Renewable Energy sources are on track for climate change mitigation: Classification of their carbon intensity by neural approach

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Abstract **During the last decades, alerts raised warning from a more and more severe climate change. In this field, country's energy policy is a main question for tackling climate change. In fact, the man is commonly condemned by the climate change intensification. This can be closely linked to his overuse of fossil fuels. Those are the biggest issuers of greenhouse gases, particularly dioxide of carbon. Hence, for reducing carbon emissions the alternative is for renewable energy. This paper aims to highlight the environmental value of renewable energy in matter of carbon emissions dejection. In that regard, the neural approach was applied to approve the weak carbon intensity of renewable energy. Our results amply support the literary thoughts about renewable energy effectiveness and its low carbon emissions. So, renewable sources are on track for climate change mitigation.**

Keywords Renewable Energy, Climate Change, Neural Networks.

I. INTRODUCTION

The nonrenewable energy sources are so limited, economically expensive and highly greenhouse gases emitters. In that, they contribute widely to the global warming (Lebot, 2005). However, the common opinion is wholly inverted toward the renewable sources. Indeed, all the recent studies mainly highlight the strong link between renewable energy and climate change mitigation (Wallaert, 2011; Tissot-Colle and Jouzel, 2013). On this lineage of thought, the special report published, in 2011, by the Intergovernmental Panel on Climate Change (IPCC) advocates better exploitation and use of renewable energy.

The present paper analyzes the effect of seven sources of renewable energy, measured by their supply indexes, on the world carbon intensity. So, in our empirical study, we use the method of Multilayer Perceptron which is an artificial neural network. It allows us to test the sensitivity of all the studied renewable sources. The sensitivity analysis will serve us for the classification of these energy sources according to their weights in matter of carbon emissions reduction (Edenhofer *et al*., 2011). The paper is structured in two sections. In the first one, we present the economic and environmental stakes of renewable energy in a growing climate change context. The last section is reserved for our empirical study and thus the classification of renewable energy sources according to their weak carbon intensity.

1. Economic and environmental stakes of renewable energy in climate change context

With the global warming intensification, there was a second energy evolution (Wallaert, 2011). Indeed, the first one consisted in the discovery of fossil fuels and their exploitation. The new or the second evolution rather concerns the exploitation of renewable energy (EnR).

This latter is said "green" or "clean" energy because it is the lowest greenhouse gas (GHG) emitter. Therefore, if these energies are well exploited, they will be effective for global climate change relieving. In fact, renewable energy promotion can solve two global challenges. Firstly, renewable sources serve the wrestling against the global warming through greenhouse gas emissions reduction, the main objective of the Kyoto protocol. Secondly, they are an alternative solution against fossil fuels insufficiency (Wallaert, 2011). Hence, renewable energy is a futuristic solution for alleviating climate change; taking up the challenge of energy access; creating income and improving living standards.

In this regard, several works deal of the link between renewable energy development and climate change mitigation. Among them, the most important is the special report of the Working Group III of the Intergovernmental Panel on Climate Change in 2011. According to this report, the demand of energy and its related services experienced an upward trend. This increasing claim is strictly linked to socio-economic development and well-being improvement. In fact, energy is the skeleton of any country's economic and social activities. In that, any society needs it to satisfy its fundamental needs (lighting, food cooking, air conditioning, transport, communications, production, etc.). In this frame, since 1850, the world exploitation of fossil fuels (coal, oil and natural gas) increased to satisfy the essential energy supplies. Consequently, the world emissions of carbon dioxide (CO2) have highly increased. As well, the others greenhouse gases, connected to the energy exploitation and its consumption, have clearly increased leading to an historic atmospheric concentration of GHG (Edenhofer et al., 2011). Indeed, in its fourth appraisal report of 2007, the IPCC concluded that: "The main part of the globe's average temperature rise, observed since the middle of the 20 century, is very probably attributable to the increasing anthropological concentrations of GHG"3 (Pachauri and Reisinger, 2007, p.5). Studies and recent inquiries confirm that fossil fuels consumption has increased. As consequence, CO2 emissions recorded, at the end of 2010, a concentration of more than 390 parts per million (ppm). This quantity is superior of more than 39% to the preindustrial levels.

