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Renewable Energies Generation and Carbon Dioxide Emission Forecasting in Microgrids and National Grids using GRNN-GWO Methodology

Azim Heydari [a,*], Davide Astiaso Garcia [a], Farshid Keynia [b], Fabio Bisegna [a], Livio De Santoli [a]

[a] *Department of Astronautics, Electrical and Energetic Engineering (DIAEE) Sapienza University, Via Eudossiana 18, Rome 00184, Italy*
[b] *Department of Energy Management and Optimization, Institute of Science and High Technology and Environmental Sciences, Graduate University of Advanced Technology, Kerman, Iran*

Abstract

Reducing CO2 emissions is a key goal of the strategy for a low-carbon economy and for the choice of greenhouse gas emission mitigation path. An effective forecasting method can represent a useful tool for managing renewable energies in microgrids and mitigating carbon dioxide emission. In this study is evaluated the trend of CO2 emission in Iran, Canada and Italy and compared the CO2 emission from consumption of energy sources: Coal - Natural Gas - Petroleum and other refined hydrocarbons – Renewable Energies. Furthermore, a proposed intelligent method has been provided for CO2 emission forecasting based on Generalized Regression Neural Network and Grey Wolf Optimization. Furthermore, the proposed method has been used for renewable energies generation (Wind power and Solar power) forecasting in the microgrid of Favignana island (Italy). The obtained results confirm the higher accuracy of the proposed method in long-term CO2 emission forecasting and short-term renewable energies generation as compared with other several methods.

Keywords: CO2 Emission Forecasting; Energy Consumption; Generalized Regression Neural Network, Grey Wolf Optimizer, Renewable Energy;

* Corresponding author. Tel.: +39-331-879-4777; fax: +0-000-000-0000 .
E-mail address: azim.heydari@uniroma1.it

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1. Introduction

CO2 is one of the major greenhouse gas (GHG) and its emission main depends on the electricity generation systems [1] and the related demand side management [2]. The way of capturing CO2 from the polluted gas mixture has attracted a great deal of attention in the past decades [3]. To better manage GHG emissions in the building sector, predicting GHG emissions by region is necessary at first. In other words, GHG emissions by region can be integrated into the national-level GHG emission data, and finally, can be constructed a part of the national GHG emission management [4]. The CO2 emission is directly related to the economic growth, which is a key factor in the world economy both for production and consumption. Furthermore, most of the CO2 emissions are raised by the gaseous/liquid/solid fuel consumption, an essential source of the internal combustion engine vehicles and industries that are closely linked to the economic development and economic growth. Consequently, the intimate association between the CO2 emissions and economic growth plays a key role in the economic and environmental policy [5].

The future energy balance and trend of CO2 and power prices in the Italian thermoelectric sector were estimated and evaluated by Bianco et al. 2015 [6], using the Plexos modeling environment, and a market based simulation tool. This study investigated the effect of the power and CO2 price and suggested a future power and CO2 price so as to decrease the coal consumption and carbon emissions. Baareh 2013, suggested an Artificial Neural Network model (ANN) with four inputs data including global oil, natural gas, coal, and primary energy consumption to handle the time series forecasting of carbon dioxide emissions [7]. Dynamic impacts of GDP growth, energy consumption and population growth on CO2 emissions were investigated by Begum et al. using econometric approaches for Malaysia [8]. Curtis et al. 2016, evaluated the CO2 emissions from wind-power generation while considering North Atlantic Oscillation. In this study the hourly wind speed, electricity demand, and fuel and carbon price data were used to simulate an electricity system using the Plexos modeling environment [9]. In this study, in order to forecast carbon dioxide emission, a novel combined method (GRNN-GWO) based on Generalized Regression Neural Network (GRNN) and Grey Wolf Optimizer (GWO) has been developed. Afterwards, the results were compared to some single and combined methods like MLP, RBF, GRNN-PSO, and GRNN-TS. The results show excellent performance of the proposed method.

