Neural Network Based Multi-Criteria Ranking Prediction - Sustainability Assessment Case Study

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Abstract

Machine learning models are high-potential tools that enable prediction in problems incorporating multiple attributes exploiting historical data. Prediction models are applicable in autonomous recommending systems development based on acquired datasets. They enable to profit from expert knowledge to support decision-makers in various fields. This paper demonstrates the application of an artificial neural network model named Multi-layer Perceptron (MLP) regressor for rankings prediction based on expert assessments performed in the past with multi-criteria decision analysis methods. The prediction given by the trained model shows high convergence with the real ranking. It proves that the MLP regressor has wide possibilities in developing autonomous recommending systems that do not need the active participation of the decision-maker. The developed methodology was applied to predict European countries' ranking regarding clean, affordable, and sustainable energy systems for the public in Sustainable Development Goal 7 (SDG 7).

Keywords: Multi-Layer Perceptron regressor, Autonomous recommender systems, Ranking prediction, Sustainable development, MCDA.

1. Introduction

Evaluation of countries based on the Sustainable Development Goal 7 (SDG 7) framework proposed by the United Nations (UN) is significant since it incorporates energy efficiency, growth of the share of renewable energy sources in industrial branches, and propagation of investment in clean energy solutions and modern energy infrastructures [9, 17]. In addition to the above aspects, SDG 7 has important social significance as it contributes to the fight against energy poverty by promoting enhanced energy access for the public [1]. Criteria preferences determined using expert knowledge are often unavailable, making it impossible to perform a multi-criteria evaluation using them [28]. This article presents a methodological framework for an information system for predicting country rankings concerning indicators within SDG 7. The proposed approach uses a Multi-Layer Perceptron regressor (MLP regressor) to assess countries based on performance data and scores without knowledge of criteria significance determined by experts. The framework for a country evaluation system for clean and affordable energy employs the MLP regressor model to predict alternatives' rankings in multi-criteria evaluation problems based on datasets evaluated by experts in the past. The basic principles of the proposed framework can be presented as follows. Suppose the goal is to evaluate countries in a multi-criteria problem focused on sustainability considering affordable and clean energy. The expert evaluation involves prioritizing the criteria by determining their weights and using the selected Multi-Criteria Decision Analysis (MCDA) method, which provides utility function values of the alternatives. Then, alternatives are ordered according to obtained utility function values. The critical point of the presented procedure is the criteria prioritization step, which depends on expert knowledge [23]. When the experts give criteria weight values, the situation is straightforward because the evaluation can be performed applying the chosen MCDA method. However, decision-makers may be confronted with a situation where it is desirable to estimate the ranking of alternatives for a new data set and experts are not available [16]. Indeed, objective weighting methods allow determining weights from the data using mathematical formulas [28]. Nevertheless, decision-makers may prefer to handle criteria relevance values previously established by domain experts for analogous problems [22]. The approach proposed in this paper is dedicated to just such cases. It uses historical datasets from several years assessed by experts using a given MCDA method. Therefore, based on them, the preference values of the alternatives can be predicted for the actual dataset using the Multi-Layer Perceptron Regressor machine learning model.

In methodical terms, the authors' main contribution is to propose applying the MLP regressor model to predict the utility function values of alternatives based on the historical datasets at disposal and the utility function values obtained with expert involvement for the same problem. Criteria performance values (training features) and evaluation scores in the form of utility values (target variable) are known. Information about the MCDA method used in the assessment to correctly rank the alternatives according to real and predicted utility values is also available. Since this attempt is a new approach and the purpose of this research is to check its applicability to the problem at hand, using experts' subjective weights was replaced by using an objective method of determining weights from data called the Gini coefficient-based weighting method. Then, for the data sets from each year, utility function values for each alternative were determined using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. TOPSIS was chosen due to its popularity for benchmarking the performance of other MCDA methods [3].

The rest of the paper is organized as follows. Section 2 provides literature review. Then, in section 3 methods applied in this research are presented in detail. Obtained results are presented and discussed in the next section 4. Finally, a summary and conclusions are provided in the last section 5, which also draws directions for further work.

