ПРЕДИКЦИЈА ПОТРОШЊЕ ЕЛЕКТРИЧНЕ ЕНЕРГИЈЕ ПРИМЕНОМ ВЕШТАЧКИХ НЕУРОНСКИХ МРЕЖА

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Резиме: У овом раду биће приказано како се коришћењем вештачких неуронских мрежа може извршити предикција потрошње електричне енергије код малих потрошача сврстаних у две категорије према врсти бројила које поседују. Потрошачи који се посматрају налазе се на територији града Ужица у периоду од четири године и осам месеци и обележени су као домаћинства која поседују једнотарифно или двотарифно бројило. Сет података обухвата преко милион инстанци (различитих мерења) за 21.643 потрошача. Део података, тачније 70% од читавог сета података, најпре је искоришћено за тренирање мреже чији је учинак након тога проверен над преосталих 30% података који припадају тестсету а који су моделу до процеса тестирања били непознати. Резултати ће показати да можемо обучити модел да на овај начин даје тачне резултате са задовољавајућом прецизношћуод 91%.

Кључнеречи: вештачке неуронске мреже, предвиђање потрошње електричне енергије, једнотарифна бројила, двотарифна бројила

PREDICTION OF ELECTRICITY CONSUMPTION USING ARTIFICIAL NEURAL NETWORKS

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Abstract: The research shows how the artificial neural networks can be used in order to predict the consumption of electricity by small consumers classified into two categories according to the type of electric meters they have. Observed consumers are located in the territory of the town of Uzice for a period of four years and eight months and they are marked as households that have a single or two-tariff electric meter. The data set covers over one million instances (various measurements) for 21,643 consumers. Part of the data, namely 70% of the entire data set, was used to train the network whose performance was then checked against the remaining 30% of the data belonging to the test set, which were unknown to the model until the testing process. The results will show that the model can be trained to produce accurate results with satisfy accuracy of 91%.

Key words: artificial neural networks, power consumption prediction, single-rate electric meters, two-rate electric meters

1. INTRODUCTION

The consumption of electricity is always actual and hot topic in the domain is possibility of prediction. Life in these days cannot even be imagined without electricity. Most of human daily activities are related to electricity. The prediction of electricity' consumption could be valuable for many interesting groups: users, EPS, different agencies which provide services close related to knowledge about electricity' consumption.

The main goal of research is related to determination of possibility of using artificial neural networks in predicting electricity' consumption. The research tasks include well known data minign steps with the main one: artificial neural network model creation.

According to specific need of reserach authors defined input and output parameters and methodology for achieving satisfyed accuracy.

There are many related research in the field. Wei *et al.* (2019) established prediction model using feed forward neural network and extreme learning. The model predicts electricity

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consumption by an air-conditioning system. Zheng, Chen and Luo (2019) use prediction of electricity consumption in order to support decision making process in home energy management system. Chang, Zhang, Chen (2019) founded that electricity price prediction depends on many factors and they propose hybrid model for prediction based on wavelet transform and optimized LTSM neural network. Kim *et al.* (2019) predict electrical energy consumption because of growing trends caused by rapid urbanization in China. For verification of used neural network model Kim et al. (2019) used data of a shopping mall as a case study. Zagrebina, Mokhov and Tsimbol (2019) used recurrent neural network in order to predict electrical energy consumption. The authors used some additional input parameters comparing to proposed research (meteorological factors and specificity of the industry in the district under consideration). Rahman, Srikumar and Smith (2018) used recurrent neural network model to make predictions of electricity consumptions. The applied model in commercial and residential buildings. Some authors used time series prediction in order to get satisfy accuracy of model. Kaur and Ahuja (2017) used ARIMA model to predict the electricity consumption in a health care institution and to find the most suitable forecasting period in terms of monthly, bimonthly, or quarterly time series. Knezevic and Blagojevic (2019) used the data for same city but for other purpose of prediction: classification of electricity consumers based on two different criteria: the type of the electric meter they possess and the zone they live in.Rankovic et al. (2015) used Feed Forward Artificial Neural Networks (FF ANNs) with backpropagation for approximating the output active power of unmonitored elements.