MLP	Multi-Layer Perceptron	PSO	Particle Swarm Optimization
RBF	Radial basis function neural network	MSE	Mean Square Error
GRNN	Generalized Regression Neural Network	RMSE	Root Mean Square Error
GWO	Grey Wolf Optimization	MAE	Mean Absolute Error
TS	Tabu Search	MAPE	Mean Absolute Percentage Error

2. Methodologies

2.1. Generalized Regression Neural Network (GRNN)

GRNN method is a type of Radial Basis Neural Network (RBNN) based on kernel regression networks [10]. It does not need an iterative method to simulate the results similar to back-propagation learning algorithms. It is able to estimate any arbitrary function between input and output data sets directly from training data [10], [11]. GRNN involves four layers of input, pattern, summation, and output. The numbers of input variables rely on the number of data sets observed from data collection in the input layer. The input layer gathers information and conveys to the pattern layer. The pattern layer is utilized to cluster the training process. Regularly the number of pattern layer neurons is equivalent to the number of data sets of training pairs [11].

2.2. Grey Wolf Optimization (GWO)

A new population-based nature-inspired algorithm called Grey Wolf Optimization (GWO) was developed by Mirjalili et al. [12]. This approach imitates the hunting behaviour and social leadership of grey wolves in nature. Four types of grey wolves including alpha, beta, delta, and omega are utilized for simulating the leadership hierarchy. The first three best position (fittest function) wolves are indicated as α, β and δ who direct the other wolves (ω) of the groups toward promising areas of the search space. Using the following mathematical equations, the encircling behaviour of each agent of the crowd is calculated:

$$\vec{D} = \left|\vec{C}.\vec{X}_p^t - \vec{X}^t\right| \quad , \quad \vec{X}^{t+1} = \vec{X}_p^t - \vec{A}.\vec{D}` \tag{1}$$

Here $\vec{X}_p^t$ and $\vec{X}^{t+1}$ are the current location and the next location of any wolf respectively. $\vec{A}$ and $\vec{C}$ are coefficient vector. $\vec{D}$ is a vector that depends on the location of the prey $\vec{X}_p^t$. The vectors $\vec{A}$ and $\vec{C}$ are formulated as the following:

$$\vec{A} = 2l.r_1 \quad , \quad \vec{C} = 2.r_2 \tag{2}$$

Here l is coefficient vector which is reduced linearly from 2 to 0 . r_1 and r_2 are the random numbers between [0,1]. To simulate the hunting behaviour mathematically, it is assumed that the alpha, beta, and delta have better information regarding the potential location of prey. Looking for prey and attacking prey: $\vec{A}$ is a random value in the gap $[-2A, 2A]$. When random value $|\vec{A}| < 1$ the wolves are forced to attack the prey. Looking for prey shows the exploration ability and attacking the prey indicates the exploitation ability. To force to search for moving away from the prey, the arbitrary values of $\vec{A}$ are utilized. When $|\vec{A}| > 1$, the members of the population are enforced to diverge from the prey.

3. Proposed Forecasting Method (GRNN-GWO)

First Stage: Input Data

At this stage, first, the input parameters of the model will be determined. Certainly, this step is one of the stages that directly correlates with the acceptable error of output prediction. In this paper, the following four parameters have been considered as input parameters of the model: 1. Coal, 2. Natural Gas, 3. Petroleum and Other Liquids, and 4. Renewable Energies. In this research, annual data for 36 years (1980-2015) are used as the input of the model.

In addition, three case studies (information about Iran, Italy, and Canada) are used to develop research and prove the efficiency of the proposed forecasting model. Figure (1) shows the rate of energy source consumptions using the U.S. Energy Information Administration (EIA) data.