2. Literature review

Advancements in developing effective systems utilizing renewable energy sources and harmless for the environment energy technologies need the information systems required to support the UN's energy goals. Special attention should be given to using renewable energy resources recommended by SDG 7. SDG 7 aims to ensure accessibility of sustainable, modern technologies producing clean energy [1]. Systems supporting sustainability assessment of clean and affordable energy development may be supported by scientific technologies such as MCDA [8], knowledge-based systems [6], data mining [27], and machine learning models [2]. Examples of integrating machine learning models with other models, such as MCDA models, can be found in the literature. For example, combining the Multi-Criteria Decision Analysis (MCDA) model with a machine learning model may contribute to catching the relationship between individual attributes and prediction, which contributes to improved prediction performance [15]. Another study integrated two MCDA methods, including AHP and ANP, with two machine learning models, namely Random Forest (RF) and Support Vector Machine (SVM), to develop flood vulnerability maps for the province of Salzburg, Austria [24]. In addition, the Multi-Layer Perceptron regressor is a popular and widely used artificial neural network prediction model that predicts target values based on collected historical data [13]. A machine-learning framework based on Multi-Layer Perceptron Regressor is widely used in prediction considering various fields. For example, this model has been applied for wave prediction [12], modeling the spread of COVID-19 infection [5] and prediction of the biomass gasification process efficiency [10]. In addition, MLP technology has proven successful in continuous and discrete variables prediction performance [13]. Furthermore, the MLP model shows potential for application in sustainable renewable energy management systems, for example, wave and ocean energy generation systems [1].

The MCDA methods proved to be a very useful tool in various domains and research disciplines. When analyzing the literature, it can be observed that MCDA methods are the foundation for evaluation problems incorporating sustainable development [18]. Many measures, indicators, and indexes [7] using MCDA methods were developed to reliably assess sustainability in different fields. The significant potential of MCDA methods in sustainability evaluation is due to the ability to incorporate multidimensional models and create transparent, structured models with the inclusion of data [18]. Additionally, MCDA methods allow involving different interest groups, including contradictions often considered in sustainability assessment [7]. MCDA methods allow solving problems requiring simultaneous consideration of multiple attributes and often conflicting objectives. The mentioned problems are represented by a decision matrix containing performance values of evaluated options regarding required attributes.

3. Methodology

This paper aims to demonstrate the applicability of the MLP regressor model in predicting rankings of alternatives based on historical performance data and the results of their evaluations obtained with MCDA methods involving decision-makers. Figure 1 shows the framework based on the MLP regressor model trained on a historical dataset evaluated using expert criteria weights and the MCDA method.

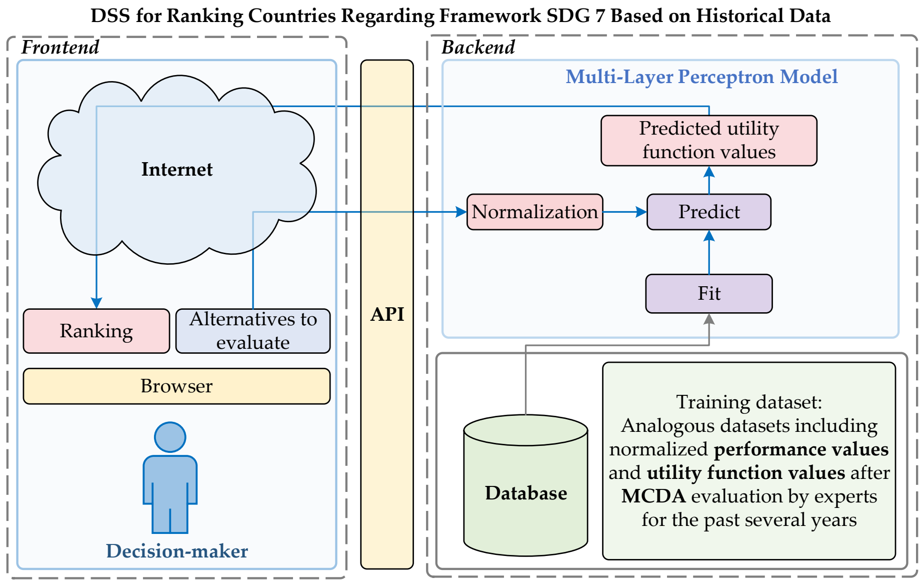

Fig. 1. Framework for rankings prediction based on MLP regressor and training dataset.