Paper is organized as follows: after introduction section a brief methodology is presented. Results and discussion give the neural network model and results of model testing. Then, conclusion section is presented.

2. METHODOLOGY

In the research was used well known methodology which is related to data mining process. This methodologyincludes following steps:

1. Collecting data: the first step in the process which is done in collaboration with EPS Užice. The authors collected data for the town of Užice and the data set consist over one million instances (various measurements) for 21,643 consumers.The target dataset included the information about electricity consumers on the territory of the City of Užicefor a period of four years and eight months.
2. Data pre-processing: after selecting all collected data the next step is pre-processing row data for further processing. In the research data set does not include incomplete or inconsistent data.
3. Data transformation: the “transformation” step includesadjustmentof data set to specific need according to desired format and data view.
4. Model creation: the step proposes artificial neural network model. In modelling of artificial neural network, the input parameters were defined, number of hidden layers and also output parameter.
5. Training and testing model: the model is trained with 70% of data and then is tested with 30%.
6. Model interpretation: for interpreting the model the knowledge in the specific field is required. In the research it is related to electricity consumption.

3. RESULTS AND DISCUSSION

3.1. Neural network model

In order to successfully predict electricity consumption, the input parameters are defined as following: zone consumers live in, type of the electric meter, period from-to, consumer, lower tariff, higher tariff. The output parameter is consumption of electricity. The model is presented in Figure 1.

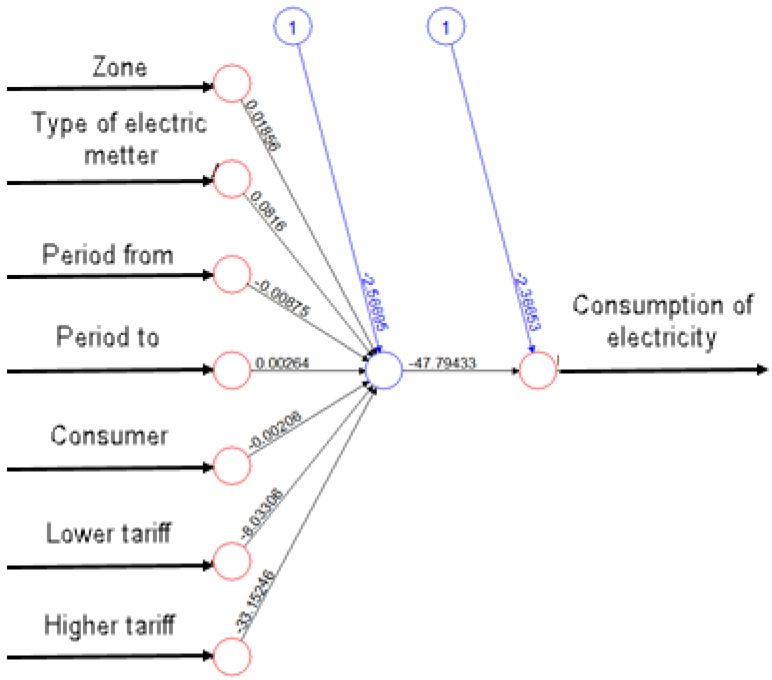

Figure 1. Neural network model

3.2. Neural network evaluation

First given data shows us results of testing the network on instances which isn't used in training process. The training process needed 10290 steps to all parameter in error function were smaller than the threshold value, in this case 0.01.The estimated weights range from -47.8 to 0.08 (Figure 2).

error	0.897600350407
reached.threshold	0.009984981396
steps	10290.000000000000
Intercept.to.1layhid1	-2.566953766423
ZONA.to.1layhid1	0.018563430742
VRSTA_BROJILA.to.1layhid1	0.081604014353
PERIOD_OD.to.1layhid1	-0.008748489796
PERIOD_DO.to.1layhid1	0.002639786062
POTROSAC.to.1layhid1	-0.002059354208
NIZA_TARIFA.to.1layhid1	-8.033060176492
VISA_TARIFA.to.1layhid1	-33.152456132027
Intercept.to.UKUPNA_POTROSNJA	-2.366532398198
1layhid.1.to.UKUPNA_POTROSNJA	-47.794330236014

Figure 2. Results of neural network model

After creating the networkconfusion matrix was created. Because of big number of instances, it is very complex, and shows all instances according to a classes created by model (Figure 3). In big number of classes no instance is provided.

