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PREDICTION OF RENEWABLE ENERGY CONSUMPTION OF EUROPEAN UNION USING ARTIFICIAL NEURAL NETWORKS

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Abstract: The increasing demand for renewable energy sources attract attention of both researchers and governments. The countries support renewable energy and technologies developed for the efficient use of renewable energy. For this reason, the assessment and prediction of renewable energy consumption is vital for governments. Furthermore, associations put forward long-term and short-term targets for countries. Therefore, European Union (EU) members provide support schemes for promoting renewable energy consumption. In this study, renewable energy consumption in EU is predicted using artificial neural networks. The World Development indicators which are renewable electricity output, energy use generated from combustible renewables and waste, electricity production from oil, gas and coal sources, energy use generated from alternative and nuclear energy, electricity production from renewable sources excluding hydroelectric, energy imports, energy use, gross domestic product (GDP) and population are evaluated as independent variables using historical data from 1990 to 2015. The results indicate that artificial neural networks provides convenient results in energy demand forecasting as seen in similar studies of the literature.

Keywords: Artificial neural networks, Renewable energy consumption, European Union, Energy policy

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1. Introduction

Renewable energy sources, with a significant increase in Europe and worldwide is a clean alternative to fossil fuels. They are used in a wide variety of application areas including industry, automobiles, agriculture, heating and cooling. Depletion of fossil fuels and global warming also steer governments to promote clean energy sources (Kitzing et al., 2012). In 2011, Intergovernmental Panel on Climate Change (IPCC) assessed six renewable energy resources involving bioenergy, solar energy, geothermal energy, hydropower, ocean energy and wind energy (Wang et al., 2019). The International Energy Agency (IEA) estimated in the Energy Technology Perspectives 2012 that clean energy technologies offer the prospect of reaching the global goal of limiting the increase of the global mean temperature to 2°C (Scarlat et al., 2015). Renewable power capacity is set to expand by 50% between 2019 and 2024, led by solar photovoltaic (PV) (IEA, 2019). Solar PV alone accounts for almost 60% of this expected growth, with onshore wind representing one-quarter. For this purpose, EU energy policy is concentrating on both the promotion of renewable energy and the technologies to use it efficiently.

As well as, putting forward renewable energy a prevalent source of clean energy, the prediction of its consumption is vital for governments to provide relevant support schemes. Several forecasting techniques are used in literature to predict and evaluate energy consumption, some of which are:

- Data envelopment analysis (Chien and Hu, 2007; Wang et al., 2012),
- Granger causality tests (Jinke et al., 2008; Apergis and Payne, 2010; Nazlioglu et al., 2011),
- Empirical studies, interviews (Hirschl, 2009; Martins and Pereira, 2011; Nagy and Körmendi, 2012),
- General evaluations (Valentine, 2011; Baris and Kucukali, 2012),
- Other (Liddle, 2012; Reuter et al., 2012), etc.

The most widely used methods for forecasting building energy consumption were categorized into three groups, which are Engineering, Statistical and Artificial Intelligence (AI) methods (Ahmad et al., 2014). Artificial neural networks (ANN), which can be defined as information-processing systems that have common performance characteristics with biological neural networks, have been developed as "generalizations of mathematical model of human cognition" (Kialashaki and Reisel, 2014). ANN models may be used as an alternative method in engineering analysis and predictions, mimicking somewhat the learning processes of a human brain (Kalogirou, 2009).

Several studies attempted to predict energy using ANN in the last decade. Wind power generation and prediction with ANN in Muppandal area (Mabel and Fernandez, 2008) provided a model for the prediction of energy from wind farms. ANN was also used to predict energy needs of buildings benefitting from orientation, insulation thickness and transparency ratio (Ekici and Aksoy, 2009). Greek long-term energy consumption for the years ahead was predicted with multilayer perceptron model in another study (Ekonomou, 2010). Similarly, in Mexico for wind power prediction, three models; ANN, Autoregressive Integrated Moving Average (ARIMA) and a hybrid of two, were compared (Cadenas and Rivera, 2010). In a recent study, the residential solar energy consumption of the United States was forecasted based on data grouping and buffer model (Wang et al., 2019).

