Pollution, 6(4): 893-908, Autumn 2020
DOI: 10.22059/poll.2020.301464.787
Print ISSN: 2383-451X Online ISSN: 2383-4501
Web Page: https://jpoll.ut.ac.ir, Email: jpoll@ut.ac.ir

Application of a Decision-Making Model to Reduce CO2 Emissions in Iran (Case Study: CHP-CCS technology and renewable energy)

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Received: 22.04.2020 Accepted: 01.07.2020

ABSTRACT: Iran is one of the largest producers of CO2 in the world. Therefore, in order to lessen its greenhouse gas production, thus complying with the Intended Nationally Determined Contributions (INDCs), it should cut its CO_2 emissions by about 4% by 2030, compared to 2010. Hence this paper aims at finding an early solution to this problem. Because the country's electricity sector is responsible for the highest annual CO_2 emissions, the paper focuses on two technologies that can effectively reduce CO_2 emissions from the electricity sector, namely renewable energy and Combined Heat And Power Plants (CHP) with CO_2 capture and storage (CCS). Further it assesses adoption of these technologies and their impact on Iran's annual CO_2 emission by 2030, considering two main scenarios: the optimistic scenario (OS) which assumes that the policies of the Sixth Development Plan (SDP) will be fully realized as well as the fair scenario (FS) which believes that SDP policies will be followed to some extent by the end of the program. To this end, twenty six micro-factors, affecting CO_2 emissions, have been identified and classified into five different groups. The detected micro factors are then introduced to a Gradient Boosting Decision Tree (GBDT) Algorithm to identify the most important specific microscopic factors in Iran. The final detected micro-factors have finally been included in a Gaussian regression model to predict CO_2 emissions in Iran by 2030. The findings suggest that if Iran intends to comply with the INDCs, CHP-CCS technology is a solution that has an early return, compared to renewable technologies.

Keywords: Fair Scenario, Gaussian Regression, Greenhouse gases, CHP.

INTRODUCTION

Climate change has become a pivotal issue in recent decades. Nowadays, nations are at a critical moment for slowing down the pace of climate change patterns by defining, adopting, and implementing clean development mechanisms (CDMs), particularly in the energy sector (Fang et al., 2018). This is one of critical global concerns to be addressed by every nation of the world. Many scientists have argued that recent climate changes are largely due to the increasing levels of carbon dioxide (CO_2) released from fossil fuels combustion, making it quite a sensitive issue, not restricted to one particular area (Pachauri et al., 2014). Excessive fossil fuel consumption, in combination with deforestation of tropical forests, has further complicated the situation, bringing about a huge concentration of CO_2 to the atmosphere. It has raised the temperature for about 0.15–0.2°C per decade, following the 1880s, and has brought about 0.8◦C of global warming on the whole (Carlowicz.,2010). Meanwhile, the inability

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of global CDMs to cut the pace of anthropogenic CO_2 emissions may further raise the figure to about 2 °C before long (Allen et al., 2019).

Iran is on the list of most CO_2-emitting countries. Ranked seventh globally in terms of CO_2 emission, it is responsible for about 1.7% of global CO_2 emission annually. (Rüstemoğluand Uğural, .2017). At the same time, despite the several CDMs the country adopted after the Kyoto Protocol (First to Sixth Development Plans), its annual CO_2 emission has followed a growing trend, since the beginning of the first development plan as shown in Fig. 1 (Hosseini et al., 2019).

Breaking down the sources of CO_2 emission in this country reveals that electricity and heat producers make up the vast majority of emissions since 1990, as can be seen in Fig. 2 (Shafiezadeh et al., 2019). In the meantime the country has largely substituted coal- and oil-burning power plants for those, consuming natural gas during this period so that it might lower the CO_2 intensity in the supply side. Adoption of renewable energy policies since 2005 also seems a fruitless attempt to settle the dispute in this country, as the government has been historically stuck to fossil fuels to meet the energy demand (Bakhtiar et al.,2020). Moreover, the government has failed to even partially fulfill the high targets imposed by the development plans. On the other hand, the high rate of CO_2 emission in this country has no meaningful correlation with its annual gross domestic product (GDP), mainly because of the high rate of energy intensity and lack of efficiency in the country, particularly in the electricity sector (Hosseini et al., 2020). As a result, the country must make more rational development plans and executive operations if it intends to meet the Kyoto Protocol, and more importantly, the Intended Nationally Determined Contributions (INDCs) targets.