	0.01	0	0.02	0.03	0.04	0.05	0.06	0.07	0.1	0.09	0.08	0.11	0.2	0.17	0.15
0.01	121741	4139	39	0	0	0	0	0	0	0	0	0	0	0	0
0	7201	114803	0	0	0	0	0	0	0	0	0	0	0	0	0
0.02	9371	0	34236	872	0	0	0	0	0	0	0	0	0	0	0
0.03	0	0	636	10424	1539	0	0	0	0	0	0	0	0	0	0
0.04	0	0	0	26	3778	1298	0	0	0	0	0	0	0	0	0
0.05	0	0	0	0	0	1740	668	0	0	0	0	0	0	0	0
0.06	0	0	0	0	0	0	961	155	0	0	0	0	0	0	0
0.07	0	0	0	0	0	0	10	452	0	0	0	0	0	0	0
0.1	0	0	0	0	0	0	0	0	0	0	51	0	0	0	0
0.09	0	0	0	0	0	0	0	0	0	0	86	0	0	0	0
0.08	0	0	0	0	0	0	0	164	0	0	63	0	0	0	0
0.11	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0
0.2	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
0.17	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0
0.15	0	0	0	0	0	0	0	0	0	1	4	0	0	0	0
0.12	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0
0.14	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0
0.18	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0
0.79	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0.13	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0
0.19	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
0.24	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
0.28	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0.16	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0
0.23	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0

	0.12	0.14	0.18	0.79	0.13	0.19	0.24	0.28	0.16	0.23
0.01	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0.02	0	0	0	0	0	0	0	0	0	0
0.03	0	0	0	0	0	0	0	0	0	0
0.04	0	0	0	0	0	0	0	0	0	0
0.05	0	0	0	0	0	0	0	0	0	0
0.06	0	0	0	0	0	0	0	0	0	0
0.07	0	0	0	0	0	0	0	0	0	0
0.1	0	0	0	0	0	0	0	0	0	0
0.09	0	0	0	0	0	0	0	0	0	0
0.08	0	0	0	0	0	0	0	0	0	0
0.11	0	0	0	0	0	0	0	0	0	0
0.2	0	0	0	0	0	0	0	0	0	0
0.17	0	0	0	0	0	0	0	0	0	0
0.15	0	0	0	0	0	0	0	0	0	0
0.12	0	0	0	0	0	0	0	0	0	0
0.14	0	0	0	0	0	0	0	0	0	0
0.18	0	0	0	0	0	0	0	0	0	0
0.79	0	0	0	0	0	0	0	0	0	0
0.13	0	0	0	0	0	0	0	0	0	0
0.19	0	0	0	0	0	0	0	0	0	0
0.24	0	0	0	0	0	0	0	0	0	0
0.28	0	0	0	0	0	0	0	0	0	0
0.16	0	0	0	0	0	0	0	0	0	0
0.23	0	0	0	0	0	0	0	0	0	0

Figure 3. Confusion matrix

Based on these data, the accuracy of this specific model was calculated and results are given in *Overall statistics*(Figure 4). It shows very high accuracy 91% (Figure 3). The very high accuracy tell usthat the classifier correctly predicted 91% consumption of electricity, but more important is that the measure „No information rate" are lower than accuracy.Very high kappa value (87%) and very low value of P-value confirms us theat reliable results.

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Overall Statistics

               Accuracy : 0.9166807
                 95% CI : (0.9157095, 0.9176442)
    No Information Rate : 0.4386994
    P-Value [Acc > NIR] : < 0.00000000000000022204

                  Kappa : 0.8737474
 Mcnemar's Test P-Value : NA
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Figure 4. Neural network result

Statistics by each class are also given in log file. Statistics by class shows all the classes with sensitivity, specificity, positive and negative predicted value for each class (Figure 5). The classes marked "NA" are those in which the model did not predict any instance so statistic value couldn't be calculated.