In this field, world efforts aims to maintain the average warming to 2°C, compared with the preindustrial level. Not exceeding this threshold means that the worldly GHG emissions from now to 2050 have to be reduced to the half compared with 2000's level (that is almost the third of current emissions). The CO2 emitted by fossil fuels causes a yearly rise of the earth's temperature of 3%. Therefore, the immense challenge that we need to face is the fast mitigation of the CO2. Hence, the prospect will be for renewable energy and carbon sober economy.

2. CLASSIFICATION OF RENEWABLE ENERGY SOURCES ACCORDING TO THEIR WEAK CARBON INTENSITY: A SENSITIVITY ANALYSIS BY THE MULTILAYER PERCEPTRON NEURAL NETWORK.

In the sequel, we begin by presenting the research's methodology. Then, we proceed to the results interpretation.

3.1. METHODOLOGY

Within the framework of this research, we make recourse to the neural approach which is capable to bring closer any problem in spite of its complexity. In reality, there are many types of networks but the most common used is the multilayer perceptron (MLP), which is a completely connected network (Rosenblatt, 1962). The MLP is settled by many layers: an entrance layer (input layer) that receives exogenous data; an exit layer (output layer) which gives results; and one or several middle layers (hidden layers). These letters are responsible for the network's compilation and they can capture all the non-linearity relationships between 3 explanatory variables. The basic components of each layer are neurons which are connected to various others in the next layer. The information passes forward of the entrance layer to the exit one without backward return. For that, the MLP is called a "feed forward" neural network. According to Minsky and Papert (1969), the MLP is powerful in training and generalization. It constitutes a useful technique for sensitivity analysis of explanatory variables. In fact, when we disrupt one of the network's entrances, the training performance measured by the mean square error (MSE) varies. This variation is the biggest if the disrupted variable has more influence on the endogenous (Jemli *et al*., 2010).
The standard formula of the MSE is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \qquad (1)$$

With: n: the number of observations in the data set ; $\hat{y}_i$: the output simulated by the network ; and y_i : the observed output or target.

3.1.1. Sensitivity Analysis by the MLP neural network

The MLP neural network is useful for undertaking the sensitivity analysis of the network's entrances. This analysis allows us testing the influence of exogenous or explanatory variables (inputs) on endogenous or dependent ones (outputs). This influence depends on the relative variation of the training MSE after any entrance disruption. This variation is generally known as "the delta's error". It allows us classifying all the exogenous variables according to their relevance for network's output (Pastor-Bárcenas *et al*., 2004). In effect, sensitivity analysis is: "the study of how the uncertainty in the output of a mathematical model or system (numerical or otherwise) can be apportioned to different sources of uncertainty in its inputs" (Saltelli et al.,

2008, p.1). The main purpose of sensitivity analysis is to estimate the weights of entrances' disturbances on the model's exit. So, significance of relationship between entrances and exits, presence of non-linearities and variables' interactions can be only detected by sensitivity analysis. Several works have applied the analysis of sensitivity by MLP. Among them: Hewitson and Crane (1994) used the sensitivity analysis to approximate the main components of local precipitation conditions for the south of Mexico; and Tangang et al. (1998) applied it for temperature anomalies' prediction for sea surface of Equatorial Pacific Ocean.
Sensitivity analysis is suited to answer a complex question such as: what is the weakest CO2 emitter source? So, we can help decisions-makers in matter of energetic effectiveness and propose to them high-quality recommendations.

3.1.2. Sample and Choice of the model

Our sample is formed by 21 observations for covering the period 1990 to 2010. The inputs data are temporal series (annual world values) of renewable energy supply indexes for seven4 sources. The output data is the value of annual world carbon intensity (Table 1).

