39252	97,77778	93,33333
6	**MLP 36-24-11**	**97,19626**	**97,77778**	**97,77778**
7	MLP 36-23-11	97,66355	97,77778	95,55556

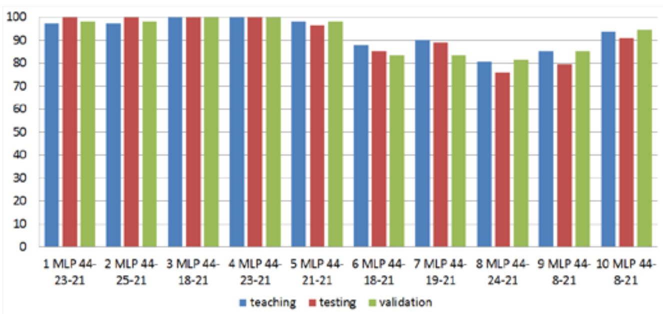

Fig. 2. Calculation results of the MLP nets obtained for 20 monitoring points [%]

Table 2. The parameters of MLP nets for 20 monitoring points; the qualities are given in %.

No	Network name	Teaching quality	Testing quality	Validation quality
1	MLP 44-23-21	97,2222	100,0000	98,1481
2	MLP 44-25-21	97,2222	100,0000	98,1481
3	**MLP 44-18-21**	**100,0000**	**100,0000**	**100,0000**
4	**MLP 44-23-21**	**100,0000**	**100,0000**	**100,0000**
5	MLP 44-21-21	98,0159	96,2963	98,1481
6	MLP 44-18-21	87,6984	85,1852	83,3333
7	MLP 44-19-21	90,0794	88,8889	83,3333
8	MLP 44-24-21	80,5556	75,9259	81,4815
9	MLP 44-8-21	85,3175	79,6296	85,1852
10	MLP 44-8-21	93,6508	90,7407	94,4444

Table 3. Calculation results of MLP nets for new data files (20 monitoring points)

Results of MLP net for new data on input											
No.	1 MLP 44-23-21	2 MLP 44-25-21	**3 MLP 44-18-21**	**4 MLP 44-23-21**	5 MLP 44-21-21	6 MLP 44-18-21	7 MLP 44-19-21	8 MLP 44-24-21	9 MLP 44-8-21	10 MLP 44-8-21	**Pattern**
1	4	4	**0**	**0**	0	0	11	0	0	0	**0**
2	3	3	**3**	**3**	3	3	3	3	3	3	**3**
3	8	8	**8**	**8**	8	8	8	8	8	8	**8**
4	15	15	**15**	**15**	15	19	15	15	15	15	**15**
5	11	11	**11**	**11**	11	11	11	11	11	11	**11**
6	13	13	**13**	**13**	13	13	13	13	13	20	**13**
7	4	4	**4**	**4**	4	4	4	4	4	20	**4**
8	16	16	**16**	**16**	16	16	16	16	16	16	**16**
9	12	12	**12**	**12**	12	2	12	12	12	12	**12**
10	7	7	**7**	**7**	7	15	7	13	1	7	**7**
11	9	9	**9**	**9**	9	9	7	13	6	9	**9**
12	20	20	**20**	**20**	20	20	20	0	20	20	**20**
13	1	1	**1**	**1**	1	2	1	13	1	13	**1**
14	2	2	**2**	**2**	0	2	2	15	0	2	**2**
15	17	17	**17**	**17**	17	15	5	13	17	17	**17**
16	5	5	**5**	**5**	5	10	5	15	16	5	**5**
17	6	6	**6**	**6**	6	19	6	13	6	14	**6**
18	14	14	**14**	**14**	14	2	10	13	6	14	**14**
19	18	18	**18**	**18**	18	2	19	15	18	14	**18**
20	19	19	**19**	**19**	19	19	19	13	7	19	**19**
21	10	10	**10**	**10**	0	10	10	13	0	10	**10**
22	13	13	**13**	**13**	13	13	13	13	0	1	**13**
Number of correct classifications	21	21	**22**	**22**	20	13	17	10	14	16	
Number of incorrect classifications	1	1	**0**	**0**	2	9	5	12	8	6	
Number of correct classifications in %	98,46	98,46	**100,00**	**100,00**	97,49	85,41	87,43	79,32	83,38	92,95	

The number of examples for determining the neural nets is 304 for the first step of calculation with 10 monitoring points and 360 for the second step with 20 monitoring points. The teaching, testing and validation files contained every time 70%, 15% and 15% of examples.

In Tables 1 and 2 and in Fig. 2 one can see the results of calculation got for the cases with 10 and 20 monitoring points. Model MLP 36-24-11 with 24 neurons on the hidden layer is best for 10 monitoring points (medium quality equals to 97,58%) and models MLP 44-18-21 and MLP 44-23-21 are equally best for 20 monitoring points (with medium quality of 100%).