Investigation of the usefulness of the proposed method is presented using an illustrative example of assessing the sustainability of European countries in terms of an efficient, clean, and affordable energy system. The assessment uses a set of criteria belonging to the Sustainable Development Indicator (SDG 7) framework proposed by the United Nations in the Agenda 2030 strategy to monitor countries regarding accessibility to modern energy services, improvement of energy efficiency, and increasing the share of renewable energy.

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3.1. The MLP Regressor

MLP regressor is a machine learning model that applies a supervised learning algorithm relying on a nonlinear function and maps input data to output data in a training process on a data set [12]. Input data are represented by $X = x_1, x_2, \dots, x_R$ where R means number of inputs. Outputs are denoted by $y = y_1, y_2, \dots, y_S$, where S means the number of outputs. The MLP model is built with three or more layers. Input, output, and one or more hidden layers can be mentioned. Each node in one layer is connected by weight to each node in the next layer. The input layer includes neurons playing the role of inputs. The output layer obtains information from the last hidden layer and transforms it into output values. After that, each neuron in the hidden layer achieves the values from the previous layer as a weighted linear sum, followed by a nonlinear activation function $f(\cdot) : X \rightarrow y$. As an example, the output of the jth node from the first hidden layer is represented by Equation (1)

$$y = f(\sum_{i=1}^{R} w_{ji}x_i + b_j) \tag{1}$$

where $f(\cdot)$ means nonlinear activation function, w_{ji} represents the weights and b_j denotes the bias. The scikit-learn library provides several types of nonlinear functions in the MLP regressor model, such as 'identity', 'tanh', 'relu', 'logistic', which are selected in the grid search procedure. Training of MLP regressor is performed by adjusting connection weights and biases after calculating the error in the output based on comparing the output result (predicted value) with the expected outcome (real value). The TOPSIS method used for the evaluation of historical datasets by experts is described in [3]. This method evaluates alternatives based on their distance from reference ideal and anti-ideal solutions. Alternative with the highest TOPSIS utility function value is best scored. For determining criteria weights, experts used Gini coefficient-based weighting method detailed in [21].

3.2. The TOPSIS method

The steps of the TOPSIS method are given below, following [3]. In each Equation presented below ($i = 1, 2, \dots, m$, $j = 1, 2, \dots, n$), m denotes alternatives number and n represents evaluation criteria number.

Step 1. Normalize the decision matrix. In Minimum-Maximum technique r_{ij} normalized values are calculated by Equation (2) for profit criteria and (3) for cost criteria.

$$r_{ij} = \frac{x_{ij} - min_j(x_{ij})}{max_j(x_{ij}) - min_j(x_{ij})} \tag{2}$$

$$r_{ij} = \frac{max_j(x_{ij}) - x_{ij}}{max_j(x_{ij}) - min_j(x_{ij})} \tag{3}$$

Step 2. Calculate the weighted normalized decision matrix as Equation (4) shows.

$$v_{ij} = w_j r_{ij} \tag{4}$$

Step 3. Determine the Positive Ideal Solution using Equation (5) and Negative Ideal Solution using Equation (6). PIS includes the maximum values of the weighted normalized decision matrix, while NIS includes its minimums.

$$v_j^+ = \{v_1^+, v_2^+, \ldots, v_n^+\} = \{max_j(v_{ij})\} \tag{5}$$

$$v_j^- = \{v_1^-, v_2^-, \ldots, v_n^-\} = \{min_j(v_{ij})\} \tag{6}$$

Step 4. Calculation of distance from PIS (7) and NIS (8) for each alternative.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{7}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{8}$$

Step 5. Calculate the score for each evaluated alternative by Equation (9). The C_i value ranges from 0 to 1, and the best is the one with the highest C_i value.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{9}$$

3.3. The Gini coefficient-based weighting method

The Gini Coefficient-based weighting method is described based on [21]. Subsequent stages of this weighting method are given below.