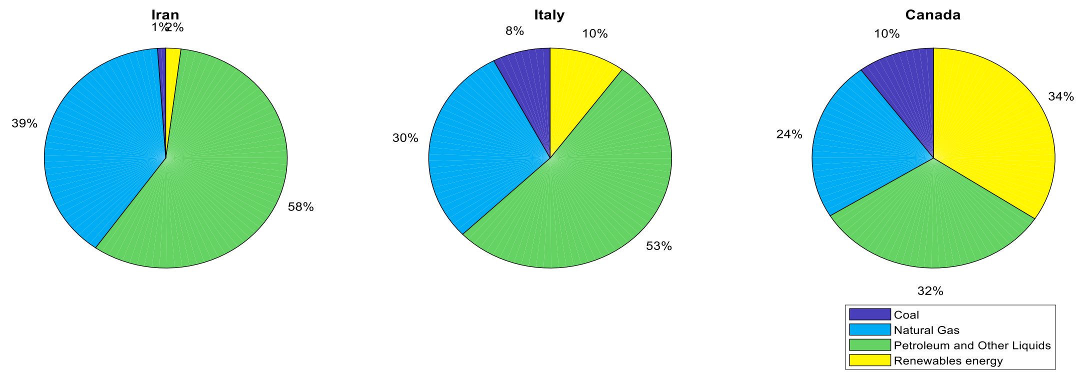

Fig. 1. Percentage of Coal, Natural Gas, Petroleum and Other Liquids, and Renewables Energies consumptions in Iran, Italy and Canada

Second Stage: Training the Method

In the training stage, the model is trained by using part of input data. Since the proposed model is a hybrid model (neural network and optimization algorithm), optimum values of the neural network parameters (weights and biases) should be optimized in the training stage by using meta-heuristic optimization algorithm. The proposed model in this article is based on combining GRNN and GWO's intelligent algorithm. Since each optimization problem has at least one objective function of the maximum or minimum type, in this study we use the objective function to reduce the error of the training stage. In this study, the MSE error function is used as the objective function. The MSE function is as follows:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(x_{act_i} - x_{for_i}\right)^2 \tag{3}$$

Here, X_{for} is the predicted value, X_{act} is the actual value, and m is the number of data. In the training of the neural network, the number of weights and bias depends on the number of layers and neurons.

Third Stage: Testing the Method

After calculating the optimal values of the model parameters (weights and bias), we test the model using the test data matrix and calculate the values of various error functions (RMSE, MAE, MAPE), and if the obtained errors are not acceptable, we return to the second stage.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(x_{act_i} - x_{for_i}\right)^2} \quad , \quad MAE = \frac{1}{m}\sum_{i=1}^{m}\left|x_{act_i} - x_{for_i}\right| \quad , \quad MAPE = \frac{100}{m}\sum_{i=1}^{m}\left|\frac{x_{act_i} - x_{for_i}}{x_{act_i}}\right| \tag{4}$$

The flowchart of the proposed forecasting method (GRNN-GWO) is shown in fig (2).

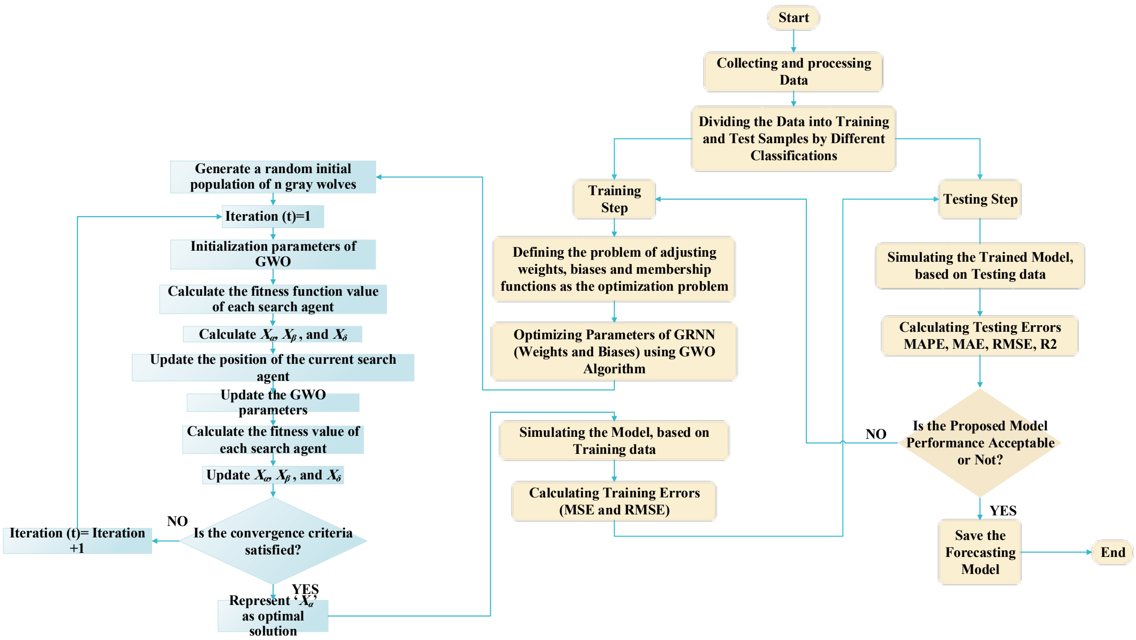

Fig. 2. Flowchart of the proposed forecasting method (GRNN-GWO)