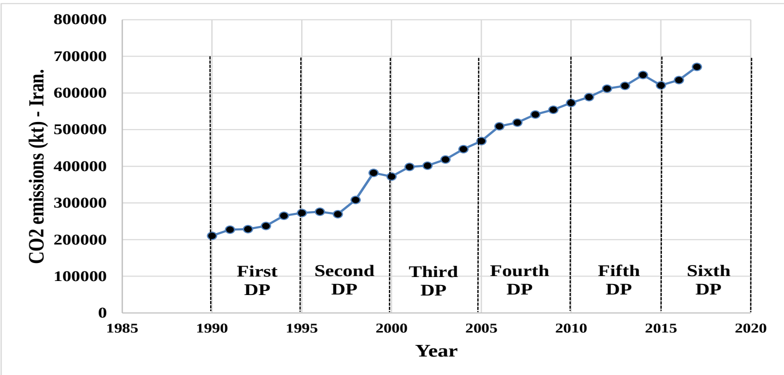

Fig.1. Growth trend of CO_2 emission in Iran (DP refers to development plan)

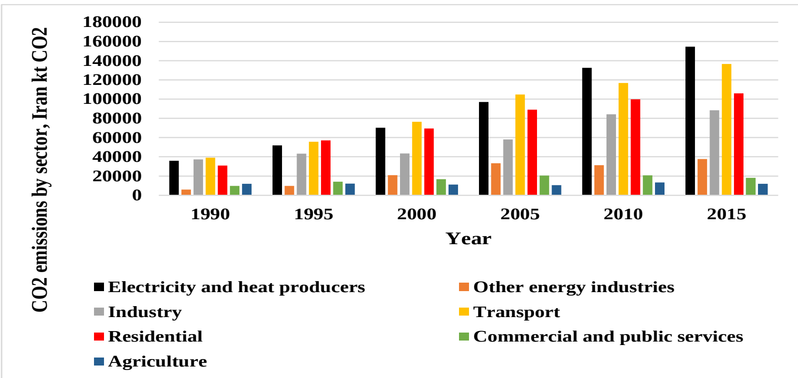

Fig. 2. CO_2 emission of Iran by sector since 1990

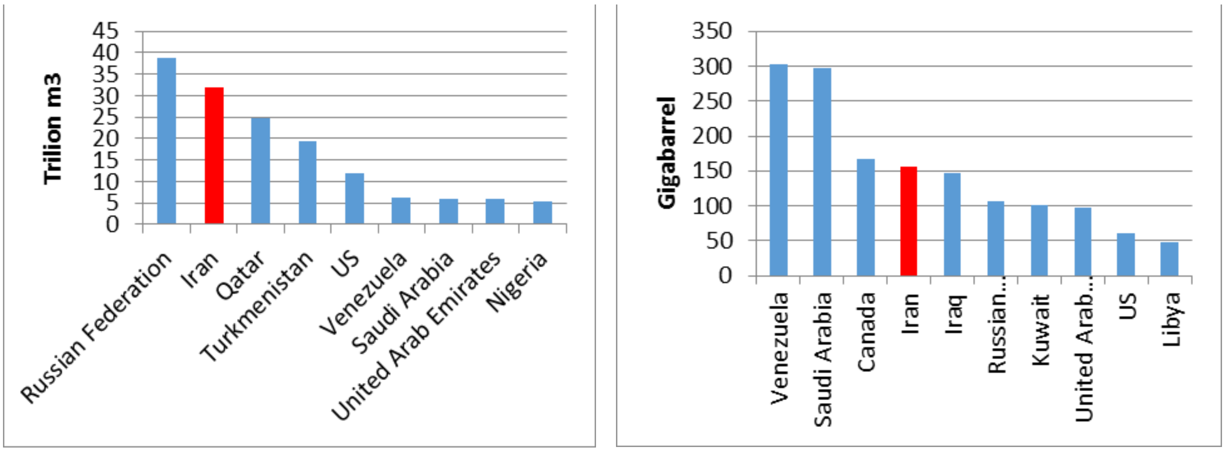

Fig. 3. Top world natural gas reserves (left) and top world oil reserves (right) by the end of 2018

According to British Petroleum, Iran is one of the countries with large natural resources, including crude oil and natural gas. After Russia, it has the largest amount of natural gas reserves in the world. Its oil reserves also rank fourth around the globe (Fig. 3) (Dudley, 2018).