Step 1. Compute the Gini coefficient value for each j-th criterion applying Equation (10)

$$G_j = \sum_{i=1}^{m} \sum_{k=1}^{m} \frac{|x_{ij} - x_{kj}|}{2m^2 E_j} \tag{10}$$

where x represents performance values in decision matrix $X = [x_{ij}]_{m \times n}$, m denotes number of alternatives $(i = 1, 2, \ldots, m)$, n is number of criteria $(j = 1, 2, \ldots, n)$, and E_j means the average value for all alternatives considering j-th criterion. If E_j is not equal to zero, Equation (10) is used. Otherwise, the Gini coefficient is computed as Equation (11) shows.

$$G_j = \sum_{i=1}^{m} \sum_{k=1}^{m} \frac{|x_{ij} - x_{kj}|}{m^2 - m} \tag{11}$$

Step 2. Calculate weights for each j-th criterion using Equation (12).

$$w_j = \frac{G_j}{\sum_{k=1}^{n} G_k} \tag{12}$$

3.4. The SDG 7 Evaluation Criteria

The SDG 7 indicator covers eleven criteria, where $\uparrow$ denotes the goal of maximizing and $\downarrow$ represents the goal of minimizing the performance value of considered criteria. Criteria set is displayed in Table 1. The indicators belonging to the framework defined by SDG 7 are suitable for assessing countries for affordable and clean energy. The set of assessed alternatives contains countries provided in Table 6. Performance values of assessed countries in terms of criteria included in SDG 7 were acquired from the Eurostat website (accessed on 14 February 2023). Data sources for each criterion included in SDG 7 are available in the GitHub repository [11]. The dataset includes performance values for 30 European countries from 2010-2020 (330 samples). This dataset was split with the intent that the test dataset was approximately 20% of the whole dataset size, according to fundamentals of machine learning procedures for MLP model [19].

Table 1. Evaluation criteria in the SDG 7 framework.

Criterion C_j	Name	Unit	Goal
C_1	Primary energy consumption	Tonnes of oil equivalent [TOE per capita]	$\uparrow$
C_2	Final energy consumption	Tonnes of oil equivalent [TOE per capita]	$\uparrow$
C_3	Final energy consumption in households per capita	Kilogram of oil equivalent [KGOE per capita]	$\uparrow$
C_4	Energy productivity	Euro per kilogram of oil equivalent [KGOE per capita]	$\uparrow$
C_5	Share of RES in gross final energy consumption in general	[%]	$\uparrow$
C_6	Share of RES in gross final energy consumption in transport	[%]	$\uparrow$
C_7	Share of RES in gross final energy consumption in electricity	[%]	$\uparrow$
C_8	Share of RES in gross final energy consumption in heating and cooling	[%]	$\uparrow$
C_9	Energy import dependency regarding all types of energy products (solid fossil fuels, oil and petroleum products excluding biofuel portion, natural gas)	[%]	$\downarrow$
C_{10}	Population unable to keep home adequately warm	[%]	$\downarrow$
C_{11}	Greenhouse gas emissions intensity of energy consumption	Index, 2000=100	$\downarrow$

Performance values for 11 criteria that represent training features were used as input data. The target variable is represented by score values acquired from the MCDA assessment. Prepared training and test datasets and Python codes are available on GitHub [11]. Because this is an early attempt involving the MLP regressor model, the target variable values representing the decision makers' assessments were obtained during simulation using the TOPSIS multi-criteria dataset evaluation procedure performed for each year from 2010 to 2020. This research covers a phase including steps related to MCDA evaluation and a stage related to training and testing the MLP regressor model. The MLP regressor model implemented in the scikit-learn Python library was employed for this research. Table 2 contains a fragment of the decision matrix representing the training dataset, including the performance values of 30 countries A_1–A_{30} for 11 attributes C_1–C_{11}.

Preparation of the training dataset involves several steps that enable obtaining target values for each year using the MCDA method.

Step 1. Create decision matrices containing m alternatives and n criteria for each year.

Step 2. Determine the significance of the criteria for each year's dataset. This step simulates the prioritization usually performed by decision-makers. For this research, criteria weights were determined using the Gini coefficient-based weighting technique [21]. However, weights may be set subjectively by decision-makers.

Step 3. Normalize the decision matrix. Due to some negative criteria values in the datasets, the Minimum-Maximum normalization technique was applied [4].

Step 4. Evaluate annual datasets using the TOPSIS method detailed in [3] to obtain preference values representing target variable values for each year. Performance values in the dataset were normalized using the Minimum-maximum normalization technique, as shown in Table 3. Pref. column includes target variable values.

Table 2. Fragment of decision matrix representing training dataset.

