Multi-Layer Perceptron Regressor for Ranking Prediction in Information Systems for Sustainability Assessment

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Abstract

Machine learning models are powerful and valuable tools for predicting results for any problems represented by multiple variables based on information contained in historical data. Predictive models have significant development potential in autonomous decision support systems based on collected and processed data and expert knowledge to effectively support decision-makers. This paper presents the application of an artificial neural network model called Multi-layer Perceptron (MLP) regressor to predict rankings based on MCDA evaluations performed earlier with expert participation. The results predicted by the model trained on training data demonstrate high consistency with the real ranking, confirming the high potential of this model in building autonomous decision support systems. The proposed approach was applied to predict European countries' ranking regarding environmentally friendly, efficient, and affordable energy.

Keywords: Multi-Layer Perceptron Regressor, Autonomous Decision Support Systems, Ranking Prediction, Multi-criteria Sustainability Assessment, SDG 7

1. Introduction

SDG 7 (Sustainable Development Goal 7) is one of seventeen Sustainable Development Goals proposed by the United Nations (UN) in the 2030 Agenda for Sustainable Development. SDG 7 aims to ensure access to modern energy services, improve energy efficiency, and increase the share of renewable energy. Thus, assessing countries concerning indicators of the SDG 7 frame is essential [1]. Evaluating countries based on SDG 7 frame requires consideration of 11 criteria. Thus, multi-criteria decision analysis methods (MCDA) are suitable for this purpose. Evaluation using MCDA methods requires the participation of domain experts (experienced decision-makers) in determining criteria weight values [6]. Then, alternatives are ranked according to MCDA utility function values. The problem occurs when there is no opportunity to get expert knowledge to obtain weights. In such a scenario, the solution may incorporate objective weighting techniques [13]. However, decision-makers may prefer to use criteria weights determined by experienced domain experts in the past. Therefore, this paper proposes a Multi-layer Perceptron for the regression problem involving the prediction task of utility function values for evaluated alternatives.

Evaluating a multi-criteria problem using MCDA methods involving experts requires criteria weight values. Experts can provide subjective weight values or choose an objective weighting method to calculate them. In this research, the authors of the paper played the role of experts, and criteria weights were determined using an objective weighting method called the Statistical Variance (SV). Then, utility function values were calculated for annual datasets using the MCDA method called the Simple Additive Weighting method (SAW). SAW is most commonly used for benchmarking purposes to evaluate the performance of other MCDA domain methods [12]. In practical terms, the proposed methodological approach can provide a "methodological engine" for autonomous recommender systems and decision support systems. An important advantage of the solution is automatizing the decision support process, particularly the construction of final rankings considering the experts' preferences [8].

The rest of the paper is organized as follows. Section 2 provides theoretical background of methods applied in this research. Next, in section 3 research methodology is presented. Then, in section 4 results are presented and discussed. Finally, in section 5 conclusions and directions for further work are drawn.

2. Theoretical Background

Developing and implementing efficient renewable energy resources and environmentally friendly energy technologies that promote clean energy requires the information systems necessary to support UN energy goals. The purpose of SDG 7 is focused on ensuring access to and use of sustainable, modern energy harvesting technologies [1]. Systems that support sustainability assessment of clean and affordable energy development can be powered by technologies such as MCDA [13], knowledge-based systems [11], data mining, and machine learning models [2].

MLP regressor is a machine learning model that uses a supervised learning algorithm based on a nonlinear function and maps input data to output data in a training procedure on a data set [9]. The detailed description of this model is given in [7]. The MLP model is constructed with three or more layers. Each node in one layer is connected by weight to each node in the next layer. The input layer contains neurons representing inputs. The output layer receives information from the last hidden layer and converts it into output values. Then, each neuron in the hidden layer gathers the values from the previous layer as a weighted linear sum, followed by a nonlinear activation function.

MCDA methods are the foundation for assessing several problems based on sustainability [16]. For reliable assessment of sustainability in various domains, many measures, indicators, and indexes [3] were constructed using MCDA methods. The high potential of MCDA methods in sustainability assessment arises from the ability to incorporate multidimensional models [13]. In addition, the evaluation using MCDA methods enables the involvement of different interest groups in the process and consideration of multiple criteria, including conflicting ones, which often need to be considered in sustainability assessment [3]. The SAW method involves the calculation of the total score by multiplying a normalized matrix by weights assigned to criteria [17]. The SV weighting method calculates criteria weights based on the statistical variance of data on performance included in the decision matrix. This technique is presented in [15] in detail with mathematical formulas.

