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# Modeling of energy consumption and related GHG (greenhouse gas) intensity and emissions in Europe using general regression neural networks

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ABSTRACT

This paper presents a new approach for the estimation of energy-related GHG (greenhouse gas) emissions at the national level that combines the simplicity of the concept of GHG intensity and the generalization capabilities of ANNs (artificial neural networks). The main objectives of this work includes the determination of the accuracy of a GRNN (general regression neural network) model applied for the prediction of EC (energy consumption) and GHG intensity of energy consumption, utilizing general country statistics as inputs, as well as analysis of the accuracy of energy-related GHG emissions obtained by multiplying the two aforementioned outputs. The models were developed using historical data from the period 2004–2012, for a set of 26 European countries (EU Members). The obtained results demonstrate that the GRNN GHG intensity model provides a more accurate prediction, with the MAPE (mean absolute percentage error) of 4.5%, than tested MLR (multiple linear regression) and second-order and third-order non-linear MPR (multiple polynomial regression) models. Also, the GRNN EC model has high accuracy (MAPE = 3.6%), and therefore both GRNN models and the proposed approach can be considered as suitable for the calculation of GHG emissions. The energy-related predicted GHG emissions were very similar to the actual GHG emissions of EU Members (MAPE = 6.4%).


## 1. Introduction

Since the Kyoto protocol in 1997, GHG (greenhouse gas) emissions have become an urgent priority of global environmental policy [1]. In the Protocol's first commitment period (2008–2012), GHG emission targets were set for industrialized countries, aiming for an overall reduction of GHG emissions by 5.2% compared to the recorded level in 1990. The GHG emission data from 2009 shows that, unlike some other countries, the 27 members of the EU have achieved their emissions reduction target of 8%, with an overall GHG reduction of 9.3% compared to the 1990 level. Central and Eastern European countries contributed notably to this reduction, since they have an emission level below their 1990 levels, by more than 8%, due to an economic slow-down in the region in the post-Soviet era [2].

In the second Protocol's commitment period (2012–2020), known as the Doha Amendment [3], the European Union committed to further reduce GHG emissions by up to 30% until 2020, compared to the 1990 levels. As in 1990, the energy-related activities remain the major source of GHG emissions, reaching the share of almost 80% of all GHG emissions within the EU [2]. Consequently, a significant reduction of GHG emissions will be needed in the energy sector and current GHG policies need to be enhanced with new emission reduction measures in order to achieve the targets for GHG reduction.

In 1999 Argentina started to use a GHG emissions target that was normalized by GDP (gross domestic product), and since 2002, when the so called GHG “intensity” concept was embraced by the USA, many other countries have since adopted various forms of GHG intensity targets [4]. As a relatively simple concept, GHG intensity measures the GHG emissions per unit of economic or energy output, and therefore it is an indicator of efficiency:

$$GHG_{intensity} = \frac{GHG_{emission}}{GDP}\left(\frac{tCO_2e}{€}\right) \quad (1)$$

where GHG emission is expressed in carbon dioxide equivalent ($CO_2e$).

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An important advantage of the GHG intensity concept is that it significantly reduces the uncertainty of future projections, especially for developing countries. The uncertainty bands range from one to several percentage points, which is up to ten times lower in comparison with the uncertainty of the absolute GHG emission projections [5].

Emission inventories, e.g. EMEP/EEA (European Environment Agency) guidebook and the US EPA (Environmental Protection Agency) AP42 guidebook, are the main sources of GHG emission data. In an emission inventory, the GHG emission data for the majority of the emission sectors is obtained by multiplying the estimated values of emission factors with the activity rate [6]. Besides the emission inventories, sectoral GHG emissions were the subject of many studies [7–14]. Under the UNFCCC (United Nations Framework Convention on Climate Change), energy-related GHG emissions for the EU are derived using the PRIMES (Price-Induced Market Equilibrium System) model which is a simulation model of the future energy balances, investment costs, prices and emissions per country [15,16].

ANNs (Artificial neural networks), among other methods, are frequently being used for the estimation of energy consumption [17–19]. Also, in many studies ANNs were used for the estimation of GHG emissions in various production [20,21] and agro-ecosystems [22,23]. Khoshnevisan et al. [24] applied ANNs for the prediction of GHG emissions based on energy inputs in the wheat production, whilst Bevilacqua et al. [25] and Radojević et al. [26] used ANNs for the estimation of $CO_2$ emissions at the national level in Italy and Serbia, respectively.