A_i	Country	Year	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
A_1	Austria	2010	3.93	3.35	845	8.49	31.205	10.705	66.361	30.959	62.779	3.8	90.2
A_2	Belgium	2010	4.89	3.48	883	5.32	6.004	4.8	7.332	6.71	78.553	5.6	91.8
A_3	Bulgaria	2010	2.35	1.19	303	2.13	13.928	1.498	12.358	24.334	40.146	66.5	117.4
A_4	Croatia	2010	2.06	1.68	645	4.81	25.103	1.123	37.521	32.881	46.693	8.3	96.5
A_5	Cyprus	2010	3.22	2.33	406	6.59	6.161	1.994	1.39	18.813	100.636	27.3	103.9
...	...	...	...	...	...	...	...	...	...	...	...	...	...
A_{30}	United Kingdom	2019	2.61	2.01	571	11.88	12.336	8.856	34.769	7.837	34.829	5.4	81.8

Table 3. Fragment of preprocessed training dataset and target variable.

A_i	Year	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	Pref.
A_1	2010	0.1459	0.3015	0.6647	0.6845	0.4322	1.0000	0.6753	0.4416	0.0617	0.9500	0.5007	0.4347
A_2	2010	0.2069	0.3190	0.7020	0.3577	0.0719	0.4484	0.0743	0.0572	0.0360	0.9227	0.4774	0.3144
A_3	2010	0.0457	0.0108	0.1333	0.0289	0.1852	0.1399	0.1255	0.3366	0.0986	0.0000	0.1036	0.1294
A_4	2010	0.0273	0.0767	0.4686	0.3052	0.3450	0.1049	0.3817	0.4721	0.0879	0.8818	0.4088	0.3387
A_5	2010	0.1009	0.1642	0.2343	0.4887	0.0741	0.1863	0.0138	0.2491	0.0000	0.5939	0.3007	0.2211
...	...	...	...	...	...	...	...	...	...	...	...	...	...
A_{30}	2019	0.0611	0.1003	0.3472	0.5564	0.0739	0.2052	0.2650	0.0200	0.0940	0.8488	0.3599	0.3066

The specificity and usefulness of all the indicators belonging to the SDG 7 framework in assessing sustainable energy policy are discussed in detail below. Indicator C_1 measures a country's total energy needs. Primary energy consumption includes energy consumption by end users such as industry, transport, households, services, agriculture, and energy consumption by the energy sector itself for energy production and transformation. Thus, the increase of indicator C_1 representing the energy demand in the country is implied by the development of industry and economy. Therefore, it is qualified as a profit-type criterion. Indicator C_2 measures final energy consumption in a given country. It excludes all non-energy use of energy carriers. Final energy consumption includes only energy consumed by end-users (industry, transport, households, services, and agriculture). This indicator excludes energy consumption by the energy sector itself and losses occurring during energy conversion and distribution. Indicator C_2, like C_1, proportionally reflects the economic growth of the country and the associated increase in energy demand. Therefore it is included in this research as a profit-type criterion. Indicator C_3 (energy consumption in households) measures the consumption of electricity and heat by each citizen in the household without including energy consumed in transport. This indicator reflects access to electricity in households. Therefore, it is a profit criterion. Energy productivity (C_4)

is a profit measure of the amount of economic production generated per unit of gross available energy representing the amount of energy products needed to supply entities in a country. Indicators C_5-C_8 representing renewable energy are significant measures of the share of renewable energy sources (RES) in end-use energy consumption. Due to the need to increase the share of RES in the economy, these indicators are among the profit criteria. The C_9 indicator represents energy dependency, namely the share of a country's total energy needs supplied by imports from other countries. Since the goal of the energy policy promoted by the UN is for governments to become less dependent on imports of energy resources, especially non-renewable ones, in favor of developing an increasing share of RES, the C_9 indicator is of the cost type. Indicator C_{10} (inability to keep home warm) represents the percentage of the population that is not provided with adequate heat at home. This indicator monitors energy poverty and is a cost criterion in the SDG 7 framework. The last indicator, C_{11} (GHG intensity of energy consumption), included in the framework for assessing sustainable, affordable, and clean energy, represents energy-related greenhouse gas (GHG) emissions in the economy. Since the concern for climate quality is to reduce GHG emissions in all sectors of the economy, indicator C_{11} is a cost criterion.