Such abundance of natural resources has increased the reliability and availability of fossil fuel power plants, compared to renewable technologies. This can be proven when noting that more than 90% of Iran's power plants are fueled by the fossil fuels, chiefly from gas production. The greenhouse effect is also related to this sector, hence the use of CCS technologies could offer a good opportunity to safely reduce the severity of CO_2 emission in Iranian electricity sector. (SATBA, 2018) Apart from renewable energies and CCS technologies, the other remaining alternative to reduce CO_2 emission from the electricity sector in this country is to improve energy efficiency in the power plants. Iran adopted "Payment of benefit of conserving fossil fuels" in 2015 as a policy for providing multiple renewable energy sources in the country mainly (SATBA, 2018). However, one clause of this policy is believed to improve energy efficiency in the electricity sector through the development of small-scale Combined Heat and Power (CHP) power plants. To display its commitment to this policy, Iran installed a 3-MW CHP power plant west of Tehran, in early 2019. It employed an amine-based post-combustion CCS plant with a CO_2 capture rate of 1.8 tons/hr. The power plant is a shining example of efficiency and sustainability in the country's electricity sector when it comes to fossil-fired power plants. Development of this power plant recently has raised a question: If Iran is inclined to meet its commitment to Intended Nationally Determined Contributions (INDCs), is it not more efficient and reliable for the country to invest in retrofitting the electricity sector by highly efficient and environmentally-friendly CHP-CCS technologies instead of renewable ones? Given that the country is ranked second in terms of largest natural gas resources around the globe and that it has a very low energy price index, it can be a viable alternative for Iran to adopt the policy and meet its commitment to the Intended Nationally Determined Contributions (INDCs) as soon as possible, prior to 2030.

As the country has not brought forward any distinct policies regarding the Paris agreement, the ambitiously-made Sixth Development Plan (SDP) remains the main source for scenario analysis in this study. Iran intends to increase the share of renewable energies of the total energy consumption to 5% by the end of the SDP period, which could be done via installing several solar and wind farms. On the other hand, the country plans to raise the overall efficiency of the thermal power plants by 7% at the same time for which it has to retrofit gas-burning power plants. This paper tries to see under which scenario the country can meet its commitment to the Intended Nationally Determined Contributions (INDCs) sooner: whether by adopting a renewable policy or the CHP-CCS one. Hence, both scenarios will be designed based on the SDP, and the annual CO_2 emission up until 2030 will be predicted accordingly. The optimist scenario (OS) assumes that all of CO_2 emission-related policies of the SDP will be fully implemented by the end of the plan period. However, the fair scenario (FS) considers that Iran will not be able to pursue the SDP's policies thoroughly. It is a business-as-usual scenario wherein the indicators are fairly predicted based on their historical trends rather than the SDP's policies. Such analysis needs sophisticated modeling that takes into account a large number of influential factors, significantly affecting the CO_2 emission on a national level. For this purpose, the present paper adopts a Thematic Analysis (TA) to identify the possible macro- and micro-factors, affecting the annual CO_2 emission of a country through its literature. Afterwards, the identified factors will be introduced to a Gradient Boosting Decision Tree (GBDT) to specify the decisive influential factors, particular to Iran. Identified driving forces are then put into a Gaussian Process Regression (GPR) model to predict Iran's CO_2 emission by 2030 based on the designed scenarios.