3. Methodology

This paper aims to demonstrate the applicability of the MLP regressor model in predicting rankings of European countries displayed in Table 3 in terms of the SDG 7 framework. Criteria with maximizing goal are: C_1 - Primary energy consumption in Tonnes of oil equivalent (TOE) per capita, C_2 - Final energy consumption in TOE per capita, C_3 - Final energy consumption in households in Kilogram of oil equivalent (KGOE) per capita, C_4 - Energy productivity in Euro per KGOE, C_5 - Share of RES in gross final energy consumption in general in %, C_6 - Share of RES in gross final energy consumption in transport in %, C_7 - Share of RES in gross final energy consumption in electricity in %, C_8 - Share of RES in gross final energy consumption in heating and cooling in %. Criteria with minimizing goal involve: C_9 - Energy import dependency regarding all types of energy products in %, C_{10} - Population unable to keep home adequately warm in %, C_{11} - Greenhouse gas emissions intensity of energy consumption measured by Index, 2000=100.

Figure 1 demonstrates the framework for rankings prediction based on the MLP regressor model trained on the training dataset evaluated earlier using chosen MCDA method with criteria weights provided by experts or determined using the selected weighting method.

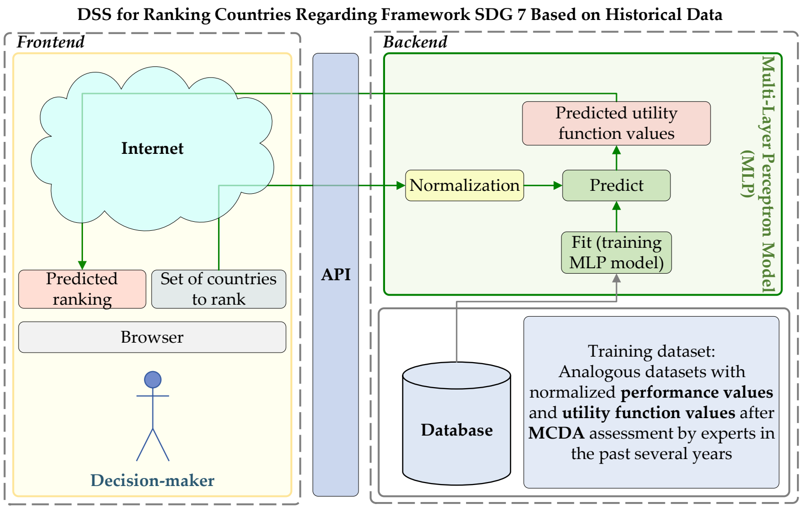

Fig. 1. Framework for rankings prediction based on MLP regressor and training dataset.

Performance values of evaluated countries were collected from the Eurostat website for 2010-2020 (accessed on 10 April 2022). Detailed data sources of evaluation criteria included in SDG 7 and datasets are provided in the GitHub repository `https://github.com/energyinpython/ISD-2022-MLP`. Performance values concerning 11 criteria playing the role of training features were used as input data. The role of the target variable is played by utility function values obtained from the MCDA assessment. The target variable values representing the decision-makers' evaluations were generated using SAW for each year from 2010 to 2020. The authors set the training dataset size with the intent that the test dataset was approximately 20% of the whole dataset size, according to basic rules of machine learning procedures, especially MLP model [10]. The dataset was split into training and test datasets randomly. The model named MLP regressor from Python scikit-learn library was applied for this research.

Then, hyperparameters for the MLP Regressor model are selected. Hyperparameters were optimized using k-fold cross-validation and grid search implemented by the GridSearchCV function in the scikit-learn Python library [4, 14]. Grid search enables the creation of combinations of hyper-parameters values for each explored hyper-parameter. L2 penalty parameter regularization was used to avoid overfitting [7]. The final stage includes training the MLP regressor model on the training dataset and predicting target variable values for the test dataset. Based on predicted target values, rankings were compared with the real ranking using the Spearman correlation coefficient to evaluate the model's effectiveness.

4. Results

This section presents and discusses results obtained by the MLP regressor model for the problem of countries' ranking prediction from historical data. Table 1 provides a summary of hyperparameters selection conducted. Then a score of the model was evaluated using a 5-fold cross-validation procedure. The cross-validation results in a metric called coefficient of determination which is regression score function R^2 are {0.9794, 0.9979, 0.9944, 0.9969, 0.9949} for each fold. It implies that the model gives predictions convergent to real values. To confirm the reliability of the MLP Regressor model results, a comparative analysis with the Ordinary Least Squares (OLS) regression benchmark model [5] was conducted.