The first stage of the model's conception consists of decomposing its data into three samples: training, test and validation. The training sample covers 60% of the total dataset which is equal to 13 observations. As for test sample, it represents 20% of the whole observations (what is equivalent to 4 observations). Also, the sample of validation is formed by 4 observations which represent 20% of the dataset. The second stage consists of running the model and testing various architectures. This step means to play on the number of layers hidden as well as on that of their neurons. These architecture's modifications entail at their tours the variation of the mean square errors for the three samples above mentioned. The 4 selection rule of the MLP supposes retaining the model that has simultaneously the weakest testing MSE and a significant reduction of its training MSE (compared with its initial value).

Table 1: Model's variables: Inputs and output of the MLP network

Data	Symbol in the model	Name in the database	Sources
Inputs	X1	Renewable Energy Supply Index - Biofuels: biogasoline and Biodiesel	*Geodata Portal UNEP (2013)*
	X2	Renewable Energy Supply Index - Geothermal	*Geodata Portal UNEP (2013)*
	X3	Renewable Energy Supply Index - Hydro	*Geodata Portal UNEP (2013)*
	X4	Renewable Energy Supply Index - Solar Photovoltaic	*Geodata Portal (2013)*
	X5	Renewable Energy Supply Index - Solar Thermal	*Geodata Portal UNEP (2013)*
	X6	Renewable Energy Supply Index - Tide, Wave, Ocean	*Geodata Portal UNEP (2013)*
	X7	Renewable Energy Supply Index - Wind	*Geodata Portal UNEP (2013)*
Output	Y1	CO2 Intensity (kg per kg of oil equivalent energy use)	*WDI (2013)*

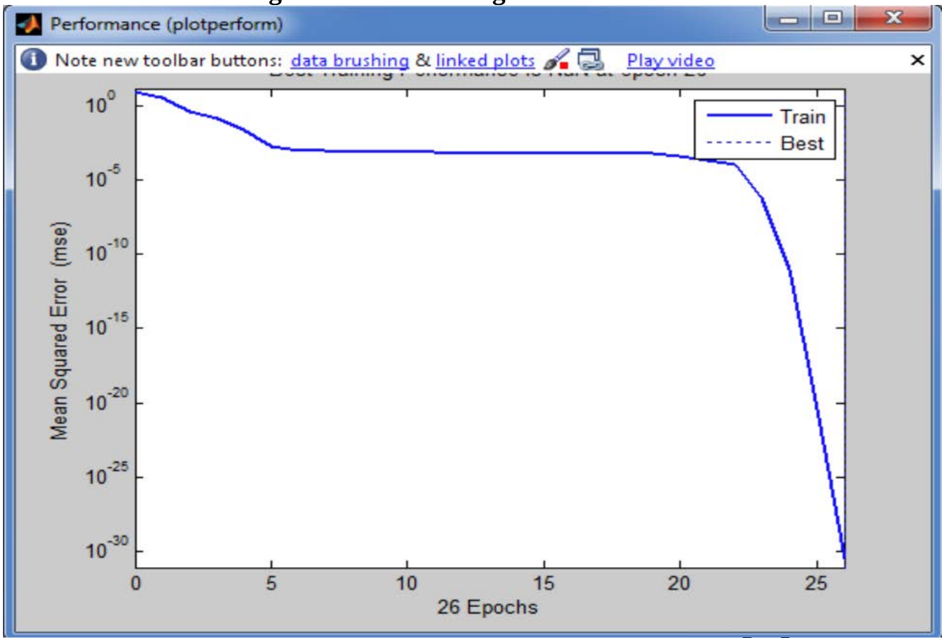
Source: World Bank, World Development Indicators - WDI - (2013) & United Nations Environment Programme - UNEP Geodata Portal - (2013).

So, in this work we retain the network R20 which is a MLP with two hidden layers and has as architecture5: [7 14 3 1]. Its testing MSE is about 0.1779 and its training one decreased considerably from 7.32 (which is too high) to 3.15E-31. This network reaches the minimum gradient after 26 iterations. Thus, it manages the training of a complex phenomenon after a reasonable number of iterations. It is not condemned by the overtraining. Indeed, the same network applied to another sample (test set) always keeps a good performance (that meaning a low testing MSE). Furthermore, the activation function for both hidden layers is the sigmoidal. While for the output layer, the activation function is the linear.