In China, the scenario analysis has been used to study long-term solutions accurately so that one could reduce both energy consumption and CO_2 emission from the steel industry (Karali et al., 2016). A similar study has combined this method with a linear planning model to prioritize alternative solutions to global warming (Tokimatsu et al., 2017). Predictive processes widely use machine learning tools, in particular, artificial neural network (ANN) models. This identification method is best matched for cases between targets variables and nonlinear relationship response (Guo et al., 2018). Behrang (2011) speculated about the state of global release of CO_2 in 2040, using a combination of ANN on the one hand, and a bee algorithm on the other. Furthermore, using a Back-Propagation Neural Networks model combined with a genetic algorithm (GA), Sun (2016) managed to predict future values of CO_2 emission for a province of China. Fang (2018) offered a new way to predict CO_2 emission in China by 2020. This approach was a combination of Gaussian Process Regression (GPR) and genetic algorithm and displayed good performance, in terms of its accuracy. A number of researchers have also made some efforts to predict carbon dioxide emission in Iran. For example, Davoodpour and Ahadi have presented a scenario-based economic model to predict annual energy demand and CO_2 emission in Iran between 2000 and 2011 (Davoodpour and Ahadi, 2006). Under a business-as-usual (BAU) scenario, the annual growth rate of CO_2 emission has been 6.8%, whereas by implementing a management scenario, the country could most likely have halved the rate. Köne and Büke (2010) have applied regression analysis to predict carbon dioxide emission from the top 25 CO_2-emitting countries by 2015 and 2030. What is more, results from a study by Lotfalipour et al. (2013) showed that CO_2 emission in Iran often hiked almost linearly. Carbon dioxide emission forecasting is based on the gray system. Moving the average of the authorization and comparing these two methods by means of RMSE, MAE, and MAPE criteria, shows that the accuracy of the gray system is more accurate than other forecasting methods. Also, according to the estimated results, Iran's carbon dioxide emission in 2020 will reach 925.68 million tons, showing a growth of 66% compared to 2010. Azadeh et al. (2017) performed a multivariate analysis in their attempt to predict CO_2 emission from Iran's industrial sector and supported the socioeconomic indicators. Heydari et al. (2019) proposed a completely unique methodology, combining a General Regression Neural Network model with a gray Wolf Optimization approach, to predict CO_2 emission from fuel consumption in Iran, Italy, and Canada.

MATERIAL AND METHODS

The present study has used Thematic analysis (TA) as a means to identify, analyze, and account the major driving forces of CO_2 emission in Iran through the literature. Searching for qualitative datasets, the methodology continually scrutinizes the entire dataset, itself, the derived micro- factors from it, and the provided data analysis. Afterwards, it creates the code applied after getting familiarized with the datasets to detect and identify the major concepts, their details, and the corresponding macro-factor in them. Thanks to this mechanism as many as 61 micro-factors have been initially derived from the relevant texts. All the following gathered data are coded and prioritized in form of each specific micro-factors, with each code representing a feature data. Comparing and analyzing the derived micro-factors lets the ones that are the same in nature to become unified, and the number of micro-factors is cut to 25. Finally, the extracted micro-factors are validated through two stages, the first of which reviews and revises the derived micro-factors so that their consistency and compatibility could be examined. The entire dataset is reviewed again in the second stage and the derived micro-factors' validity is examined against the whole dataset. Following the validation, the identified micro-factors are gathered and sorted into seven diverse macro-factors.

The identified macro-factor are defined and named at this stage. Also, the identified macro- and micro-factors are further analyzed, and the final composition of micro-factors in each macro-factor is presented.

Identified macro- and micro-factors that affect CO_2 emission on a national level are as follows:

1) The macro-factor, called *"Economic Status"* includes the micro-factors of GDP [constant 2010 US$ billion], net investment in nonfinancial assets (NINA) [% of GDP], trade-to-GDP ratio [%] (TGDP), foreign direct investment, net inflows [US$] (FDI), urbanization rate [%] (UR), and research and development expenditure [%] (R&D) (Niu et al., 2020; Pata, 2019; Aldakhil, 2019).

2) The macro-factor *"Population Status"* contains the micro-factors of total population (TP) [million people], population density (PD) [people per sq. km of land area], and urban population (UR) [million], and population aging between 15-64 [%] (PA) (Meng & Han, 2018; Usman et al., 2019; Magazzino & Cerulli, 2019).

3) The macro-factor named *"Energy Status"* is consisted of micro-factors of Energy Intensity (EI) [MJ/$2011 PPP GDP], energy consumption per capita (ECPP) [kg of oil equivalent], share of fossil fuels in total energy consumption (SFFEC) [%], share of renewables in total energy consumption (SREEC) [%], share of coal in total energy consumption (SCEC) [%], total electricity consumption (TELC) [Billion Kwh], national nominal price of electricity and fossil fuels (NNP), consumer price index (CPI), global nominal oil price (GNOP) [US$], and overall thermal power plants efficiency (OTPPE) [%] (Abokyi et al., 2019; Wang et al., 2019; Njoke et al., 2019).