3.5. The Dataset

The following step of this research incorporates choosing the best hyperparameters for the MLP regressor model. Hyperparameters were established using the k-fold cross validation grid search procedure available in the GridSearchCV function from the scikit-learn Python library [26]. In order to avoid overfitting L2 penalty parameter regularization was set [12]. The final step of the presented research incorporates training the MLP regressor model on the training dataset to predict target variable values for the test dataset. Then, predicted utility function values are ranked in descending order like in the TOPSIS method. Predicted rankings are compared with real rankings to establish the efficiency of the MLP regressor model. Results obtained using the MLP regressor model were compared with results provided by benchmarking Linear regression model [20]. Convergence of rankings is determined using the Weighted Spearman rank correlation coefficient [25].

4. Results

This section provides and details results received using the MLP regressor model for ranking prediction based on historical data. The results presented include selecting the best hyperparameters of the MLP regressor model using k-fold cross-validation and grid search and testing the model's prediction performance for the test dataset. Table 4 presents a summary of hyperparameters selection performed.

Table 4. 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'	'relu'
Alpha	0.001, 0.0001, 0.00001	0.0001
Maximum iterations number	200, 500, 1000	1000

After selecting the most suitable parameters for the MLP regressor model, the prediction with the MLP regressor model was performed for the test dataset, constituting 20% of the whole dataset. Then a 5-fold cross-validation procedure was applied to evaluate the MLP regressor model score using regression score function R^2. Results for each fold are high and close to 1: {0.9905, 0.9879, 0.9922, 0.9810, 0.9771}. It confirms the high efficiency of the examined model. Results of MLP prediction were compared with ranking predicted by benchmarking model Linear regression (LR) and with real ranking as shown in Figure 2. The results are similar because MLP and linear regression had comparable performance and robustness [14].

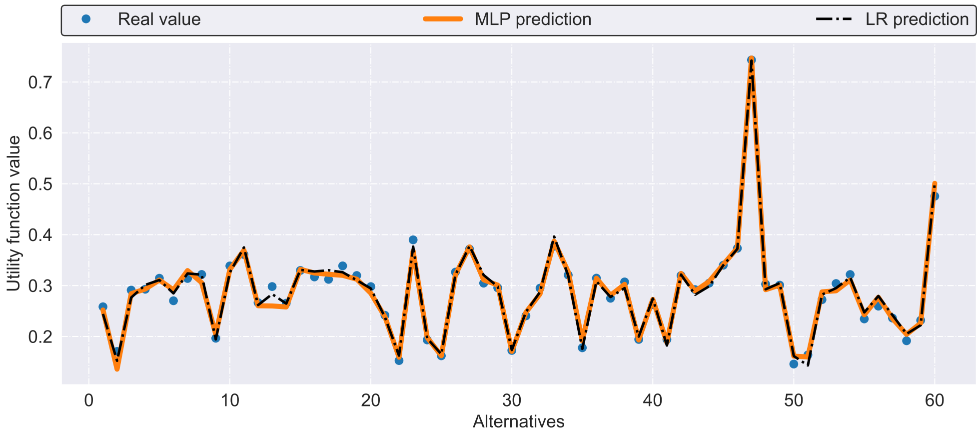

Fig. 2. Comparison of real and predicted rankings.

The consistency of predicted values for two test datasets, including 60 randomly chosen samples and 30 samples from 2020, was determined by the Weighted Spearman correlation coefficient and regression score function R^2. The results are presented in Table 5. It can be noted that the convergence of results provided by compared models with real results is high and comparable.

Table 5. Scores reached by MLP and LR models for different test datasets.

Test dataset, prediction model	Weighted Spearman	R^2
60 samples, MLP	0.9999995	0.9824702
60 samples, LR	0.9999996	0.9856510
30 samples, MLP	0.9999967	0.9808376
30 samples, LR	0.9999956	0.9741465

Then utility function values predicted by MLP for 2020 were ranked and compared with real ranking and ranking generated based on values predicted by the LR model. The results are displayed in Table 6 and Figure 3.

Table 6. Comparison of real and predicted rankings for 2020.