In this study, the focus is to predict renewable energy consumption for EU using ANN. Therefore, the EU renewable energy consumption data are collected between 1990 and 2015. The variables that are related with energy consumption, are selected from the list of World Development Indicators. An ANN model with a single hidden layer and a single output is constructed. Here, section 2 briefly describes the renewable energy targets and support schemes in EU countries. In Section 3, the data used in ANN model is defined. Section 4 explains the methodology and analysis. Finally, Section 5 concludes the study and puts forward the results.

2. Material and Methods

2.1. Renewable Energy Targets and Support Schemes in EU

Renewable energy usage reduces greenhouse gas emissions, diversification of energy supplies and dependency on fossil fuel markets (in particular, oil and gas) (EU, 2019a). Besides, renewables are expected to create new jobs on green technologies, fostering employment in EU countries (EU, 2019a). Renewable energy sources include wind power, solar power (thermal, photovoltaic and concentrated), hydro power, tidal power, geothermal energy, ambient heat captured by heat pumps, biofuels and the renewable part of waste (EU, 2019b).

The EU's target for 2020 is 20% share of renewables and in 2018 this rate in gross final energy consumption stood at 18.9 % in the EU (EU, 2020). When compared with 9.6% in 2004, the share has been doubled in 14 years (EU, 2020).

The EU targets a 20% share of its gross final energy consumption from renewable sources by 2020. In order to aim at this rate, the EU Member States compose national action plans for the development of renewable energy usage. Besides they are close to meet 2020 targets, both in the gross final energy consumption and specifically transport. Those, that are already top of the class, are: Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, Italy, Hungary, Lithuania, Romania and Sweden (WEF, 2019). The highest rate in 2017 is captured by Sweden with 54.5% followed by Finland, with 41%, and by Latvia with 39% and Denmark with 35.8% (EuroStat, 2019). In Table 1, support schemes which are used to promote renewable energy use in EU Member States are compiled in 3 categories, Electricity, Heating and Cooling, and Transport (Res-Legal, 2019).

2.2. Data

ANN is used for prediction of energy consumption in the EU. The data used in this study are collected from World Development Indicators for years between 1990 and 2015 (WB, 2021). Renewable energy consumption is set the output variable as a percentage of the total final energy consumption. Hence, the remaining are the input variables used to predict renewable energy consumption. Moreover, the input parameters are analyzed to highlight their importance in energy consumption forecasting. Table 2 briefly describes the variables used.

2.3. Methodology and Analysis

A generalized solution must be provided by ANN for the prediction to be close to observed values. For this purpose, the data set is divided into 3 categories. The first set of the data, training data set, is used to train the model by using Levenberg-Marquardt algorithm (LMA). LMA is frequently used as a training algorithm in ANNs. Basically LMA is the combination of two different numerical methods, gradient decent algorithm and Gauss-Newton method. This hybrid structure of LMA provides to use the advantages of both algorithms. LMA can behave like gradient decent algorithm if the parameters are far from their optimal values. On the other hand it operates like the Gauss-Newton method if the parameters are closer to their optimal values. General procedure of the LMA can be found in esteemed reference (Gavin, 2019).

The second set, validation data set, is used to stop the training to prevent overfitting so that the solution can be generalized. The third set, test data set, is used to tune the hyperparameters of the system. In other words, this set measures the accuracy of the model. The entire data set is randomly separated into training, test and validation subsets respectively as 60%, 20% and 20%. Same data separation is used for each simulation. The first stage of simulation is focused on finding the best number of neurons in the hidden layer of the ANN. For this purpose, the number of neurons in the hidden layer was changed from 1 to 20. Throughout the result, the number of neurons with the best prediction performance will be chosen for the final network. Stopping parameters are given in Table 3.

The ANN algorithm is based on randomness which means that initial parameters of the ANN is randomly assigned in the beginning of each simulation. ANN with identical number of neurons in hidden layer may give different results if the simulation is repeated. For this reason a statistical approach is required to make a fair designation of best number of neurons in hidden layer. In order to provide a fair comparison among the particular number of neurons in hidden layer, simulation is repeated for 100 times for each ANN architecture. Afterwards averages of mean squared errors (MSE) of each data set and the correlation (r) of test data are calculated to determine the possibility of best ANN model according to number of neurons in the hidden layer. The performance index given in Table 4 enumerate each scenario with their averages of MSE values for each data set and correlation values of test data.