Statistics by Class:

	Class: 0.01	Class: 0	Class: 0.02	Class: 0.03	Class: 0.04	Class: 0.05	Class: 0.06	Class: 0.07
Sensitivity	0.8801848	0.9652015	0.9806651	0.92068539	0.71055106	0.572745227	0.586333130	0.586251621
Specificity	0.9762964	0.9631909	0.9633736	0.99282772	0.99571876	0.997855779	0.999504688	0.999968133
Pos Pred Value	0.9668199	0.9409773	0.7697115	0.82736725	0.74049392	0.722591362	0.861111111	0.978354978
Neg Pred Value	0.9121566	0.9785064	0.9975009	0.99702623	0.99502700	0.995841943	0.997837024	0.998984435
Prevalence	0.4396849	0.3781062	0.1109790	0.03599165	0.01690228	0.009657536	0.005210237	0.002450941
Detection Rate	0.3870040	0.3649487	0.1088332	0.03313698	0.01200993	0.005531308	0.003054935	0.001436868
Detection Prevalence	0.4002855	0.3878400	0.1413948	0.04005112	0.01621881	0.007654821	0.003547666	0.001468658
Balanced Accuracy	0.9282406	0.9641962	0.9720194	0.95675656	0.85313491	0.785300503	0.792918909	0.793109877

	Class: 0.1	Class: 0.09	Class: 0.08	Class: 0.11	Class: 0.2	Class: 0.17
Sensitivity	NA	0.00000000000	0.2100000000	NA	NA	NA
Specificity	0.9998378755	0.99972659615	0.9994781607	0.9998601279	0.999993642175	0.999990463263
Pos Pred Value	NA	0.00000000000	0.2775330396	NA	NA	NA
Neg Pred Value	NA	0.99993640437	0.9992460537	NA	NA	NA
Prevalence	0.0000000000	0.00006357825	0.0009536737	0.0000000000	0.000000000000	0.000000000000
Detection Rate	0.0000000000	0.00000000000	0.0002002715	0.0000000000	0.000000000000	0.000000000000
Detection Prevalence	0.0001621245	0.00027338646	0.0007216131	0.0001398721	0.000006357825	0.000009536737
Balanced Accuracy	NA	0.49986329808	0.6047390804	NA	NA	NA

	Class: 0.15	Class: 0.12	Class: 0.14	Class: 0.18	Class: 0.79	Class: 0.13
Sensitivity	NA	NA	NA	NA	NA	NA
Specificity	0.99998410544	0.99992052719	0.99996821088	0.999990463263	0.999996821088	0.99994595849
Pos Pred Value	NA	NA	NA	NA	NA	NA
Neg Pred Value	NA	NA	NA	NA	NA	NA
Prevalence	0.00000000000	0.00000000000	0.00000000000	0.000000000000	0.000000000000	0.00000000000
Detection Rate	0.00000000000	0.00000000000	0.00000000000	0.000000000000	0.000000000000	0.00000000000
Detection Prevalence	0.00001589456	0.00007947281	0.00003178912	0.000009536737	0.000003178912	0.00005404151
Balanced Accuracy	NA	NA	NA	NA	NA	NA

	Class: 0.19	Class: 0.24	Class: 0.28	Class: 0.16	Class: 0.23
Sensitivity	NA	NA	NA	NA	NA
Specificity	0.999993642175	0.999993642175	0.999996821088	0.99998728435	0.999996821088
Pos Pred Value	NA	NA	NA	NA	NA
Neg Pred Value	NA	NA	NA	NA	NA
Prevalence	0.000000000000	0.000000000000	0.000000000000	0.00000000000	0.000000000000
Detection Rate	0.000000000000	0.000000000000	0.000000000000	0.00000000000	0.000000000000
Detection Prevalence	0.000006357825	0.000006357825	0.000003178912	0.00001271565	0.000003178912
Balanced Accuracy	NA	NA	NA	NA	NA

Figure 5. Statistics by class

4. CONCLUSION

According topresented results in can be conclude in the following ways:

- Artificial neural networks could be successfully applied in electricity consumption. The error is relatively small so the results could be discussed as reliable;
- The insight in future results could effect on all target groups: EPS, consumers and consumers in order to adjust the behaviour according to results.

Future work is related to applying cluster technique along with artificial neural network.

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