Table 3 shows the results of calculation with the MLP models determined for 20 monitoring points and with new data files prepared for checking the models correctness under new conditions of computation. One can see that the best models MLP 44-18-21 and MLP 44-23-21 that have been received with the old data confirm also their efficiency by means of these checking runs.

2.4. Creation of the neuronal classifier locating the failures using the Kohonen networks

The models for failure location in the water net are presently created by use of the neural networks of Kohonen type. Kohonen nets are one of the basic types of self-organizing nets. Just thanks to ability of self-organization they open completely new possibilities and one of them is the adaptation to the input data which were previously not known [12]. Kohonen nets are usually one-way nets in which each neuron is connected with all components of N-dimensional input vector x. The weight coefficients of neurons connections create the vector $w_i=[w_{i1}, w_{i2}, \ldots, w_{iN}]^T$. The input signals are on the begin of computation normalized, i.e. $||x||=1$, what could be written down as follows:

$$x_i = \frac{x_i}{\sqrt{\sum_{v-1}^{N} (x_v)^2}} \tag{3}$$

After stimulating the network by the input vector x a kind of competition occurs between the neurons and the winner w_w fulfills the relation:

$$d(x, w_w) = \min_{l \le i \le n} d(x, w_i) \tag{4}$$

where $d(x, w_i)$ means the distance between vector x and vector w in Euclidean space. Each neuron is enclosed with a topological neighborhood $G(i,x)$ and in the classic Kohonen algorithm function $G(i,x)$ is defined as follows:

$$G(i,x) = \begin{cases} 1 & \text{dla } d(i,w) \le R \\ 0 & \text{dla } d(i,w) > R \end{cases} \tag{5}$$

where R means the neighborhood radius. While calculating a Kohonen net the radius R shall diminish to 0.

By the calculation of Kohonen models the nets were parameterized by two parameters: the number of neurons in the so called topological layer and the number of teaching epochs. The first parameter has taken the values 2x8, 5x5, 10x10 and the second parameter has taken the values from 1000 to 20000. Similarly to the previous investigation the network inputs are the flow values for normal and failure states of the water net in the nodes selected for the water leaks simulation and additionally the number of the most sensitive monitoring point is also considered as the input signal. In a Kohonen network does not exist an output. Two investigation steps have been performed regarding 10 and 20 monitoring points and 36 and 44 water net nodes have been selected for the water leak simulations in respective steps.

In Fig. 3 the structure of the teaching file for the first step of investigation is shown in which all columns mean the input data for the neural nets calculated. In the calculations 304 examples were used for the investigation step with 10 monitoring points and 360 examples were used for the second step. The teaching, testing and validation files contain in the following 70%, 15% and 15% examples. In Tables 4 and 5 and in Fig. 4 the calculation results obtaining for the Kohonen nets while performing the first and second steps of investigation are shown. In the first case the model SOFM 37-100/100 and in the second case the model SOFM 45-225/1000 are the best.

24	25	26	27	28	29	30	31	32	33	34	35	36	37
2158	2186	2447	2740	2779	3028	6144	3587	3596	4138	4181	4250	4411	Monitoring point
-25,7	-4,2	-4,83	-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	4
-5,74	-20,2	-4,83	-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	6
-5,74	-4,2	-20,8	-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	6
-5,74	-4,2	-4,83	-25	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	7
-5,74	-4,2	-4,83	-5,04	-470,5	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	10
-5,74	-4,2	-4,83	-5,04	-94,46	-10,7	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	4
-5,74	-4,2	-4,83	-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-20,8	2
-5,74	-4,2	-4,83	-5,04	-94,46	-2,71	-2,79	-3,1	-8,43	-6,31	-2,2	-1,69	-4,76	0

Fig. 3. The structure of teaching set for Kohonen nets

Table 4. The parameters of Kohonen nets for 10 monitoring points

No	Network name	Teaching quality	Testing quality	Validation quality
1	SOFT 37-16/1000	81,9384	14,3036	7,4902
2	SOFT 37-16/20000	20,0225	20,9363	11,9975
3	SOFT 37-25/1000	20,3248	17,1003	12,9749
4	**SOFT 37-100/1000**	**80,8903**	**79,7651**	**83,4712**
5	SOFT 37-100/10000	82,7746	76,2847	78,0958
6	SOFT 37-100/20000	83,1150	73,5965	79,7852

Table 5. The parameters of Kohonen nets for 20 monitoring points

No	Network name	Teaching quality	Testing quality	Validation quality
1	SOFT 45-25/15000	9,7870	4,7473	4,7570
2	SOFT 45-100/1000	71,1903	66,3754	70,7134
3	SOFT 45-100/10000	61,7010	61,5446	59,4152
4	SOFT 45-100/15000	69,1089	68,1126	62,5354
5	SOFT 45-100/20000	69,4488	67,6256	61,6244
6	**SOFT 45-225/1000**	**97,3839**	**99,1899**	**97,9011**