Table 1. Support schemes in EU member states

	Electricity							Heating and Cooling					Transport			
EU Countries	Feed-in Tariff	Premium Tariff	Net Metering	Loans	Tax Regulation Mechanisms	Subsidies	Tenders	Feed-in Tariff	Premium Tariff	Loans	Subsidies	Tax Regulation Mechanisms	Biofuel Quota	Subsidies	Premium Tariff	Tax Regulation Mechanisms
Albania	•		•		•		•									
Austria	•					•					•		•	•		•
Belgium			•			•				•	•	•	•			•
Bosnia and Herzegovina	•															
Bulgaria	•	•								•		•	•			•
Croatia	•	•		•									•			•
Cyprus			•			•										
Czech Republic	•	•			•	•					•	•	•			•
Denmark		•	•	•			•					•	•			•
Estonia		•					•				•			•		
Finland		•				•	•				•		•			•
France	•	•			•		•			•	•	•	•			
Germany	•	•		•		•	•			•	•		•	•		
Greece	•	•	•		•	•	•				•	•	•	•		•
Hungary	•	•	•	•		•	•				•		•	•		
Iceland						•										
Ireland	•					•					•	•	•			
Italy		•	•		•							•	•		•	
Kosovo	•															
Latvia	•		•									•	•			•
Liechtenstein	•															
Lithuania			•	•	•	•	•						•	•		•
Luxemburg	•	•				•	•				•		•			
Macedonia	•															
Malta	•						•			•			•			
Moldova	•		•				•									
Montenegro	•															
Netherlands		•	•	•	•		•		•	•	•	•	•			•
Norway																
Poland	•	•		•	•	•	•			•	•		•			
Portugal	•										•		•			•
Romania						•					•		•			
Serbia	•															
Slovakia	•				•	•					•		•			•
Slovenia				•		•	•			•	•					•
Spain							•						•			
Sweden					•	•						•	•			•
Switzerland	•															
Turkey	•						•									
Ukraine	•															
United Kingdom	•				•		•						•			

Table 2. Variables used for ANN model

Variable	Unit	Definition
RenewConsm: Renewable energy consumption	%	Renewable energy consumption is the share of renewable energy in total final energy consumption.
RenewElecOut: Renewable electricity output	%	Renewable electricity is the share of electricity generated by renewable power plants in total electricity generated by all types of plants.
ComRenewWas: Combustible renewables and waste	%	Combustible renewables and waste comprise solid biomass, liquid biomass, biogas, industrial waste, and municipal waste, measured as a percentage of total energy use.
ElecProdOilNatGasCoal: Electricity production from oil, gas and coal sources (% of total)	%	Sources of electricity refer to the inputs used to generate electricity. Oil refers to crude oil and petroleum products. Gas refers to natural gas but excludes natural gas liquids. Coal refers to all coal and brown coal, both primary (including hard coal and lignite-brown coal) and derived fuels (including patent fuel, coke oven coke, gas coke, coke oven gas, and blast furnace gas). Peat is also included in this category.
AltNuc: Alternative and nuclear energy (% of total energy use)	%	Clean energy is the energy that does not produce carbon dioxide when generated. It includes hydropower and nuclear, geothermal, and solar power, among others.
ElecProdRenewExHydro: Electricity production from renewable sources, excluding hydroelectric (% of total)	%	Electricity production from renewable sources, excluding hydroelectric, includes geothermal, solar, tides, wind, biomass, and biofuels.
EnergyImp: Net energy imports (% of total energy use)	%	Net energy imports are estimated as energy use less production, both measured in oil equivalents. A negative value indicates that the country is a net exporter.
EnergyUse: Energy use (kg of oil equivalent per capita)	kg	Energy use refers to use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport.
GDP	Current U.S. dollars	GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products.
Population	millions	Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship.