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

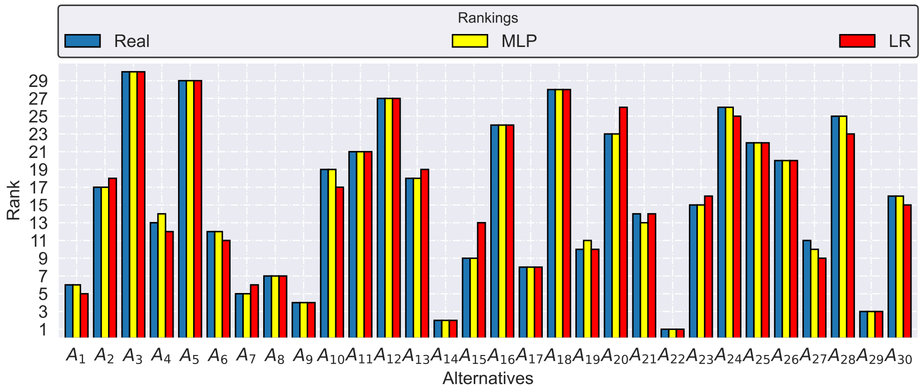

Fig. 3. Comparison of real and predicted rankings for 2020.

It can be observed that convergence between real ranking and rankings predicted by MLP and LR model is high and comparable. It is demonstrated in a heat map with high correlation values close to 1 displayed in Figure 4.

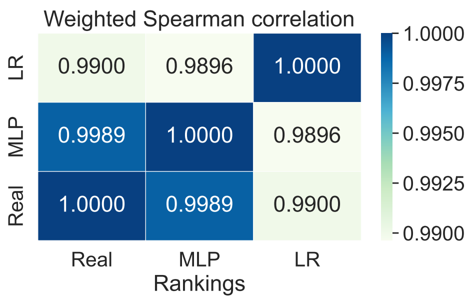

Fig. 4. Correlation of real and predicted rankings for 2020.

The top nine ranks provided by the MLP model are identical to the real ranking. It is important because the top of the ranking is the most interesting for decision-makers and stakeholders. The leader in rankings is Norway (A_{22}). The second place was taken by Iceland (A_{14}) and third place by Sweden (A_{29}). Finland (A_9) took fourth rank and Denmark (A_7) fifth rank. Obtained results prove that Nordic countries are well scored in terms of clean and affordable energy systems. It can be noted that there occur only four differences between real ranking and ranking based on utility function values predicted by MLP. They involve A_4 (Croatia), A_{19} (Luxembourg), A_{21} (Netherlands), and A_{27} (Slovenia). Noticed differences do not exceed one rank. Thus, the MLP regressor model proved to be a suitable and effective tool for ranking prediction.

5. Conclusions

This paper aimed to demonstrate the usefulness of the MLP regressor model in solving multi-criteria assessment problems. This research showed a successful integration of information included in data and experts' knowledge represented by assessments from the past. Performed research proved that the MLP regressor model has the potential to support autonomous recommender systems for ranking prediction based on historical datasets evaluated previously by decision-makers. Future work directions involve extended investigations applying autonomous systems incorporating machine learning for prediction based on historical data and scores provided by experts obtained from trusted databases. It is also advisable to build and examine neural network models based on more compound architecture involving more hidden layers of neurons and explore the applicability of other machine learning regression models in multi-criteria assessment problems. Future work directions also cover research using larger datasets representing other problems in sustainable development.

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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. Bera, B., Shit, P.K., Sengupta, N., Saha, S., Bhattacharjee, S.: Susceptibility of deforestation hotspots in Terai-Dooars belt of Himalayan Foothills: A comparative analysis of VIKOR and TOPSIS models. Journal of King Saud University-Computer and Information Sciences (2021)
4. Bielinskas, V., Burinskienė, M., Podviezko, A.: Choice of abandoned territories conversion scenario according to MCDA methods. Journal of Civil Engineering and Management. 24(1), pp. 79–92 (2018)
5. Car, Z., Baressi Šegota, S., Anđelić, N., Lorencin, I., Mrzljak, V.: Modeling the spread of COVID-19 infection using a multilayer perceptron. Computational and mathematical methods in medicine. 2020 (2020)
6. Carayannis, E.G., Ferreira, J.J., Jalali, M.S., Ferreira, F.A.: MCDA in knowledge-based economies: Methodological developments and real world applications. Technological Forecasting and Social Change 131, pp. 1–3 (2018)
7. Cinelli, M., Spada, M., Kim, W., Zhang, Y., Burgherr, P.: MCDA Index Tool: An interactive software to develop indices and rankings. Environment Systems and Decisions 41(1), pp. 82–109 (2021)
8. D'Adamo, I., Gastaldi, M., Imbriani, C., Morone, P.: Assessing regional performance for the Sustainable Development Goals in Italy. Scientific reports. 11(1), pp. 1–10 (2021)
9. Elavarasan, R.M., Pugazhendhi, R., Irfan, M., Mihet-Popa, L., Campana, P.E., Khan, I.A.: A novel Sustainable Development Goal 7 composite index as the paradigm for energy sustainability assessment: A case study from Europe. Applied Energy 307, pp. 118173 (2022)
10. Elmaz, F., Yücel, Ö., Mutlu, A.Y.: Predictive modeling of biomass gasification with machine learning-based regression methods. Energy. 191, pp. 116541 (2020)
11. energyinpython: Neural Network Based Multi-Criteria Ranking Prediction - Sustainability Assessment Case Study (2023), `https://github.com/energyinpython/MLP-MCDA`
12. 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)
13. Fesghandis, G.S., Pooya, A., Kazemi, M., Azimi, Z.N.: Comparison of multilayer perceptron and radial basis function neural networks in predicting the success of new product development. Engineering, Technology & Applied Science Research. 7(1), pp.

