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Article

Current status investigation and predicting carbon dioxide emission in Latin American countries by connectionist models

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Abstract: Nowadays, one of the biggest concern of human being is greenhouse gas emission, especially carbon dioxide emission in developed and under-developing countries. In this study, connectionist models including LSSVM (Least Square Support Vector Machine) and evolutionary methods are employed for predicting the amount of CO2 emission in six Latin American countries, i.e. Brazil, Mexico, Argentina, Peru, Chile, Venezuela, and Uruguay. The studied region is modelled based on the available input data in terms of Million tons including oil (Million tons), gas (Million tons oil equivalent), coal (Million tons oil equivalent), R_{ew} (Million tons oil equivalent), and Gross Domestic Product (GDP) in terms of billion US dollars. Moreover, the available patents in the fields of climate change mitigation in six Latin American countries namely Brazil, Mexico, Argentina, Peru, Chile, Venezuela, and Uruguay has been reviewed and analyzed. The results show that except Venezuela, all other mentioned countries have invested in renewable energy R&D activities. Brazil and Argentina have the highest share of renewable energies which account for 60% and 72% respectively.

Keywords: CO2; Modeling; Environment; South America; Connectionist Model

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1. Introduction

The continuous rise of carbon dioxide emissions is a major cause of global warming. Global warming is one of the biggest and probably most difficult environmental, social and economic threats that the world has faced so far in the recent century [1]. Increasing carbon dioxide emission into the atmosphere is one of the main reasons for global warming with adverse environmental effects such as sea level rise, floods, droughts, etc. During the 20th century, the average temperature of the earth has increased by 0.6 degrees, and it is estimated that it will increase 1-5 more degrees in the next century [2]. According to the studies conducted by the world meteorological organization, the average global temperature in 2015 has been the highest one ever recorded. Based on research, a combination of El Nino streams and global warming resulted by human activities has led to the highest recorded average global temperature in 2011 to 2015. COP21 conference in Paris could be regarded as a sign of solidarity and amenability for tackling the problem of climate change. The primary aim of COP21 is to prevent the increase of global temperature under 2 Celsius degrees and also to limit this increase under 1.5 degrees compared to the time before industrialization. One of the outcomes of this treaty was the enactment of supporting plans for providing financial resources for countries to reconstruct damaged structures w polluting the environment.

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One of the substantial solutions in facing climatic changes is a reduction of carbon dioxide emission [2,3] and the best way to prevent destructive environmental outcomes is capturing and storing this gas [4]. One of the key researches in the field of carbon capture and storage technology was about analyzing the potential of carbon capture and storage in power plants [5]. Due to the fact that the available systems in such power plants were the same as the kind of available capture systems in coal power stations, an estimation has been made about the reduction of greenhouse gas effects until 2030 via Carbon capture and storage technology. In the first stage, researchers have found that the initiation time and dispersion rate of the technology are of importance when it comes to determining the emission reduction rate and fuel consumption for Carbon capture and storage technology [6]. The influential approaches which are currently carried out are namely, making energy systems more efficient to decrease the and restrict the increasing consumption rate of fossil fuels, applying practical strategies for carbon capture and storage technologies, take benefits of CO2 by converting it into useful products, introducing renewable energies to the energy mix, limiting the deforestation and replanting, respectively. Based on the records, the foremost sources of CO2 production, i.e. one third of global carbon dioxide production, are conventional fossil fuel power plants, oil and gas refineries [1].

Modeling the CO2 emission in order to predict the influence of other factors such as utilized energy will be helpful for the researchers and policy makers to have a broad vision about future energy demand which is twisted to the sustainable environment. Amount of CO2 production of a country is highly affected by some factors such as the transportation system, efficiency of the power plants, and specifically energy consumption pattern of the residents [7–10]. Ruiz-Mendoza an Sheinbaum-Pardo [11] analyzed the effect of performed reforms in Electricity generation sector and their effect on carbon dioxide production in Latin American countries. The authors monitored 1990-2006 and reported that except Columbia which increase its capacity on renewable energies, specifically in hydropower sector, the other countries in this region decreased the installation capacity of renewable sites. Therefore, the amount of CO2 emission was remained almost constant in other countries. Jardon et al. [12] proposed an empirical correlation between the production of carbon dioxide (per capita) and economic issues. In this study, the authors analyzed the validation of the hypothesis that in long-term periods, the economic growth would be possible if environmental issues addressed, as well, and rejected this statement for Caribbean and Latin countries. Zaman and Moemen [13] carried out an investigation to analyzed the relation between utilization of renewable energies, fixed cropland, technology of exporting, health issues, and CO2 production in 14 selected countries in Latin and Caribbean countries. It was found out that fixed cropland and electricity production from fossil fuels have negative effect and increase the amount of CO2 production, while utilization of renewable technologies and using high-level technologies lower the negative impacts on the environment. Hanif [14] analyzed the impact of fossil fuel consumption, electricity generation, amount of imported oil, and urbanization on energy-environment-economic nexus in Latin American countries (1990-2015). It was concluded from the findings that it is necessary for these countries to develop and apply renewable energy programs to increase the quality of their environment and also decrease their dependency on oil importing.

Evolutionary algorithms, as well as machine learning, are considered as powerful tools in the modeling of different energy systems [15]. For instance, group method of data handling and least square support vector machine are applied to model several engineering systems by selecting appropriate input data for proposing precise model [16,17].

The major distinction that gives superiority to renewable energy is the lower amount of GHGs (greenhouse gases) emission in comparison to typical fossil fuels. Different techniques and equipment are employed in energy systems for electricity production or other possible energy conversion targets such as heating or cooling, etc. [18–23].

Geothermal, Solar, and Wind are the most practical sources of renewable energies which are developed vastly in recent years [24–32]. These sources are utilized in various applications such as power production, proving heating loads, freshwater production systems, etc. [33–38]. The amount of GHGs emission can be reduced by either increasing the portion of renewable energies in the total

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energy consumption or by improving the operational efficiency of energy conversion systems. Various investigations have concentrated on optimization and enhancement of energy conversion systems to reach more desired operating statuses [39–41]. One of the powerful tools which is highly utilized in modeling process of the energy conversion systems is Machine learning. A recent method based on machine learning is introduced as Least Square Support Vector Machine (LSSVM) which has been vastly used in modeling of engineering systems [42–51].

Applicable and fit data is required to have an accurate model. In this investigation, the input of the designed model is fuel consumption (i.e. oil, natural gas, coal, and possible renewable energy sources) of countries in the South America and the GDP of each studied countries in the period of 1990 to 2016. The amount of carbon-dioxide emission in each year is defined as the output of the study. Here, all of the influential items which were considered by other researches are gathered in order to give an inclusive model. Moreover, the most highlighted novelty of this study is to propose a mathematical model to estimate the amount of carbon dioxide emission of different countries in the region of the South America and Mexico. The precision of the introduced model is examined and evaluated by statistical methods including relative error and R2 (R-Squared).