Table 3. Stopping parameters

Parameter	Value
Maximum number of epochs	100
Performance goal	0
Maximum validation failures	50
Maximum performance gradient	$1e^{-30}$

The ANN architecture with 5 neurons achieves the best prediction performance. Average MSE of test data is the lowest and average correlation is the highest among all other architectures which implies that the architecture with 5 neurons in hidden layer is more suitable for used data. The final ANN is set to 5 neurons in the hidden layer. Beyond this point the second stage is focused on the acquisition of the best ANN with 5 neurons in hidden layer. The final architecture of the proposed ANN is given in Figure 1.

3. Results and Discussion

After the designation of possible best number of neurons for the problem, the acquired model is then trained 100 times more and the best ANN among them is separated. The results given in Table 5 yielding very accurate results. It can be seen that MSE values are lower than average MSE values of the ANN including 5 neurons given in Table 4. The low MSE values of each set and high correlation value of test set is showing that, the simulation results are highly accurate.

In Figure 2 observed versus predicted renewable energy consumption values are given graphically with coefficient of determination (R^2) of entire data. Data points are almost adjacent to y=x line which is showing that obtained ANN provides a highly reliable fit as the observed and predicted values are very close to each other.

Apart from ANN, various methods were used to predict renewable energy, recently. Modified Econometric Mathematical model (Iniyan et al., 2006), Gray Models for smart grid technologies (Tsai et al., 2017) and Hybrid improved multi-verse optimizer support vector machine model (Li et al., 2019) were applied for forecasting renewable energy. However, these applications usually require expert knowledge of renewable energy. Besides, the methodology of ANN recovers users to deal with complex analytical equations as well as a comprehensive background of the topic and researchers can implement dynamic analysis even if recent data are added to the time series. Furthermore, it is possible to carry out analysis with inserted fresh indicators. ANN is thought to be an effective tool for future work as it can also be used in hybrid models providing improved and accurate results.

Table 4. Performance index

Hidden layer neurons	Average MSE train	Average MSE validation	Average MSE test	Average r test
1	0.1934	0.1875	0.2713	0.9880
2	0.0377	0.1305	0.2261	0.9924
3	0.0359	0.1392	0.2004	0.9919
4	0.0363	0.1026	0.2291	0.9928
5	0.0383	0.1060	0.1424	0.9953
6	0.0604	0.1061	0.2145	0.9915
7	0.0323	0.1299	0.1584	0.9942
8	0.0430	0.1247	0.1811	0.9935
9	0.0265	0.1788	0.2134	0.9911
10	0.0348	0.1929	0.2273	0.9916
11	0.0282	0.2066	0.2170	0.9909
12	0.0329	0.2045	0.3409	0.9851
13	0.0746	0.2779	0.3584	0.9847
14	0.0374	0.2619	0.3589	0.9797
15	0.0490	0.3329	0.4290	0.9711
16	0.0647	0.4315	0.4827	0.9769
17	0.0384	0.3537	0.4711	0.9556
18	0.0663	0.4334	0.5452	0.9631
19	0.0885	0.5926	0.7175	0.9496
20	0.0701	0.5867	0.6813	0.9447

MSE= mean squared errors

Table 5. Performance index

MSE train	MSE validation	MSE test	r test
0.0064	0.0292	0.0325	0.9994

MSE= mean squared errors

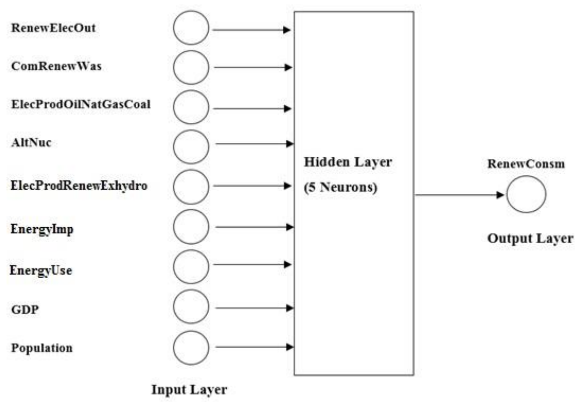

Figure 1. Proposed ANN architecture.