4) The macro-factor, *"Economic Structure"*, involves the following micro-factors: value added of agriculture, forestry, and fishing (VAA) [%], and value added of industry, construction, tourism, transport and services (VAI) [%] (Anwar et al., 2019; Azam & Khan, 2017).

5) The macro-factor, named "*Environment Status"* contains micro-

factors of access to electricity (AE) [% of population], agricultural land (AL) [% of land area], forest area (FA) [% of land area], and $PM_{2.5}$ mean annual exposure (PMAN) [$\mu g/m^3$] (Adeleke & Josue, 2019; Dogan & Kan, 2018; Gokmenoglu et al., 2019; Anenberg et al. 2019).

The current study employs GBDT as a means to calculate the importance rate of the identified micro-factors and rank them in order of their priorities. Through this approach, each micro-factor with an importance rate below 50% is considered insignificant and will not be allowed in the predictive model. This in turn helps selecting the most decisive micro-factors for the predictive model and lowering the chance of over fitting on the one hand and reducing the time of training on the other.

A viable machine learning tool for decision-making and classification, GBDT adopts a learning approach that continuously updates the generated model and minimizes the sum of loss function for each encompassing tree. It creates new base-learners in each iteration that is highly interrelated with the negative gradient to the loss function such as below:

$$\hat{F}^{*} = arg\ min \sum_{i=o}^{N} L\left(y_i, F\left(x_i\right)\right) \qquad (1)$$

where, $\hat{F}^{*}$ is an estimation for model F in each iteration. L represents the loss function in the above equation and N stands for the number of samples. Also, y_i is the updated target label in each iteration and x_i, its corresponding training sample. It determines the importance of micro-factors based on a log-likelihood estimation framework. For the j^{th} micro-factor in the GBDT model, the importance$\widehat{I_j}$ is defined as below, (Li, C., 2016):

$$I_j = \frac{1}{M} \sum_{m=1}^{M} \sum_{i=1}^{L'-1} I_i^2 l\left(S_i = j\right) \qquad (2)$$

where, $\acute{L}$ represents the number of splits of each individual tree, and M is the number of trees. Also $I_i^2 l$ calculates the square improvement when the j^{th} micro-factor is chosen for splitting.

Machine Learning: Gaussian Process Regression

Once both macro- and micro-factors are identified, the relevant data will be gathered from valid databases, such as IEA, EIA, the World bank, etc. They will serve as inputs to a GPR (Gaussian Process Regression) model to predict the annual CO_2 emission of Iran based on two scenarios.

Machine learning tools are known as viable instruments for forecasting purposes. With unerring accuracy, GPR provides more precise forecasting models than various machine learning tools in majority of cases (Rasmussen & Nickisch, 2010; Seeger, 2004). It works based on a probabilistic framework, considering an arbitrary N-element dataset, $D = \{(y_n, x_n), n = 1, 2, 3, \ldots, N\}$ as input vectors, which it generalizes to the distribution of noisy scalar output. Each scalar micro-factor in the GPR model are transformed into an input vector in the form of$x_n \hat{I} R^L$. Annual CO_2 emission of Iran is the output, a noisy scalar variable that encompasses all the external uncertainties such as truncation and observation errors. Based on the study of Rasmussen & Williams (2006), an additive white Gaussian noise can be defined as follows,

$$y = f(x) + \varepsilon, \quad \varepsilon \gg N(0, s_{noise}^2) \qquad (3)$$

The basic concept of GPR is to use Gaussian process for the representation of the latent variables. Through this mechanism, the latent variable, f, is indexed by the input variables; therefore, any finite assemblage of the latent variables with particular indices will have a consistent normal distribution. For this, it is highly important to take into account those functions, whose relevant values are favorably correlative in Gaussian space. This is the same as the process of using the

GP prior to the functions in the Bayesian framework. Making assumptions about the consistency helps examining the function values and their relevant unseen inputs by introducing a finite set of training data.