Also, Patent can provide visual information about the future of the technology and the amount of investment on a policy. Accumulated numbers of published patent by a country not only determine the industrial orientation, but also demonstrate the future program of that country on a specific domain. Therefore, mentioned countries are investigated by the term of the published patent in the technologies for mitigating greenhouse gases emission domain. In this paper, all patents which have published by Brazil, Chile, Argentina, Uruguay, Mexico, Peru and Venezuela are extracted and analyzed. Finally, the top five published patent by mentioned Latin countries in mitigating CO2 emission technology are indicated.

2. Methodology

Based on Ahmadi et al. [52,53] applying some non-population optimization methods such as Levenberg-Marquardt (LM), and Simplex Simulated Annealing Algorithm (M-SIMPSA) is not practical since these approaches are not able to handle the SVM techniques since the nonlinearity factor is high. Therefore, GA which is a population-based optimization method was employed in order to assess the two major factors of γ and σ^2. In addition, a fitness function is used in the external optimization process, i.e. the mean squared error (MSE) of estimated data. In order to specify the most optimum result of the fitness function, the optimization process was repeated for several times. Here, the LSSVM machine learning technique is hybridized with GA, PSO, ICA, and GAPSO to model an accurate estimation of CO2 production in Latin American countries. Each methodology is briefly discussed in the following.

2.1. Least Square Support Vector Machine (LS-SVM)

Suykens and Vandewalle introduced the least square support vector machine, LSSSVM, for the first time in 1999 and applied to the primary kind of support vector machine, SVM, in order to specify the regression and function. Over fitting issues are recognized as the challenging situation when dealing either with conventional support vector machine (SVM) or feed-forward neural networks. Therefore, the LSSVM is proposed to surmount this specific barrier. Here, Xi, Rew, and GDP are defined as the input values of the problem and Yi is the objective output. The time series of Xi consists of Oil (Million tons), Gas (Million tons oil equivalent), Coal (Million tons oil equivalent). Rew and GDP are measured as million tons oil equivalent and in billion 2005 US dollars, respectively. In overall, the LSSVM nonlinear function can be demonstrated as follows [54–59]:

$$f(x) = w^T \phi(x) + b \tag{1}$$

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f illustrates the relation between input variables and the objective function of CO2 production (Million tons). Input variables are Oil (Million tons), Gas (Million tons oil equivalent), Coal (Million tons oil equivalent), R_{ew} (Million tons oil equivalent), and GDP (billion 2005 US dollars). w represent the weight vector (m-dimensional), ϕ maps x into the characteristic vector (m-dimensional), and b states the bias [54–56].

In order to minimize the topology, defining a fitting error function is necessary for solving the regression problem [45-50]:

$$minJ(w,e) = \frac{1}{2}w^T w + \gamma \sum_{k=1}^{m} e_k^2 \tag{2}$$

Although a constraint should be noted as follows [45-50]:

$$y_k = w^T \phi(x_k) + b + e_k \; k = 1, 2, \ldots, m \tag{3}$$

In Eq. (3), y is defined as the margin variable and e_k indicate the loose parameter of x_k [55–59].

Employing the Lagrange multipliers α_i in order to change the previous limited problem to a unlimited problem is a strong and efficient tool to determine the optimization problems which are stated in Eq. (2) [55–59]:

$$L(w,b,e,\alpha) = J(w,e) - \sum_{k=1}^{m} \alpha_i \{w^T \phi(x_k) + b + e_k - Y_k\} \tag{4}$$

As stated in the investigation of Karush–Kuhn–Tucker (KKT), considering the stated-variables including w, b, e, and α and also performing the partial derivatives of Equation (4), the optimum condition can be expressed as follows [55–59]:

$$\begin{aligned} w &= \sum_{k=1}^{m} \alpha_i \phi(x_k) \\ \sum_{k=1}^{m} \alpha_i &= 0 \\ \alpha_i &= \gamma e_i \\ w^T \phi(x_i) &+ b + e_i - Y_i = 0 \end{aligned} \tag{5}$$

Therefore, the linear equations are specified as [55–59]:

$$\begin{bmatrix} 0 & -Y^T \\ Y & ZZ^T + 1/\gamma \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{6}$$

In Eq. (5), Y, Z, I, and α are defined as: $\{Y = Y1, \ldots, Y_m\}$ and $Z = \phi(X_1)^T Y_i, \ldots, \phi(X_m)^T Y_m$, $I = [1, \ldots, 1]$, $\alpha = [\alpha_1, \ldots, \alpha_1]$, respectively. By Applying kernel function of $K(X, X_k) = \phi(X)^T \phi(X_k)$, $i = 1, \ldots, m$ the discussed LSSVM regression is formulated as follows [55–59]:

$$f(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \tag{7}$$

The radial basis function kernel (RBFK) typically utilized in regression errors. This function is stated as follows [55–59]:

$$K(x, x_k) = exp\left(-\frac{||x_k - x||^2}{\sigma^2}\right) \tag{8}$$

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In Eq. (8), σ^2 indicates the squared bandwidth. This parameter should be calculated during of any optimization procedures, such as GA optimization method, in order to have a potent optimization approach. The mean squared error (MSE) of the results of the LSSVM optimization approach is defined as the target function. The MSE of the results of the LSSVM method can be expressed as follows [60–67]:

$$MSE = \frac{\sum_{i=1}^{n} CO2_{rep/pred_i} - CO2_{meas_i}}{ns} \tag{9}$$

where CO2 illustrated the amount of CO2 emission (Million tons), subscripts rep/pred and meas denote predicted and measured amount of CO2 emission, respectively. The number of samples from original population is indicated by ns. In this investigation, the evolved model of the LSSVM method which previously implemented by Pelckmans et al. [59] and Suykens and Vandewalle [60] was applied.

In general, Eq. (10) simply states the optimization issue:

$$Min\ F(\gamma, \sigma^2) = Min(MSE) \tag{10}$$

2.2. Evolutionary algorithms

2.2.1. Genetic algorithm

The preliminary stage of the genetic algorithm (GA) procedure is to form the primary population. Then, every stages are being precisely assessed to form a statistical fitness function. In the following, every stages should be evaluated to be compatible. The "Global Best Satisfactory" result which is the result with a range of acceptable error ended the algorithm and then the parameters are extracted and reported. When the global best satisfactory result is not achieved, weaker individuals are opted to be deleted in the next stage. In the next stage, in order to decrease the error, mutation and cross over operations are applied. This stage is then so called the "Evaluation Fitness" [68–71]. The process of the genetic algorithm- LSSVM is demonstrated in Figure 1.