Table 1. MLP regressor model parameters optimized and applied in this research.

Parameters	Values tested in GridSearchCV	Optimized value
Solver	'lbfgs', 'sgd', 'adam'	'lbfgs'
Hidden layer sizes	(100), (200), (500)	(500)
Learning rate	constant', 'adaptive'	'adaptive'
Activation function	'logistic', 'tanh', 'relu'	'tanh'
Alpha	0.001, 0.0001, 0.00001	0.0001
Maximum iterations number	200, 500, 1000	1000

Figure 2 compares utility function values predicted by MLP and OLS models. It can be noted that values predicted by compared models are convergent.

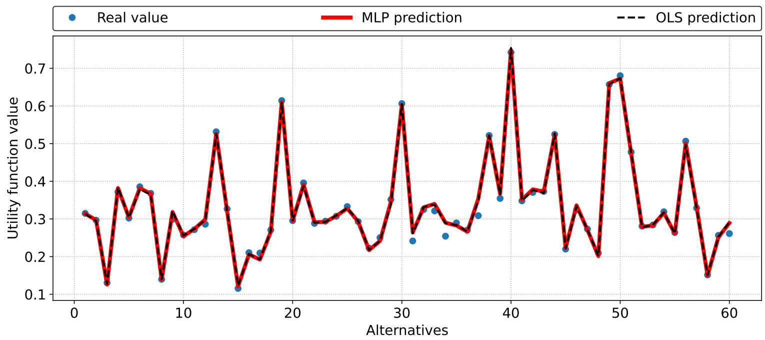

Fig. 2. Comparison of utility function values predicted by MLP and OLS models.

Then, the investigation was conducted for a test dataset containing annual performance data for 30 countries collected for 2020. In this examination, rankings determined based on predicted utility function values were compared. Table 2 includes regression score function values achieved by MLP and OLS models for prediction for a test dataset containing 60 randomly selected samples from a dataset with 300 samples.

Table 2. Scores achieved by MLP and OLS models for different test datasets.

Test set, model	Spearman	R^2	Test set, model	Spearman	R^2
60 samples, MLP	0.9999997	0.9908720	30 samples, MLP	0.9999995	0.9966128
60 samples, OLS	0.9999998	0.9933660	30 samples, OLS	0.9999994	0.9960011

Values of the regression score function for both models are high, close to 1, and comparable. Table 3 compares real rankings with rankings determined based on utility function values predicted by MLP and OLS models. Correlations between them are displayed in Table 4. Both models demonstrated high and comparable accuracy in predicting utility function values. MLP and OLS models successfully identified the top-three countries, including the Nordic countries: Iceland, Norway, and Sweden. Both models identified Iceland (A_{14}) as the ranking leader, which is also the best-scored country in real rank. Norway (A_{22}) took second place and Sweden (A_{29}) third place. The ranking prediction of the MLP model for 18 countries is identical. Differences occurring for 12 countries do not exceed two ranks. The results prove that the MLP regressor model is suitable for predicting rankings based on MCDA utility values for previous years.

Table 3. Comparison of real ranking and rankings predicted by MLP and OLS models for 2020.

A_i	Country	Real	MLP	OLS	A_i	Country	Real	MLP	OLS
A_1	Austria	6	6	6	A_{16}	Italy	19	19	19
A_2	Belgium	18	20	20	A_{17}	Latvia	8	8	8
A_3	Bulgaria	30	30	30	A_{18}	Lithuania	28	28	28
A_4	Croatia	11	11	11	A_{19}	Luxembourg	10	9	10
A_5	Cyprus	29	29	29	A_{20}	Malta	27	27	27
A_6	Czechia	13	15	16	A_{21}	Netherlands	20	18	18
A_7	Denmark	5	4	5	A_{22}	Norway	2	2	2
A_8	Estonia	7	7	7	A_{23}	Poland	25	25	25
A_9	Finland	4	5	4	A_{24}	Portugal	14	14	14
A_{10}	France	16	16	15	A_{25}	Romania	24	23	23
A_{11}	Germany	15	13	13	A_{26}	Slovakia	21	22	22
A_{12}	Greece	26	26	26	A_{27}	Slovenia	12	12	12
A_{13}	Hungary	22	24	24	A_{28}	Spain	23	21	21
A_{14}	Iceland	1	1	1	A_{29}	Sweden	3	3	3
A_{15}	Ireland	9	10	9	A_{30}	United Kingdom	17	17	17

Table 4. Correlation of real ranking with rankings predicted by MLP and OLS models for 2020.