4. CO2 Emission Forecasting Results in National Grids

Nowadays, soft computing is extremely helpful in solving various complex problems, such as predicting sensitive parameters for the next stages, optimization, image processing, classification, and so on. As discussed previously, the purpose of this paper is to anticipate the amount of produced carbon dioxide by energy consumption using data about the amount of produced carbon dioxide from different energy sources. In this study, various intelligent approaches (MLP, RBF, GRNN-PSO, GRNN-TS) are used as predictive intelligence models. Table (1) shows the predicted results of the proposed model and other intelligent approaches presented in this study using the relevant data of Iran.

Table. 1. Performance of the proposed method and other methods for CO2 emission forecasting (Iran)

Iran												
Error Function		CNN [13]	ANN-DE [14]	MLP-RCGA [15]	EL-ICA [16]	EL-PSO [16]	MLP	RBF	GRNN		
									TS	PSO	GWO
RMSE	Best Error	0.0356	0.0342	0.0226	0.0241	0.0231	0.0498	0.0371	0.0234	0.0228	**0.0155**
	Average Error	0.0387	0.0364	0.0322	0.2388	0.2362	0.0534	0.0353	0.0254	0.0232	0.019
MAE	Best Error	0.0251	0.0387	0.0311	0.0572	0.028	0.0459	0.0257	0.01782	0.0168	**0.0133**
	Average Error	0.0259	0.0399	0.0461	0.0667	0.0412	0.0482	0.0257	0.02019	0.0179	0.0162
MAPE	Best Error	5.8934	6.0161	5.9002	6.89	6.129	7.0012	6.2349	6.806	5.598	**4.8641**
	Average Error	7.4231	7.7334	7.8902	7.82	6.72	7.6744	7.63543	8.3366	8.4931	6.3923

As shown in table (1), the performance of the proposed approach is very better than the other proposed approaches (MLP, RBF, GRNN-PSO, GRNN-TS). Table (2) shows the predicted results of the proposed model and other intelligent presented approaches in this study by using the relevant data of Italy.

Table. 2. Performance of the proposed method and other methods for CO2 emission forecasting (Italy)

Italy											
Error Function		CNN [11]	ANN-DE [12]	MLP-RCGA [13]	EL-ICA [14]	EL-PSO [14]	MLP	RBF	GRNN		
									TS	PSO	GWO
RMSE	Best Error	0.0534	0.0323	0.0273	0.02419	0.04341	0.0398	0.0711	0.0475	0.04768	**0.0111**
	Average Error	0.0701	0.0611	0.0514	0.07482	0.06331	0.06592	0.07393	0.0639	0.0508	0.0178
MAE	Best Error	0.0424	0.0351	0.0211	0.0675	0.058	0.03046	0.04683	0.0377	0.0371	**0.0094**
	Average Error	0.0561	0.0425	0.0334	0.0777	0.0822	0.04732	0.05194	0.05267	0.0426	0.01352
MAPE	Best Error	6.1531	5.3351	4.0035	7.121	5.494	5.1191	6.6198	7.3186	6.4318	**2.3268**
	Average Error	8.0171	7.4561	5.7112	7.771	6.812	8.07923	8.92648	10.1164	8.9794	3.42765

Table (3) shows the predicted results of the proposed model and other intelligent presented approaches in this study by using the relevant data of Canada.