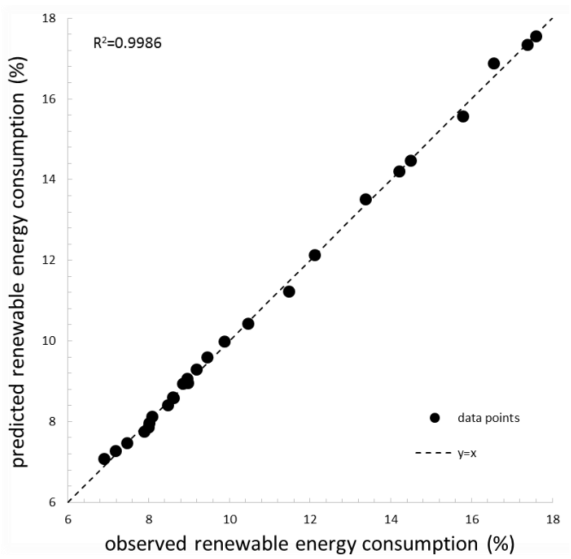

Figure 2. Observed vs predicted renewable energy consumption.

4. Conclusion

Depletion of natural resources and environmental damage of petroleum-based energy sources force governments to develop renewable energy technologies. EU Member States support renewable energy for electricity, transport heating and cooling. The schemes for this purpose include feed-in tariff, premium tariff, net metering, loans, subsidies, and tax regulation mechanism. The most supporting countries in EU are Netherlands (11), Greece (11), Germany (9), and Poland (9). In order to reach long-term initiatives the evaluation of renewable energy usage requires reliable data analysis. In this study, an ANN has been developed for the prediction of renewable energy consumption in EU using World Development Indicators through years 1990-2015. The output variable, renewable energy consumption, is predicted using the input variables renewable electricity output, energy use generated from combustible renewables and waste, electricity production from oil, gas and coal sources, energy use generated from alternative and nuclear energy, electricity production from renewable sources excluding hydroelectric, energy imports, energy use, GDP and population. It is determined that an ANN with 5 neurons predicted renewable energy consumption with accurate results. The future of the study can focus on prediction by using hybrid algorithms and a comparative evaluation. Thus, this study provided similar results with the existing literature in that ANN is a powerful technique in energy demand forecasting. A future research area for this particular study is comparing ANN with certain other methods used in energy demand forecasting such as adaptive neuro fuzzy inference system (ANFIS) or Multiple Linear Regression. Moreover, the use of hybrid models, combining ANN with Support Vector Machine, for instance, is a promising research area in this field.

Author Contributions

All authors have equal contribution. All authors reviewed and approved the manuscript.

Conflict of Interest

The author declared that there is no conflict of interest.

References

Ahmad AS, Hassan MY, Abdullah MP, Rahman, HA, Hussin F, Abdullah H, Saidur R. 2014. A review on applications of ANN and SVM for building electrical energy consumption forecasting. Renew Sust Energy Rev, 33: 102-109.

Apergis N, Payne JE. 2010. Renewable Energy Consumption and Economic Growth: Evidence from a Panel of OECD countries. Energy Pol, 38(1): 656-660.

Baris K, Kucukali S. 2012. Availibility of renewable energy sources in Turkey: Current situation, potential, government policies and the EU perspective. Energy Pol, 42: 377-391.

Cadenas E, Rivera W. 2010. Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA–ANN model. Renew Energy, 35(12): 2732-2738.

Chien T, Hu JL. 2007. Renewable energy and macroeconomic efficiency of OECD and non-OECD economies. Energy Pol, 35(7): 3606-3615.

Ekici BB, Aksoy UT. 2009. Prediction of building energy consumption by using artificial neural networks. Adv Eng Softw, 40(5): 356-362.

Ekonomou L. 2010. Greek long-term energy consumption prediction using artificial neural networks. Energy, 35(2): 512-517.

European Union (EU). 2019a. Eurostat statistics explained. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php/Renewable_energy_statistics (access date: October 21, 2019).

European Union (EU). 2019b. Eurostat glossary. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Renewable_energy_sources (access date: October 21, 2019).

European Union (EU). 2020. Eurostat statistics explained. https://ec.europa.eu/eurostat/statistics-explained/index.php/Renewable_energy_statistics#Consumption_of_renewable_energy_almost_doubled_between_2004_and_2018 (accessed date: 20.02.2020).