	Real	MLP	OLS
OLS	0.9929	0.9987	1
MLP	0.9933	1	0.9987

5. Conclusion

This paper demonstrates the applicability of MLP regressor in a multi-criteria evaluation support system integrating knowledge contained in historical datasets and expert evaluations. This paper's main advantage is demonstrating the applicability of autonomous recommender and decision support systems in automated final ranking considering the knowledge of the decision maker's preferences contained in data. Results provided by MLP are comparable to reference model OLS. Directions for further work include in-depth research using autonomous predictive systems based on machine learning models incorporating historical data on other assessment problems. It is also recommended to explore neural network models with more complex architecture containing more hidden layers and investigate the potential of other machine learning regression models in multi-criteria evaluation problems. Other future works include investigations for datasets representing other problems in the sustainability domain for larger datasets.

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References

1. Ali, M., Prasad, R., Xiang, Y., Deo, R.C.: Near real-time significant wave height forecasting with hybridized multiple linear regression algorithms. Renewable and Sustainable Energy Reviews. 132, pp. 110003 (2020)
2. Asadikia, A., Rajabifard, A., Kalantari, M.: Systematic prioritisation of SDGs: Machine learning approach. World Development. 140, pp. 105269 (2021)
3. Boggia, A., Massei, G., Pace, E., Rocchi, L., Paolotti, L., Attard, M.: Spatial multicriteria analysis for sustainability assessment: A new model for decision making. Land Use Policy. 71, pp. 281–292 (2018)
4. Buitinck, L., Louppe, G., Blondel, M., Pedregosa, F., Mueller, A., Grisel, O., Niculae, V., Prettenhofer, P., Gramfort, A., Grobler, J., Layton, R., VanderPlas, J., Joly, A., Holt, B., Varoquaux, G.: API design for machine learning software: experiences from the scikit-learn project. In: ECML PKDD Workshop: Languages for Data Mining and Machine Learning. pp. 108–122 (2013)
5. Bun, M.J., Harrison, T.D.: OLS and IV estimation of regression models including endogenous interaction terms. Econometric Reviews. 38(7), pp. 814–827 (2019)
6. Deepa, N., Ganesan, K., Srinivasan, K., Chang, C.Y.: Realizing sustainable development via modified integrated weighting MCDM model for ranking agrarian dataset. Sustainability. 11(21), pp. 6060 (2019)
7. Feng, X., Ma, G., Su, S.F., Huang, C., Boswell, M.K., Xue, P.: A multi-layer perceptron approach for accelerated wave forecasting in Lake Michigan. Ocean Engineering. 211, pp. 107526 (2020)
8. Guo, M., Zhang, Q., Liao, X., Chen, F.Y., Zeng, D.D.: A hybrid machine learning framework for analyzing human decision-making through learning preferences. Omega. 101, pp. 102263 (2021)
9. Hwang, J., Lee, J., Lee, K.S.: A deep learning-based method for grip strength prediction: Comparison of multilayer perceptron and polynomial regression approaches. Plos one. 16(2), pp. e0246870 (2021)
10. Khishe, M., Mohammadi, H.: Passive sonar target classification using multi-layer perceptron trained by salp swarm algorithm. Ocean Engineering. 181, pp. 98–108 (2019)
11. Li, W., Li, H., Gu, S., Chen, T.: Process fault diagnosis with model-and knowledge-based approaches: Advances and opportunities. Control Engineering Practice. 105, pp. 104637 (2020)
12. Mousavi-Nasab, S.H., Sotoudeh-Anvari, A.: A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems. Materials & Design. 121, pp. 237–253 (2017)
13. Oppio, A., Bottero, M., Arcidiacono, A.: Assessing urban quality: a proposal for a MCDA evaluation framework. Annals of Operations Research. pp. 1–18 (2018)
14. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research. 12, pp. 2825–2830 (2011)
15. Rao, R., Patel, B.: A subjective and objective integrated multiple attribute decision making method for material selection. Materials & Design. 31(10), pp. 4738–4747 (2010)
16. Sahabuddin, M., Khan, I.: Multi-criteria decision analysis methods for energy sector's sustainability assessment: Robustness analysis through criteria weight change. Sustainable Energy Technologies and Assessments. 47, pp. 101380 (2021)
17. Seyedmohammadi, J., Sarmadian, F., Jafarzadeh, A.A., Ghorbani, M.A., Shahbazi, F.: Application of SAW, TOPSIS and fuzzy TOPSIS models in cultivation priority planning for maize, rapeseed and soybean crops. Geoderma. 310, pp. 178–190 (2018)