2.2.2. Particle swarm optimization

In the commencement of particle swarm optimization (PSO), pattern arbitrary locations and velocities are used to initialize the primary population. The particle's fitness is then performed by utilizing statistical function. The desired factors have been extracted, when the particle's fitness rate meet the stopping norms. In cases that the desired fitness rate is not achieved, in order to fulfill the requested rate the particle's velocity and locations are varied under specific conditions. In the first step, the global best factor should be evaluated and monitored that how is the particle fitness in comparison to the global best. An update to the pertinent factors of the prime particle is needed when the fitness is greater than the global paramount fitness. At last, subsequent particles should be assessed again by changing the direction to the 2nd stage [73–76]. The schematic process of the PSO-LSSVM is illustrated in Figure 2.

2.2.3. Hybrid PSO and GA

This Hybridization is started by forming arbitrarily the primary population and its following assessment. The process is stopped when the regulated values of the amount of produced error of the best individual is achieved. If the regulated values are not meet, then the procedure continues to reach to the closest acceptable range by utilizing the PSO algorithm. In this algorithm, the number of leaders are increased, the tournament selection is carried out based on the chaining processes, mutations and cross over operations are applied, and finally the fresh off springs are generated. New populations with improved characterizations of elites and off springs are generated by merging the effects of these two methods on each other [77,78]. The box chart of the Hybrid GA-PSO-LSSVM method is shown in Figure 3.

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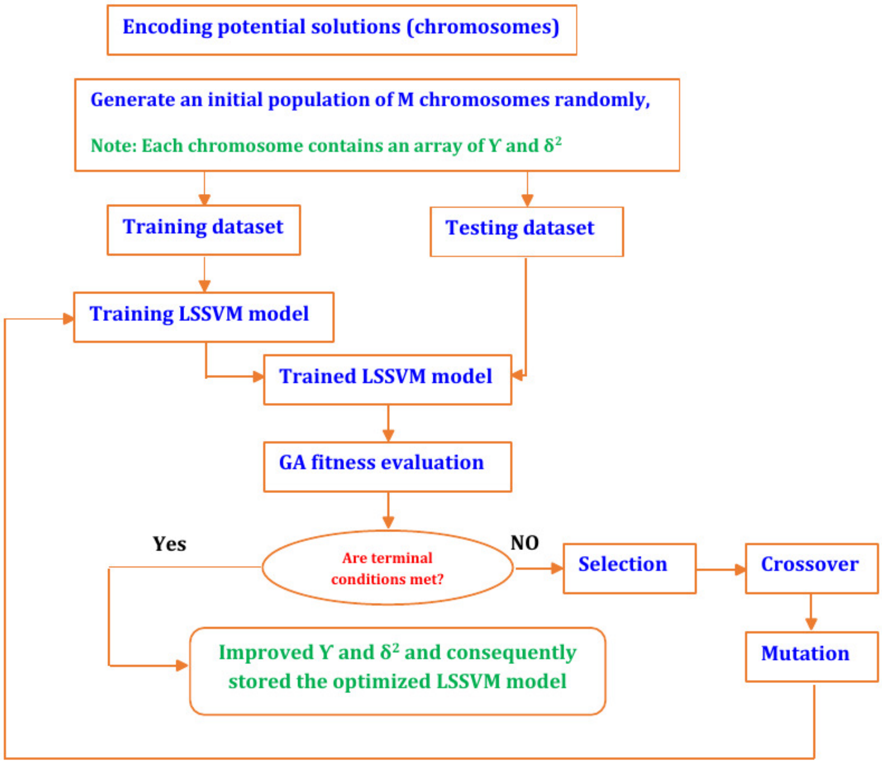

Figure 1. The overall scheme of the GA-least squared support vector machine method [72]

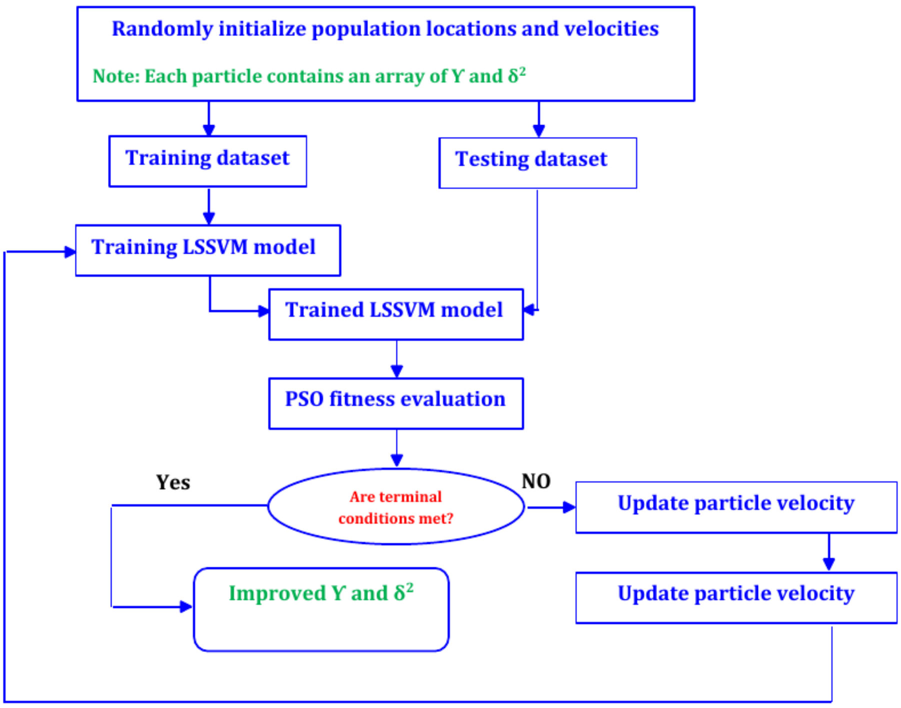

Figure 2. The overall scheme of the PSO- least squared support vector machine [72]

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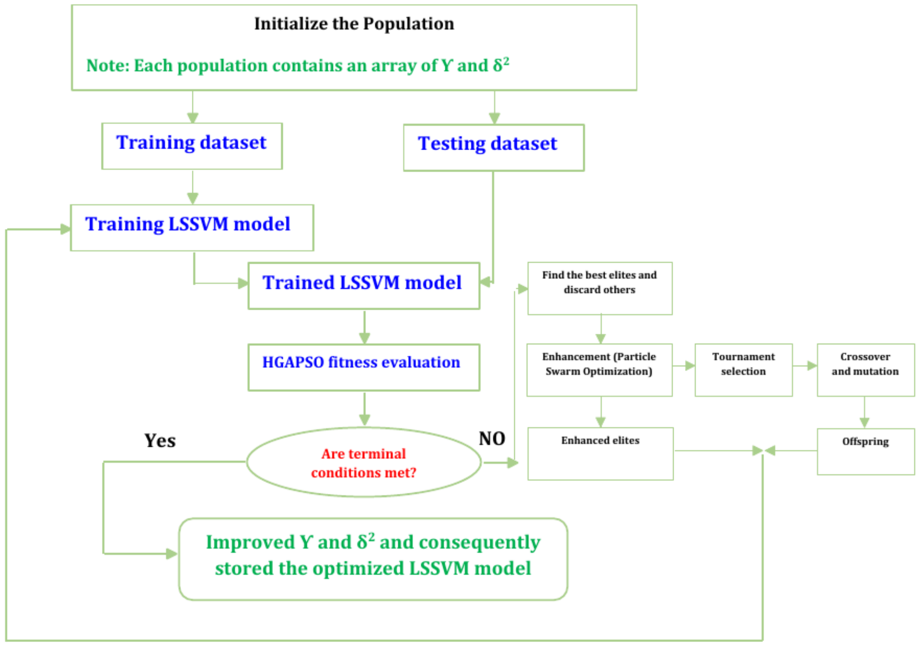