EuroStat. 2019. Share of energy from renewable sources. URL: https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_ind_ren&lang=en (access date: October 21, 2019).

Gavin H. 2019. The Levenberg-Marquardt algorithm for nonlinear least squares curve-fitting problems. URL: https://people.duke.edu/~hpgavin/ce281/lm.pdf (access date: August 27, 2021).

Hirschl B. 2009. International renewable energy policy—between marginalization and initial approaches. Energy Pol, 37(11): 4407-4416.

Iniyan S, Suganthi L, Samuel AA. 2006. Energy models for commercial energy prediction and substitution of renewable energy sources. Energy Pol, 34(17): 2640-2653.

International Energy Agency (IEA). 2019. Renewables 2019: Analysis and forecast to 2024. URL: http://www.iea.org/renewables2019 (access date: November 18, 2020).

Jinke L, Hualing S, Dianming G. 2008. Causality relationship between coal consumption and GDP: Difference of major OECD and non-OECD countries, Appl Energy, 85: 421-429.

Kalogirou S. 2009. Artificial neural networks and genetic algorithms in energy applications in buildings. Adv Build Energy Res, 3: 83-119.

Kialashaki A, Reisel JR. 2014. Development and validation of artificial neural network models of the energy demand in the industrial sector of the United States. Energy, 76: 749-760.

Kitzing L, Mitchell C, Morthorst PE. 2012. Renewable energy policies in Europe: Converging or diverging? Energy Pol, 51: 192-201.

Li LL, Wen SY, Tseng ML, Wang CS. 2019. Renewable energy prediction: A novel short-term prediction model of photovoltaic output power. J Clean Prod, 228: 359-375.

Liddle B. 2012. Breaks and trends in OECD countries' energy–GDP ratios. Energy Pol, 45: 502-509.

Mabel MC, Fernandez E. 2008. Analysis of wind power generation and prediction using ANN: A case study. Renew Energy, 33(5): 986-992.

Martins FR, Pereira EB. 2011. Enhancing information for solar and wind energy technology deployment in Brazil. Energy Pol, 39(7): 4378-4390.

Nagy K, Körmendi K. 2012. Use of renewable energy sources in light of the “New Energy Strategy for Europe 2011–2020”. Appl Energy, 96: 393-399.

Nazlioglu S, Lebe F, Kayhan S. 2011. Nuclear energy consumption and economic growth in OECD countries: Cross-sectionally dependent heterogeneous panel causality analysis. Energy Pol, 39(10): 6615-6621.

Scarlat N, Dallemand JF, Monforti-Ferrario F, Banja M, Motola V. 2015. Renewable energy policy framework and bioenergy contribution in the European Union–An overview from national renewable energy action plans and progress reports. Renew Sust Energy Rev, 51: 969-985.

Res-Legal. 2019. Legal sources on renewable energy, URL: http://www.res-legal.eu/ (access date: November 16, 2019).

Reuter WH, Szolgayová J, Fuss S, Obersteiner M. 2012. Renewable energy investment: Policy and market impacts. Appl Energy, 97: 249-254.

Tsai SB, Xue Y, Zhang J, Chen Q, Liu Y, Zhou J, Dong W. 2017. Models for forecasting growth trends in renewable energy. Renew Sust Energy Rev, 77: 1169-1178.

Valentine SV. 2011. Japanese wind energy development policy: Grand plan or group think? Energy Pol, 39(11): 6842-6854.

Wang ZH, Zeng HL, Wei YM, Zhang YX. 2012. Regional total factor energy efficiency: an empirical analysis of industrial sector in China. Appl Energy, 97: 115-123.

Wang ZX, He LY, Zheng HH. 2019. Forecasting the residential solar energy consumption of the United States. Energy, 178: 610-623.

World Bank (WB). 2021. World development indicators URL: https://databank.worldbank.org/source/world-development-indicators (access date: August 27, 2021).

World Energy Forum (WEF). 2019. These 11 EU states already meet their 2020 renewable energy targets. URL: https://www.weforum.org/agenda/2019/02/these-11-eu-states-already-meet-their-2020-renewable-energy-targets/ (access date: October 21, 2019).