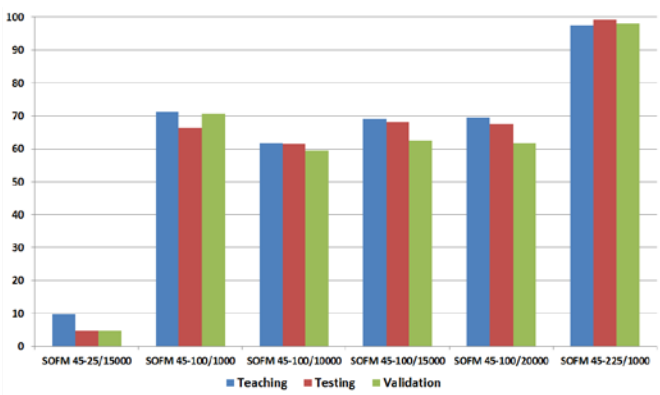

Fig. 4. Calculation results of the Kohonen nets obtained for 20 measurement points [%]

Table 6. Calculation results of Kohonen net for new data files (20 measurement points)

Results of Kohonen net for new data on input							
No.	1 SOFT 45-25/15000	2 SOFT 45-100/1000	3 SOFT 45-100/10000	4 SOFT 45-100/15000	5 SOFT 45-100/20000	**6SOFT 45-225/1000**	**Pattern**
1	15	0	0	0	0	**0**	**0**
2	3	3	3	3	3	**3**	**3**
3	8	8	8	8	8	**8**	**8**
4	0	15	7	15	9	**7**	**15**
5	11	11	11	11	11	**11**	**11**
6	16	13	13	13	13	**13**	**13**
7	4	4	4	4	4	**4**	**4**
8	13	16	16	16	16	**16**	**16**
9	7	12	12	12	12	**12**	**12**
10	12	7	15	7	7	**15**	**7**
11	1	9	20	9	15	**9**	**9**
12	20	20	9	20	20	**20**	**20**
13	9	2	1	1	1	**1**	**1**
14	17	1	2	2	2	**2**	**2**
15	2	17	5	17	5	**17**	**17**
16	6	6	17	6	17	**5**	**5**
17	5	5	14	5	18	**6**	**6**
18	18	14	6	19	14	**14**	**14**
19	14	19	19	18	6	**18**	**18**
20	10	18	18	14	10	**19**	**19**
21	19	9	8	9	19	**10**	**10**
22	11	13	13	13	13	**13**	**13**
Number of correct classifications	5	15	11	17	14	**21**	
Number of incorrect classifications	17	7	11	5	8	1	
Number of correct classifications in %	22,73	68,18	50,00	77,27	63,64	**98,16**	

Table 6 shows the results of calculation with the Kohonen models received for 20 monitoring points and with the new data files prepared for checking the models correctness under new conditions of computation. The results confirm once again that model SOFM 45-225/1000 is the best and its quality equal to 98,16% is similar to this one from earlier calculations.

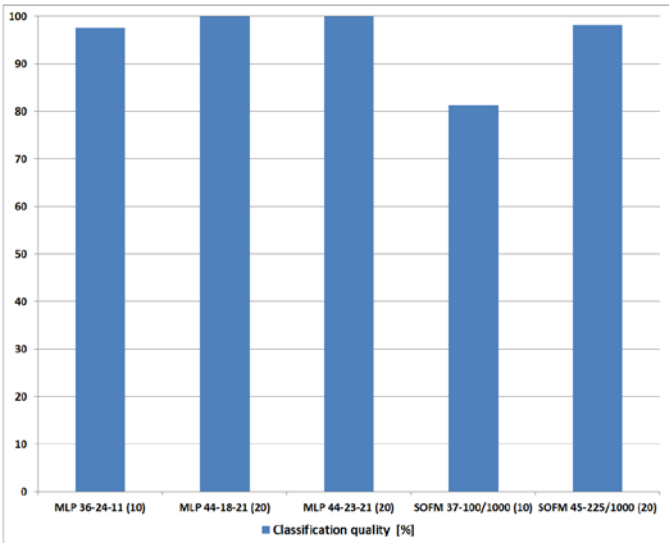

Fig. 5. Comparison of MLP and Kohonen nets.

Table 7. Comparison of MLP and Kohonen nets

No	Net name	Number of measurement points	Classification quality [%]
1	MLP 36-24-11	10	97,58
2	MLP 44-18-21	20	100,00
3	MLP 44-23-21	20	100,00
4	SOFM 37-100/1000	10	81,38
5	SOFM 45-225/1000	20	98,16

2.5. Comparison of MLP and Kohonen nets and choice of the best classifier

In Table 7 and in Fig. 5 the results of comparison between MLP and Kohonen nets is presented. The results show a supriority of MLP models in relation to the Kohonen ones while detecting and locating the water network failures. MLP nets have got in general shorter times of teaching and they give the better classification nof the water leaks.

3. Conclusions

The received results of computation show the usefulness of neural networks by the solution of such complicated problems as detection of water net failures and their localization. This means that the neuronal models can be used as efficient tools included as integral elements into computer aided IT systems applied for management of waterworks.

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