Table. 3. Performance of the proposed method and other methods for CO2 emission forecasting (Canada)

Canada											
Error Function		CNN [11]	ANN-DE [12]	MLP-RCGA [13]	EL-ICA [14]	EL-PSO [14]	MLP	RBF	GRNN		
									TS	PSO	GWO
RMSE	Best Error	0.0563	0.0289	0.0241	0.0619	0.0314	0.0213	0.0757	0.0255	0.0662	**0.02**
	Average Error	0.0678	0.0319	0.0266	0.0708	0.0435	0.0244	0.0702	0.0286	0.0582	0.0230
MAE	Best Error	0.0481	0.0271	0.0202	0.0371	0.0328	0.0147	0.0592	0.0221	0.0599	**0.0121**
	Average Error	0.0588	0.0327	0.0261	0.0401	0.0389	0.0204	0.0549	0.02411	0.0509	0.0168
MAPE	Best Error	6.9458	5.8825	4.0112	5.167	3.819	4.8055	7.1163	2.6407	4.6577	**2.2194**
	Average Error	8.0102	7.2721	6.1211	6.112	4.012	6.4501	9.5757	3.7715	6.2493	2.9665

As shown in tables 1-3, the proposed approach is presented in three case studies. The results show that the proposed approach has a good efficiency and has the least error. According the factors that have been provided in the figure (1), all factors have different fluctuations and there are fluctuations for the three countries studied. Therefore, as you can see from the results of the methods presented in the tables (1-3), the proposed method is well able to predict the amount of carbon dioxide emissions by 5 inputs, given the complexity of the problem. This prediction model is highly able to predict and manage greenhouse gas emissions, including carbon dioxide emissions.

5. Renewable Energies Management Results in Microgrids

5.1. Effective of Renewable Energies on CO2 Emission in Microgrids

As described in the above sections related to the CO2 emission prediction, the percentage of CO2 emissions from different energy consumption varies in the three countries studied. According to figure (1), the amount of CO2 emission due to the consumption of renewable energies versus their high efficiency is negligible. This means that the CO2 emissions from renewable energies in Italy are an average of 10%. In this section, an attempt has been made to investigate a microgrids electricity based on renewable energies generation. In this study, the Favignana region has been used as a microgrids with a high potential for renewable energies generation in Italy. In the next section, we have predicted the wind and solar energy generation in Favignana using the proposed forecasting method.

5.2. Renewable Energies Forecasting in FAVIGNANA

The prediction of renewable energies in microgrids is a highly effective approach to energy management in these grids. In this study, data on the renewable energy generation (wind and solar energy) in Favignana, Italy (as a microgrid), was used to provide an efficient model for predicting renewable energy generation in microgrids. In this section, the proposed forecasting method is used to predict renewable energy generation. Table (4) shows the performance of the proposed method and other methods.

Table. 4. Performance of the proposed method and other methods for renewable energies forecasting in Microgrids (FAVIGNANA)

Methods

Renewable Energies	Error Function	CNN [11]	ANN-DE [12]	MLP-RCGA [13]	EL-ICA [14]	EL-PSO [14]	MLP	RBF	GRNN		
									TS	PSO	GWO
Solar Power Generation	RMSE	0.6732	0.7732	0.5476	0.5019	0.4119	0.8219	0.73529	0.39987	0.3798	0.215529
	MAE	0.3891	0.4523	0.3381	0.1515	0.0972	0.4918	0.4183	0.1015	0.0965	0.07166
	MAPE	6.91	7.02	5.23	3.65	2.91	7.2	7.28	3.12	2.22	1.89
Wind Power Generation	RMSE	0.6243	0.6634	0.5487	0.6649	0.6019	0.8889	0.6729	0.5911	0.5189	0.3901
	MAE	0.6011	0.5784	0.5198	0.5515	0.1179	0.8132	0.6239	0.2729	0.1065	0.0911
	MAPE	8.211	6.023	5.812	5.43	3.912	9.1	8.84	4.1	371	3.117

6. Conclusion

In this study, we endeavor to provide the forecasting method more efficient and effective for CO2 emission prediction in 3 national grids and renewable energy prediction in microgrid. The major contribution of the paper is combining the Generalized Regression Neural Network based on optimizing the hyper parameters in the training process of the GRNN method through Grey Wolf Optimizer algorithm. In addition, the proposed method is tested with the total carbon dioxide emissions data of Iran, Italy, and Canada in 1980-2015. Furthermore, the proposed method is used to predict renewable energies with data of Favignana in 2009 (daily). Also, the forecasting performances of the proposed method has been compared with BP some intelligent methods (MLP, RBF, GRNN-PSO, and GRNN-TS). As outlined in the results section, the proposed method is well able to manage the generation of renewable energies and environmental emission in national and microgrids.

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