1425–1428 (2017)

14. Gaudart, J., Giusiano, B., Huiart, L.: Comparison of the performance of multi-layer perceptron and linear regression for epidemiological data. Computational statistics & data analysis 44(4), pp. 547–570 (2004)
15. 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)
16. Ibarz, B., Leike, J., Pohlen, T., Irving, G., Legg, S., Amodei, D.: Reward learning from human preferences and demonstrations in atari. Advances in neural information processing systems 31 (2018)
17. Jayachandran, M., Gatla, R.K., Rao, K.P., Rao, G.S., Mohammed, S., Milyani, A.H., Azhari, A.A., Kalaiarasy, C., Geetha, S.: Challenges in achieving sustainable development goal 7: Affordable and clean energy in light of nascent technologies. Sustainable Energy Technologies and Assessments 53, pp. 102692 (2022)
18. Karimi Firozjaei, M., Sedighi, A., Jelokhani-Niaraki, M.: An urban growth simulation model based on integration of local weights and decision risk values. Transactions in GIS 24(6), pp. 1695–1721 (2020)
19. Khishe, M., Mohammadi, H.: Passive sonar target classification using multi-layer perceptron trained by salp swarm algorithm. Ocean Engineering. 181, pp. 98–108 (2019)
20. Kim, M.K., Kim, Y.S., Srebric, J.: Predictions of electricity consumption in a campus building using occupant rates and weather elements with sensitivity analysis: Artificial neural network vs. linear regression. Sustainable Cities and Society 62, pp. 102385 (2020)
21. Lai, H., Liao, H., Šaparauskas, J., Banaitis, A., Ferreira, F.A., Al-Barakati, A.: Sustainable cloud service provider development by a Z-number-based DNMA method with Gini-coefficient-based weight determination. Sustainability 12(8), pp. 3410 (2020)
22. Martyn, K., Kadziński, M.: Deep preference learning for multiple criteria decision analysis. European Journal of Operational Research 305(2), pp. 781–805 (2023)
23. Mokarram, M., Mokarram, M.J., Gitizadeh, M., Niknam, T., Aghaei, J.: A novel optimal placing of solar farms utilizing multi-criteria decision-making (MCDA) and feature selection. Journal of Cleaner Production 261, pp. 121098 (2020)
24. Nachappa, T.G., Piralilou, S.T., Gholamnia, K., Ghorbanzadeh, O., Rahmati, O., Blaschke, T.: Flood susceptibility mapping with machine learning, multi-criteria decision analysis and ensemble using Dempster Shafer Theory. Journal of hydrology 590, pp. 125275 (2020)
25. Pamučar, D., Lukovac, V., Božanić, D., Komazec, N.: Multi-criteria FUCOM-MAIRCA model for the evaluation of level crossings: case study in the Republic of Serbia. Operational Research in Engineering Sciences: Theory and Applications 1(1), pp. 108–129 (2018)
26. 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)
27. Sebestyén, V., Domokos, E., Abonyi, J.: Focal points for sustainable development strategies—Text mining-based comparative analysis of voluntary national reviews. Journal of Environmental Management. 263, pp. 110414 (2020)
28. Zhang, K., Liu, X., Wang, W., Li, J.: Multi-criteria recommender system based on social relationships and criteria preferences. Expert Systems with Applications 176, pp. 114868 (2021)