Figure 3. The Overall scheme of the hybrid approach of PSOGA- least squared support vector machine method [72]

2.2.4. Imperialist competitive algorithm

Imperialist competitive algorithm (ICA) follows a similar process than GA to solve optimization problems. However, ICA is based on human socio-political organization and evolution strategy instead of the biological evolution in which lies GA. ICA creates several social domains transferring a number of colonies to their related domains. Then, the colony's cost of an empire should be evaluated. A variation in locations of domains and colonies is needed when the colony's cost of a colony is high for a specific domain. After that, the cost of all domains is computed in the next step. In the following phase, the greatest colony of the greatest domain owns the colony with the lowest potential. Afterwards, all domains without colonies should be cut. The next level is to examine the breaking sets to monitor the amount of satisfaction to cease the algorithm [79,80]. The schematic diagram of the ICA-LSSVM method is demonstrated in Figure 4.

LSSVM Lab 1.8 free toolbox and GA Toolbox of MATLAB R2009a was used to optimize the GA-LSSVM problem. In addition, other optimization techniques including ICA, PSO, and Hyper PSOGA are coded and run in MATLAB software in order to determine the hyper parameters of the LSSVM. When the data set is identified and collected, now the model is formed and the input parameters into the model and the target output of the model are specified. Based on the reported date from the mentioned literatures, amount of carbon dioxide emission (Million tons) were selected as the output of the LSSVM model and forecasted.

The collected real data was classified into three subclasses. 80% of the total data which is 68 data point or 55 data lines are employed in the training process. The other 20% of the data establish the test and validation process to verify the recommended method.

The RBF was opted for this problem, since there are few variables in this optimization problem and also the 1st-rate total performance of RBF kernel function. Based on the literature, the RBF is in agreement with other kernel functions and also is highly practical [81,82]. In the process of modeling the problem with utilizing the LSSVM with RBF kernel function, the feature of parameters γ and σ^2 is a fundamental task (See Eq. (8)). These parameters have a noticeable role in verifying the acceptance

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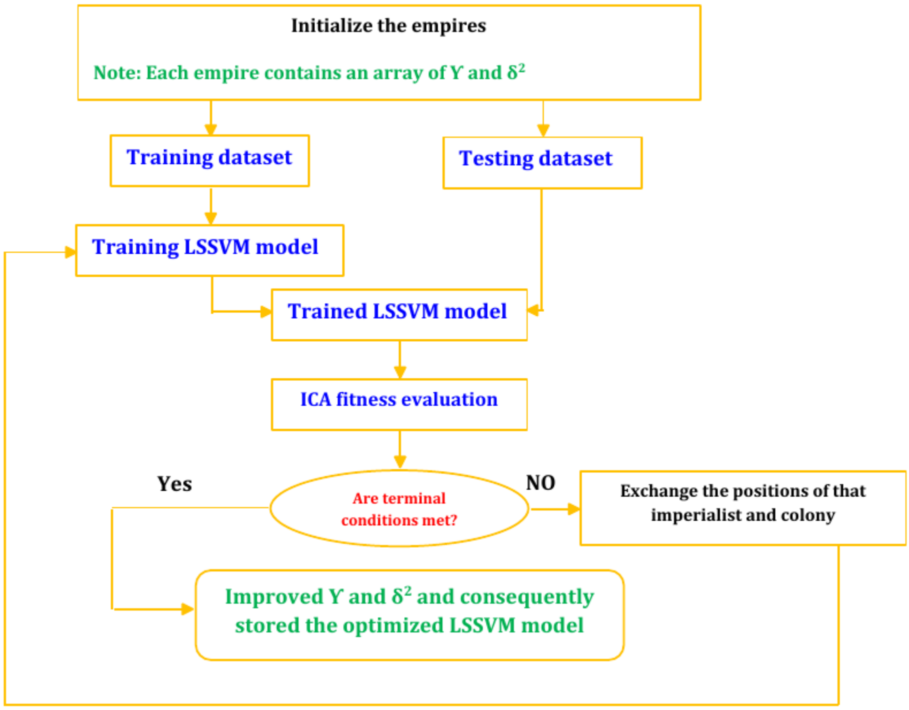

Figure 4. The overall scheme of ICA- least squared support vector machine method [72]

212 of the used LSSVM approach. Here, regularization factor is indicated by γ and σ denotes the kernel
213 sample variance [83] (see Figure 5.

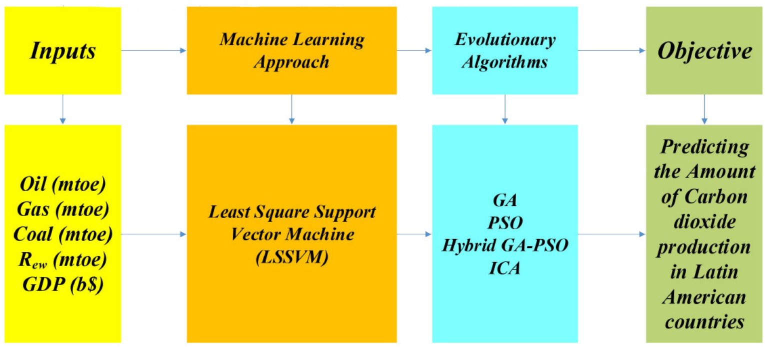

Figure 5. Schematic diagram of the employed methodology to predict the amount of produced carbon dioxide in Latin American countries (mtoe: million ton oil equivalent; b$:billion dollars)

214 ## 3. Patent analyzing

215 Is there any helpful technology for mitigating greenhouse gases emission? What are the
216 technological roles of South American countries in mitigating greenhouse gases emission? One
217 of the reliable approaches to denote technological profile of countries is patent analyzing. While patent
218 has a technical value, determine the market potential [84,85]. The economics of patent can be an
219 indicator of a market tendency of that technology. The patent provides useful information for the
220 business developer, policy makers and researcher. To extract this information visual them, analyzing
221 of the patent is required [86]. Patent analyzing besides of showing technology trend can demonstrate

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countries orientation on the specific technology sector. The total published patents in the specific technology by a country may indicate their movement that specific industry. Additionally, one of the interesting analyzed of the patent can be the indication hot area of technology. Indeed, the specific groups of technology that used by a country is done by this analyzing.