A GRNN (general regression neural network) provides relatively accurate predictions of the total national GHG emissions using sustainability, economical and industrial indicators as inputs [27]. The GRNN model is convenient because, being a non-parametric technique, it can be trained to estimate behavior of complex systems, provided that sufficiently representative datasets are available. Also, GRNNs require a selection of a single parameters and, unlike conventional ANNs, does not need iterative training [28].

In this paper, the EC (energy consumption) and GHG intensity of energy consumption are estimated using a GRNN model and basic country and energy statistics, while the prediction of energy-related GHG emissions was performed by multiplying the EC and GHG intensity of energy consumption estimated by the GRNN model.

The paper is organized as follows: the second section provides an overview of methodology used, including the data sources and calculation of GHG intensity of energy consumption, regression techniques and model performance metrics used in the current study. Section 3 provides the results obtained using the tested models, as well as the estimates of energy-related GHG emissions, while section 4 presents the paper's conclusions.

## 2. Materials and methods

### 2.1. GHG intensity data

In this study, GHG emissions are expressed in $CO_2e$ (carbon dioxide equivalents) and the GHG intensity of energy consumption is calculated as the ratio between energy-related GHG emission and GIEC (gross inland energy consumption). The GHG emissions included in the calculation are those of source category 1 (Energy) under the UNFCCC [29]. GIEC indicates consumption by the energy sector itself, distribution and transformation losses and final energy consumption by end users. Eurostat calculates GIEC as follows: primary production + production from other sources + recovered products + imports - exports + variations of stock bunkers [30]. The GHG intensity of energy consumption is calculated for all EU28 members except Malta and Lichtenstein, for the period 2004–2012. The mean values of energy-related GHG emissions, GIEC and GHG intensity of energy consumption and their change in the studied period are presented in Table 1.

In Table 1 it can be seen that the energy-related GHG emissions for this nine year period have been reduced by up to 28%, in all countries, except Poland, Estonia and Bulgaria. GIEC data also indicates a reduction in energy consumption for up to 23%, in the case of Lithuania, and also a notable increase in the case of Estonia and Poland. Consequently, for the majority of countries GHG intensity of energy consumption has been reduced, but also in the case of Lithuania, Bulgaria and Germany it has increased by 28%, 7% and 1%, respectively.

The calculated GHG intensity of energy consumption for 2012 is presented in Fig. 1. The GHG intensity of energy consumption ranges from 0.84 $tCO_2e$/toe, in the case of Finland, to 3.26 $tCO_2e$/toe in the case of Poland.

### 2.2. Input data

Only widely available basic energy statistics, obtained from Eurostat, were used as inputs to the GRNN GHG intensity model: GIEC [30] normalized per capita in order to allow comparison of countries of different sizes, SRE (share of renewable energy in gross final energy consumption) [31], CHP (combined heat and power) generation [32], SRET (share of renewable energy in fuel consumption of transport) [33], and implicit tax rate on energy (TAX) [34]. The indicator “combined heat and power generation” gives a share of used cogeneration to improve energy efficiency through the generation of heat and power in the same plant, while the implicit tax rate on energy is an indicator of the ratio between energy tax revenues and final energy consumption.

Considering that Aydin [17] created a highly accurate regression model for the prediction of annual energy consumption in Turkey utilizing only two inputs, CP (country population) and GDP (gross domestic product), the GRNN-EC (energy consumption) model was initially created using the same two inputs. However, since Ayden's regression model was country specific and the model in this study covers 26 countries, several additional inputs, namely ED (energy dependence), UP (urban population), SI (share of industry) and MR (motorization rate), were added as alternatives, in order to enhance the accuracy and generality of the model. The country population, GDP and energy dependence data were obtained from Eurostat [35], while the urban population, share of industry and motorization rate data were obtained from the World Bank [36].

The data from 2004 to 2011 was randomly divided into two subsets used for training and validation, in the ratio 4:1. Data from the year 2012 was used as the test dataset. Descriptive statistics of input and output data used for the GRNN development and evaluation are presented in Table 2.

### 2.3. General regression neural network

The GRNN is a one-pass learning algorithm that can be used for the estimation of continuous variables, and converges to the underlying regression surface. The principal advantages of the GRNN are its quick learning and fast convergence to optimal regression surface as the number of samples becomes large [37]. It consists of four layers, which are presented in Fig. 2.

The GRNN, as a supervised network, measures the distance ($D_j$) of the training patterns in $N$-dimensional space, and then the calculated $D_j$ is processed in the pattern layer using an exponential activation function. The summation neurons $S_1$ computes the sum of the weighted outputs of the pattern layer, while $S_2$ calculates the un-weighted outputs of the pattern neurons [11]. The output layer divides the output of the $S_1$ neuron by the output of the $S_2$ neuron