3.2. Results Interpretations

Our MLP ("R20") is endowed with a good training capacity. During this phase, the MSE of the training dataset diminishes significantly and then converges to its minimum gradient: 3.15E-31 (Figure 1).

Figure 1 : The training MSE's evolution



The retained network is composed of 7 neurons on the entrance layer, 14 on the first hidden layer, 5 on the second hidden layer and 1 on the output layer.
Source: Authors' Estimations (2013).

So, this neural network has a high-quality convergence during its training process. Moreover, this network is marked by its robustness (the capacity of learning from new inputs-output couples). In fact, we notice low values for the test and validation MSE which are respectively 0.1779 and 0.
In addition, this MLP is characterized by a high-quality linear adjustment between its real output "Target" (the observed value of carbon intensity) and its simulated one (the network's output). Indeed, the R-value is equal to 1. And, its linear adjustment regression is given as follows:

$$Output = 1 * Target + 1.2^{-0.16} \qquad (2)$$

According to sensitivity analysis' results, each one of the seven renewable sources has a significant effect on the carbon intensity. The relative variation of the training MSE is very high. It is included between a minimum value of 7.77E+28 and a maximum of 2.04E+30. Thereby, deleting any of them leads to a sharp increase in the training MSE. Hence, each one of these renewable sources has a significant effect on the carbon intensity mitigation (Table 2).

Table 2: Sensitivity analysis and energy sources classification according to their weak carbon intensity

	Relative variation of the training MSE	Sensitivity Order	Classification of renewable sources starting by the weakest carbon intensity
Training MSE (X2 = 0)	2.04 E $^{+30}$	1	Geothermic
Training MSE (X6 = 0)	1.11 E $^{+30}$	2	Marine
Training MSE (X3 = 0)	1.05E $^{+30}$	3	Hydraulic
Training MSE (X4 = 0)	7.88 E $^{+29}$	4	Solar Photovoltaic
Training MSE (X7 = 0)	6.37 E $^{+29}$	5	Wind
Training MSE (X5 = 0)	1.34E $^{+29}$	6	Solar Thermal
Training MSE (X1 = 0)	7.77 E $^{+28}$	7	Biomass

Source: Authors' Estimations (2013).

CONCLUSION

Several studies highlighted the utility of renewable energy in the fight against the global warming. For testing the weak carbon intensity of renewable energy we analyze the sensitivity, by a MLP neural network, of seven EnR sources. The results of the sensitivity analysis consolidate the strong link between each of renewable sources (measured by its supply index) and carbon emissions reduction. This analysis allows us to classify these sources according to their weakest carbon intensity. So, the geothermal energy is the weakest source of carbon emission. Indeed, its deleting entailed the biggest increase of the carbon intensity estimation error. In fact, its relative variation of the training MSE is about 2.04E+30. Nevertheless, it has certain disadvantages such as its scarce geographical availability as well as its serious consequences on the under-terrain temperature if it is over-exploited. The biomass is classified as the biggest carbon emitter renewable energy. The deleting of this source leads to the lowest increase of the training MSE among all the studied renewable sources. The relative variation of its training MSE is around 7.77E+28. In effect, its exploitation requires the transport and raw materials treatment, which are already activities of high CO2 emitting. In its turn, this source if over-exploited, it will have big threats on biodiversity, forests and grounds.

However, the country's commitment in one or other of renewable energy sources is pre-conditioned by multiple criteria such as: availability, technical feasibility, investment costs, financial profitability, and environmental repercussions. As a consequence, it would be interesting to combine the exploitation of several renewable sources. This combination could be useful for moderating their carbon emissions as well as their environmental disadvantages. In that, it is interesting to compensate between renewable sources that are relatively less CO2 emitter and those having small environmental disadvantages.

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