So, what are the technological approaches of these countries for mitigating CO2 emission? Have they matured in their technology? For estimating their technological approaches, investigating patent analyzing could be helpful. To find out the technology status, the technological life cycle is curved. As it said earlier patents are used as data for this investigation. Patent can be assumed as one of the most reliable indexes for estimating technology development. Patent by stimulating the economy and technology innovation, motives firms to develop the technology[79,81]. Patent plays climatically role to hindsight better technology life cycle and each step through emerging to innovation, technology development to market growth[78]. The data are extracted from SaaS online data based, Patentispiration[1]. Finding the best approach for mitigating CO2 emission technologies that are employed by mentioned countries are determined by investigating obtained patents. Thus, the exactness of extracted patent is the key factor of this investigation. Since searching patent by keywords may not be the efficient method, the combination of keywords and patent codes significantly increase the data accuracy. In the first place, interviewing with experts have been done to refine the main keywords. Then, the patents are searched by keywords, which are shown in Figure 6. These keywords are candidate of the result of interviewing.

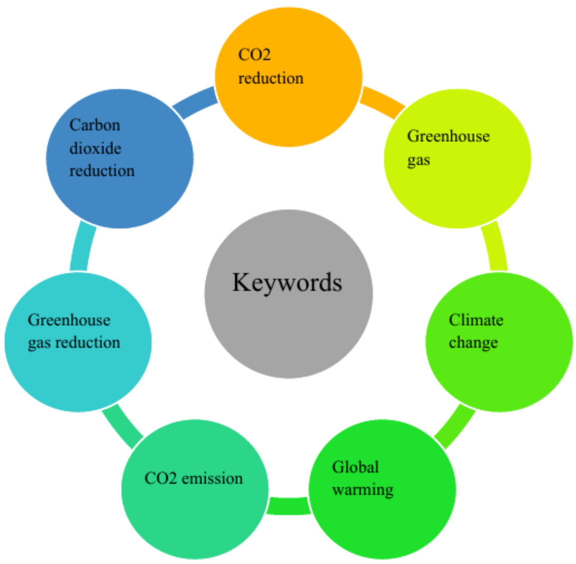

Figure 6. Related keywords for searching patents

After searching by keywords the extract patents have screened to find key codes. Key codes refer to CPC, Cooperative Patent Classification, which organizes the patent by nine classes. Searching patent by codes averts extracting irrelevant patents; therefore this approach certifies the accuracy. For better insight of technology categories, the hierarchy of CPC classification of patent survey is presented in Table 1.

After finding key codes, the patents of Brazil, Argentina, Mexico, Peru, Venezuela, Chile and Uruguay have been analyzed. The extracted patents database is from 1970 to 2017.

[1] Patentispiration.com

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Table 1. The hierarchy of extract patents on climate change mitigation technologies

Section	Class	Subclass	Definition
Y	Y02	Y02A	Technologies for adaptation to climate change
		Y02B	Indexing scheme related to buildings
		Y02C	Capture, Storage, Sequestration or disposal of greenhouse gases
		Y02D	Information and communication technologies
		Y02E	Reduction of GHG emission related to energy generation and distribution
		Y02P	Production or processing of goods
		Y02T	Transportation
		Y02W	Wastewater treatment or waste management

4. Results and discussion

The values of the σ^2 and γ for the studied methods including GA, PSO, ICA, and hybrid GA-PSO have been obtained and listed in Table 2. In addition, sensitivity analysis is performed on the numbers of the introduced digits of the mentioned variables.

Table 2. The hierarchy of extract patents on climate change mitigation technologies

	σ^2	γ
Genetic Algorithm (GA)	5.32	51088.13
Particle Swarm Optimization (PSO)	5.3178	51037.11
Imperialist Competitive Algorithm (ICA)	5.3069	50099.84
Hybrid GA-PSO (HGAPSO)	5.3296	52039.38

The predicted obtained values through the GA-LSSVM model in comparison to the real amount of measured carbon dioxide emission for south of America is depicted in Figure 7a. In order to obtain the best linear fit line between the predicted and real amount of CO2 emission a correlation coefficient of 0.9965 is resulted in the GA-LSSVM. The closeness of the coefficient to unit demonstrates that the forecasted and measured data points are similar. The scatter plot of the amount of forecasted CO2 emission through PSO-LSSVM vs. the measured data is illustrated in Figure 7b. Applying the PSO-LSSVM method resulted in the correlation coefficient of 0.9957 for the best linear fit line between the predicted and measured values of CO2 emission. It can be seen than the calculated correlation coefficient is closer to unity in PSO-LSSVM than GA-LSSVM method, and it states that the precision of PSO-LSSVM model is higher and the estimations are close enough to the measurements of the carbon dioxide emission. The regression plot of obtained results from HGAPSO-LSSVM method and related actual amount of carbon dioxide emission is demonstrated in 7c. The regression of the predicted results through ICA-LSSVM model in comparison to actual measured data of the carbon dioxide emissions is depicted in Figure 7d. As it is clearly understood, based on the values of the correlation coefficient, the ICA-LSSVM approach gained the lower amount among all other models including PSO-LSSVM, GA-LSSVM, and HGAPSO-LSSVM.

It is concluded that among all the discussed intelligent methods, HGAPSO-LSSVM technique is more accurate based on the obtained correlation coefficients. In addition, the relative deviation of the calculated results through discussed methods vs. corresponding oil production (Million tons) are demonstrated in Figure 8. It is monitored from Figure 8a that the obtained results from the GA-LSSVM model deviates from actual measured carbon dioxide emission values between 20%. It means that the deviation of the obtained results by the GA-LSSVM model from the real measured amount of carbon dioxide is about 15%. It is understood from Figure 8b that the deviation of obtained results through PSO-LSSVM model is in the range of 22%. It states that the error of estimations from the PSO-LSSVM model is between error lines of -22% and +22%, respectively. The relative error graph of the estimations based on the HGAPSO-LSSVM model in comparison to the actual measured data to carbon dioxide emission is depicted in Figure 8c. It is clearly monitored from Figure 8c that the highest error of the HGAPSO-LSSVM model is in the range of 12%. The relative deviation results of

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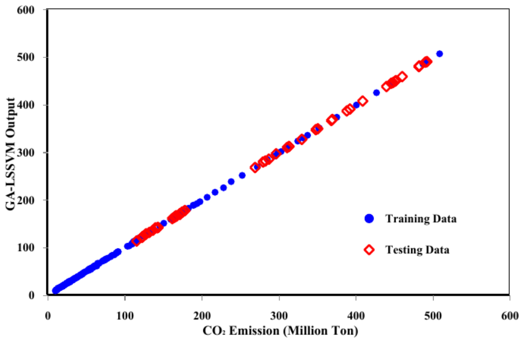
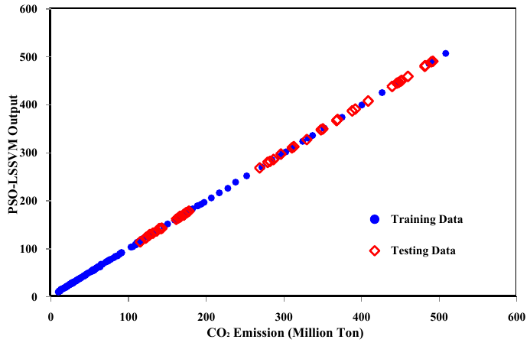
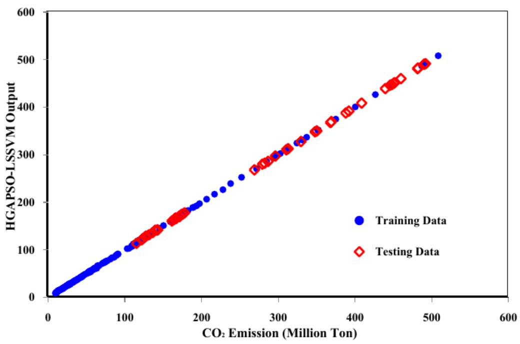


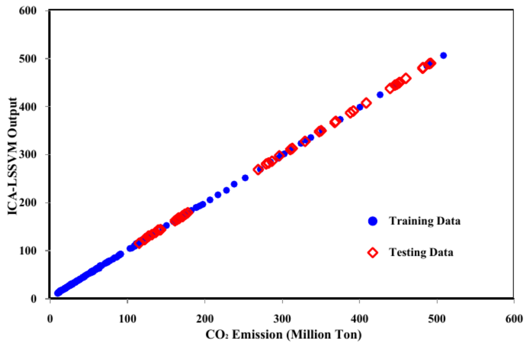
(a) Estimated values obtained from GA-LSSVM approach Vs. actual measured values of CO2 emission



(b) Output of the PSO-LSSVM model Vs. actual measured data of CO2 emission



(c) Estimations based on HGAPSO-LSSVM model Vs. actual CO2 emission



(d) Prediction based on ICA-LSSVM technique Vs. actual measured CO2 emission

Figure 7. Model comparison

ICA-LSSVM model is shown in Figure 8d. It is monitored from Figure 8d that the highest deviation of the ICA-LSSVM approach from actual CO2 emission is -22%. The relative error distribution interprets that the HGAPSO-LSSVM method has dominance in comparison to other discussed LSSVM models. In overall, two dependable statistical benchmarks including average absolute relative deviation (AARD%) and mean squared error (MSE) are applied to determine forceful intelligent techniques among recommended LSSVM models.

The obtained AARD (%) from the LSSVM methods and the actual logged data of carbon dioxide emissions is compared and demonstrated in Figure 9a. In addition, Figure 9b depicts the comparison between the resulted MSE of different LSSVM models. It is monitored from Figure 9 that the HGAPSO-LSSVM technique accurate and precise method for estimating CO2 emission in gas injection processes.

The obtained programming codes and the required instructions are straightforwardly accessible and will be shared contentedly with others. Therefore, people can easily use the model to re-calculate all of our results and may predict carbon dioxide emission at any circumstances.

The patent analysis result of technology trend for mitigation CO2 shows that Brazil with accounting 5885 patents is the leader in mitigation CO2 emission technology so far. Total published patents of the South American countries are illustrated in Figure 10.

Mexico has published 2644 patents and after Brazil is the second pioneer country. According to the extracted data, which is patent in this case, only 101 patents have been published by Uruguay. The trends of published patent by these countries from 2007 to 2017 are illustrated in Figure 11. What

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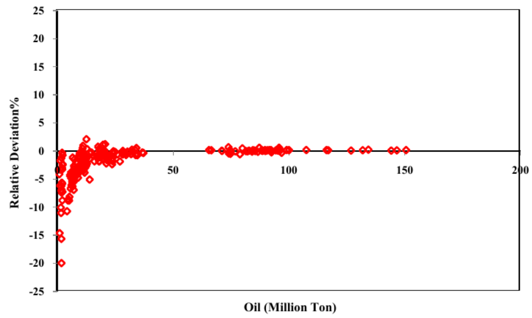
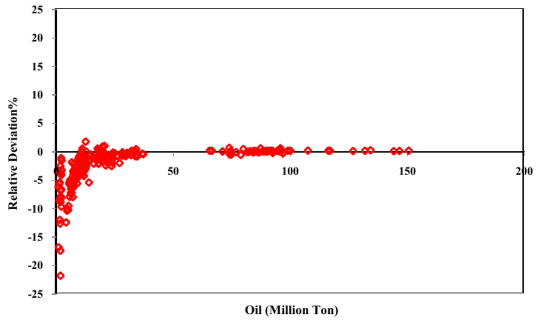
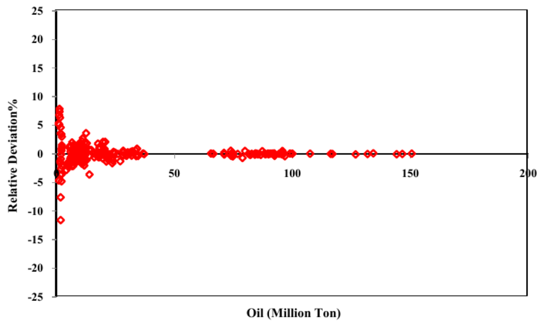


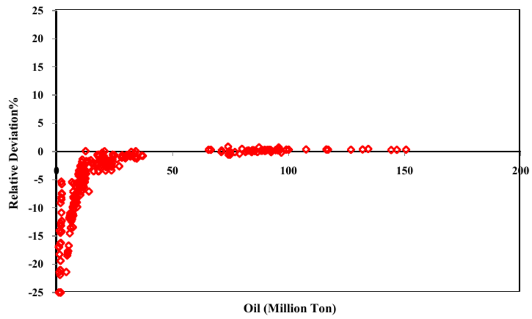
(a) Relative error of the estimations based on GA-LSSVM



(b) Relative error of the estimations based on PSO-LSSVM

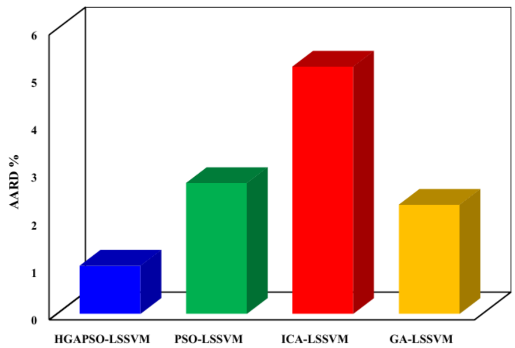


(c) Relative error of the estimations based on HGAPSO-LSSVM

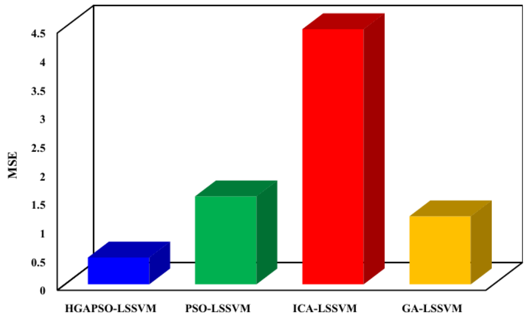


(d) Relative error of estimations based on ICA-LSSVM

Figure 8. Relative error per model



(a) Average absolute relative deviation (AARD) of the Studied LSSVM approaches



(b) Mean squared error (MSE) of the Studied LSSVM approaches

Figure 9. Errors for the LSSVM-based models

can be noted in the countries trend is that Chile and Peru have accelerated in working on mitigating technologies. The top patent main technology groups which indicate movement of these countries to mitigate CO2 emission will be discussed further. The country with the modest behavior would be Venezuela. Also, Mexico can be considered as the next modest country in published patent. In fact, the published patent by country in the specific technology determines R&D activities and expenditure have been directed to mitigate CO2 emission.

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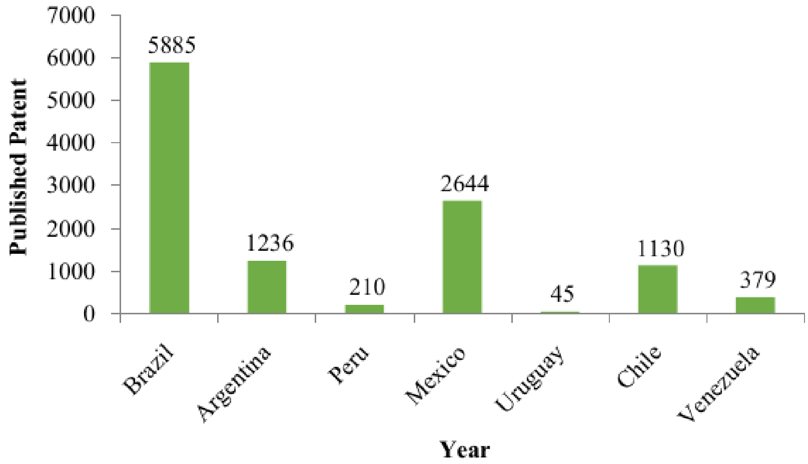

Figure 10. The number of published patent in South American countries

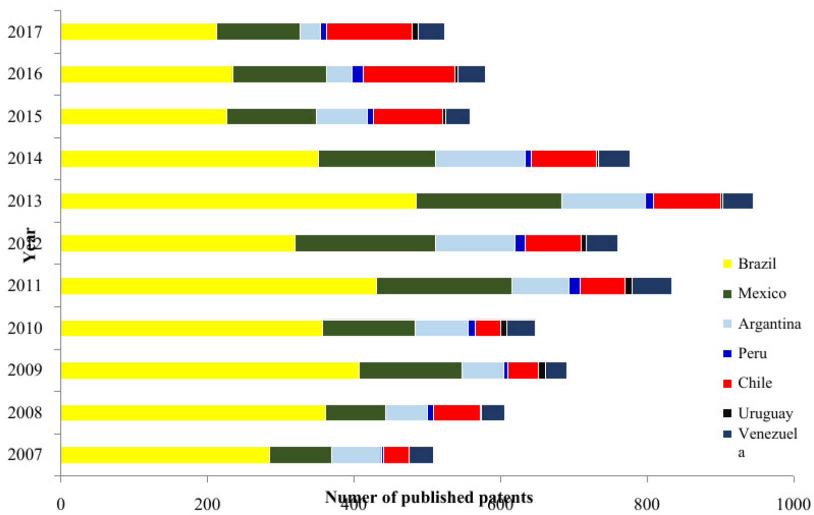

Figure 11. South American countries activity in the recent decade

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Brazil and Mexico have the biggest economy in the Latin America so far, which determines their remarkable role in CO2 mitigation. Although the CO2 emission form Brazil and Mexico are not the highest one, their policy and program to enhance mitigation action are considered globally [87]. Argentina is the 4th country with the high economy in the Latin America. In spite of being relatively small CO2 emitter, Argentina has made efforts in mitigating CO2 emission recently. Peru is one of the prior countries that ratified the Paris agreement. The annual rate of CO2 emission of Peru in 2016 was 2.67% which determines 0.68 metric tons CO2 increasing from 1997 to 2016 [88]. As it is obvious in Figure 11, Uruguay patent trends have not increased or faced a considerable change during the last decade. About 80% of CO2 in Uruguay has been produced by the agriculture sector in 2013 [89]. According to its GDP, Venezuela is the 7th country in the Latin America. The main source of CO2 emission is energy source in Venezuela. The total produced CO2 by Venezuela in 2014 was 6.03 metric tons [89]. Chile is another important Latin America country with high GDP. The total CO2 emission by Chile in 2016 was 5.45 metric tons [90]. To find out the technological orientation of mentioned Latin countries, the main technology groups of each country patents are illustrated by Figure 12 which considers the technologies for mitigating CO2 emission which published as patents by mentioned Latin American countries, except Uruguay. The reason for considering Uruguay as an exception is the low number of patents. Only 45 patents have been published by this country, which analyzing them demonstrates that the major activity by Uruguay is to promote renewable energies. Being a developing country and less industrialized, not significant, does Uruguay have an influence on CO2 emission. However, the Uruguay approach to reducing CO2 is promoting renewable energies. The energy sector in Uruguay contributes in more than 90% of CO2 emissions which the ambition is to reduce 29% by 2025 [91].

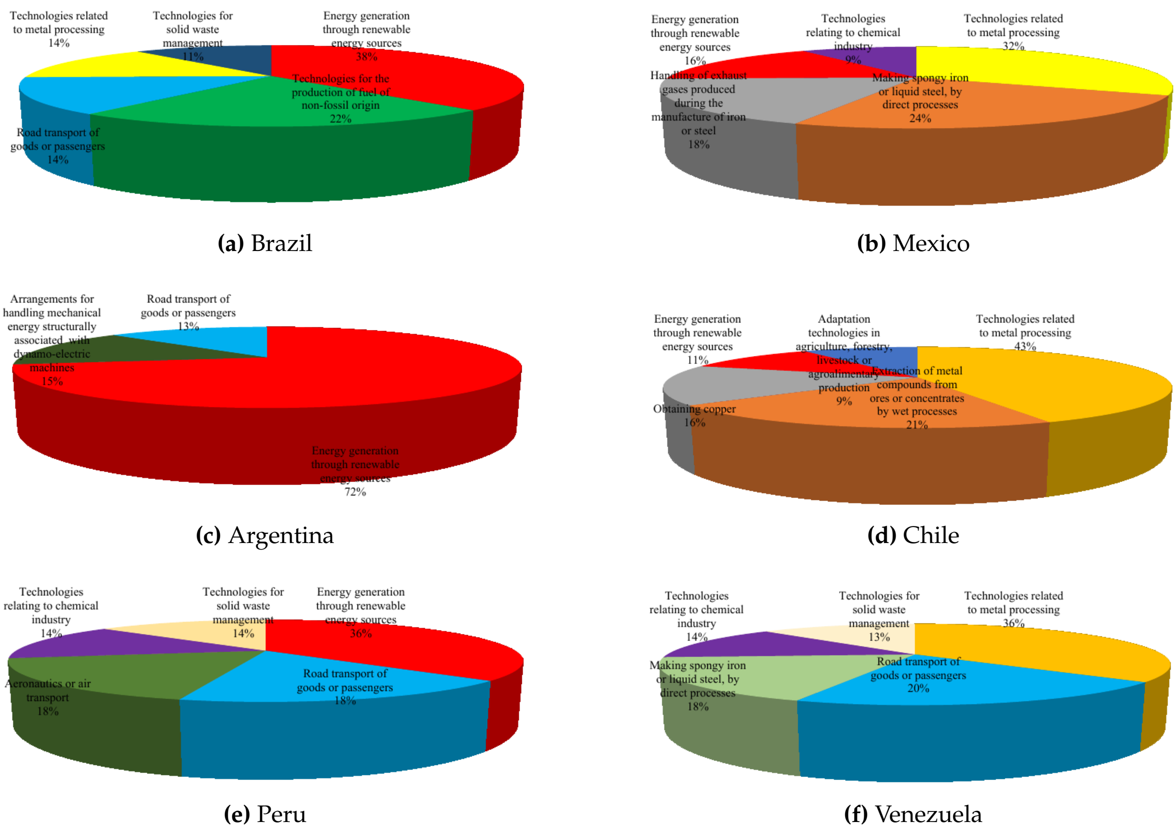

Figure 12. Top five published patent by country in mitigating CO2 emission technology

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Figure 12a demonstrates the top five patent technology scopes that have been published by Brazil since 1970. Energy generation through renewable energy resources and technologies for the production of fuel of non-fossil origin, which stands 60%, have the lion's share of technologies for mitigation CO2 emission. Production of fuel from non-fossil fuel origin includes only biofuel technologies. One of the programs for achieving 10% reduction of greenhouse gasses by 2028 is biofuels Brazil's mix stimulation from current 20% to 28.6% [92]. In fact, Brazil key strategies include deforestation action plan and developing renewable energies. The other approach in order to reduce CO2 emission involves in the industrial sector; modifying the efficiency of processes [93]. Mexico as the second biggest economy in the region besides of developing renewable energies program, concentrates more in specific regulatory tools in the industrial sector. As it is obvious in Figure 12b, only 13% of the top five technologies allocates to energy generation through renewable energy resources. Mexico is the 13th largest steel producer in the world, which produces more than 14% CO2 [94]. For the reason, the four others areas of technologies which the R&D activities make more efforts on is the metal and related chemical industries. So, the main program for mitigation CO2 emission in Mexico would be improving the energy efficiency. Regarding Figure 12c which demonstrates the technology sector in Argentina published patents, energy generation through renewable energy resources accounts more than 70% of patents. Road transport of goods or passengers and arrangements for handling mechanical energy structurally associated with dynamo-electric machines are the next highlighted ones. Their target; the net emissions must not exceed more than 483 MtCO2eq, is divided into three main sectors which are energy, forest and transport. The main scenario of Argentina to mitigate CO2 reduction is renewable energies promotion [95]. Indeed, developing the renewable energies has gained the majority of funds in Argentina through renewable energy auction program of Argentina (RenovAr). As a result of the first round of this program the total wind and solar capacities were 3469 MW and 2813 MW respectively [96]. Top five patents technologies that have been published by Chile from 1970 to 2017 illustrate in Figure 12d. As being the world's largest exporter of copper [97], the main published sector of technology by Chile is the industrial sector. Although expanding the renewable capacity and transition from coal to non-conventional resource for energy supply is the main action plan of Chile in order to reduce CO2 emission, enhancing the efficiency of industrial processes is high received attention sector in their R&D activities. Regarding Figure 12e, Peru technology sectors in published patents are somehow similar to Brazil. The energy generation through renewable energy sources accounts 36%, while the four sectors two by two have the same shares. Forestry, energy and agriculture are the three main greenhouse gases emitter sources in Peru. The main energy sources in Peru for electricity and transportation are gas power plants and imported oil and gasoline respectively. The renewable energy can be the best opportunity for addressing electricity demand and the transportation sector demands can be met by low-carbon [98]. The auction plan for developing renewable energies by Peru is illustrated in Figure ??.

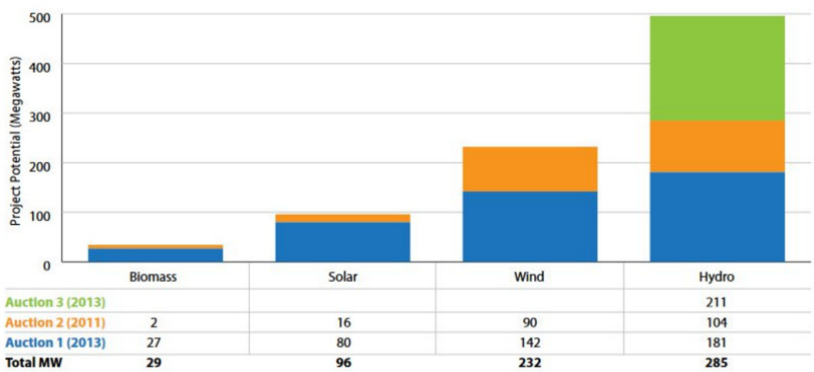

Figure 13. Renewable energies auction in Peru [98]

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Despite other mentioned Latin American countries, in top five published patents technology sectors, there is no share of energy generation through renewable energy sources in Venezuela published patents. The lion's share of the technology sector in the published patent by Venezuela is technologies related to metal processing which account 36%, according to Figure 12f.

5. Conclusions

In this investigation, two artificial intelligence techniques are discussed to estimate the CO2 emission. The LSSVM and evolutionary methods have been used to precisely predict the CO2 emission. The information used here is gathered from the accessible data in the literature. A comparison is made between the estimated amounts of CO2 from the optimization techniques and the measure actual data of carbon dioxide emission. Based on the recommended methods, the following major conclusions have been extracted:

1. All of the discussed optimization approaches show an appropriate agreement for forecasting the amount of carbon dioxide emission. However, the HGAPSO-LSSVM demonstrated a more accurate result and showed a higher reliability and compatibility. In addition, under specific circumstance with restricted field information, the significance of these methods highlighted more than other predicting techniques.
2. The HGAPSO has this potential to integrate with other evolutionary algorithms in order to optimize its parameters and additionally enhance its strength and accuracy.

Moreover, the patent related to the climate change mitigation are evaluated in six Latin American countries namely Brazil, Mexico, Argentina, Peru, Chile, Venezuela and Uruguay has been done. The results show that except Venezuela, all other mentioned countries have invested in renewable energy R&D activities. Brazil and Argentina have the highest share of renewable energies which account for 60% and 72% respectively.

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