The use of Gaussian before making any assumptions in the modeling process, allows the relevant functions to be defined by a mean function, *m(x)*, as well as a covariance one, $k(x, x')$, as follows:

$$m(x) = E[f(x)] \tag{4}$$

$$k(x, x') = E[f(x) - m(x)(f(x') - m(x'))] \tag{5}$$

where E stands for the exception in the above equations. The mean function is commonly considered zero except for unseen areas of the input space. The covariance function is a non-negative symmetric and finite function for all binary points in the input space. To form the prior distribution on *f(x)*, some free parameters, called hyper parameters, are introduced to the covariance function. Four main covariance functions, commonly used in the GPR process, are as follows:

- Squared Exponential Kernel:

$$k(x_i, x_j \,|\, 0) = \sigma_f^2 \exp[-\frac{1}{2}\frac{(x_i - x_j)^T (x_i - x_j)}{\sigma_l^2}] \tag{6}$$

where σ_f represents the signal standard deviation, and σ_l, the characteristic length scale.

- Exponential Kernel:

$$k(x_i, x_j \,|\, 0) = \sigma_f^2 \exp[-\frac{\sqrt{(x_i - x_j)^T (x_i - x_j)}}{\sigma_l}] \tag{7}$$

- Matern 5/2 Kernel:

$$k(x_i, x_j \,|\, 0) = \sigma_f^2 (1 + \frac{\sqrt{5(x_i - x_j)^T (x_i - x_j)}}{\sigma_l} + \frac{5(x_i - x_j)^T (x_i - x_j)}{3\sigma_l^2}) \exp(-\frac{\sqrt{5(x_i - x_j)^T (x_i - x_j)}}{\sigma_l}) \tag{8}$$

- Rational Quadratic Kernel:

$$k(x_i, x_j \,|\, 0) = \sigma_f^2 (1 + \frac{(x_i - x_j)^T (x_i - x_j)}{2\alpha\sigma_l^2})^{-\alpha} \tag{9}$$

Here, α is a scale-mixture parameter, which is always positive, while σ_f, σ_1, and σ_n are the hyper parameters, defined as a vector, $\sigma = [\sigma_f, \sigma_l, \sigma_n]$, and used to generate a random vector. The GPR examines the training dataset, thence to choose the most coherent realization of the dataset for prediction. Assuming that f is a vector for training latent variables and f^*, a vector for latent test variables, then a joint Gaussian distribution will be:

$$p(f, f^*) = N\left(0, \begin{bmatrix} K_{f,f} & K_{*,f} \\ K_{f,*} & K_{*,*} \end{bmatrix}\right) \tag{10}$$

where K is the symmetric covariance matrix. The ijth element in the K matrix defines the covariance between the ith element in the f vector and jth element in the f^* vector. The precision of the developed models will be calculated, using root mean square error (RMSE) and the correlation coefficient (R^2) as follows, (Pham.,2019):

$$RMSE = \sqrt{\sum_{j=1}^{n} (d_j - p_j)^2} \tag{11}$$

$$R^2 = 1 - \frac{\sum_{j=1}^{n} (d_j - p_j)^2}{\sum_{j=1}^{n} (d_j - \bar{d})^2} \tag{12}$$

For the jth pattern, d_j will be the ith factor of the actual output, and p_j, the ith factor of the predicted output; $\bar{d}$ and $\bar{p}$ are the mean values of actual and predicted values, respectively. And N stands for the number of observations.

This paper uses GPR for the development of both univariate and multivariate forecasting models. Univariate models are developed to forecast the future values of micro-factors, identified by TA and GBDT, whereas a multivariate GPR model intends to find the possible correlations between the micro-factors as inputs, and the annual CO_2 emission of Iran as output. Predicted values by the univariate models will be correspondingly put into the multivariate forecasting model to forecast the possible amount of CO_2 emission in the coming years. All relevant analyses have been conducted in the Matlab environment.

RESULTS AND DISCUSSION

Implementing a TA led to the identification of 26 possible influential micro-factors which were categorized in 5 different clusters. The relevant data were gathered from valid databases, such as The World Bank, International Energy Agency (IEA), Energy Information Administration (EIA), OECD I Library, and The Ministry of Energy of Iran. They got introduced to a GBDT model to be ranked in order of priority with the redundant micro-factors with importance rates below 50% being eliminated. By classifying the data set (30% test sample and 50% subsample), the GBDT model got developed and verified against the test sample. Table 1 contains the developed tree structure. Moreover, Fig. 4 shows the importance rate of the identified micro-factors in connection with the annual CO_2 emission of Iran. Regardless of NINA and TGDP, the other micro-factors were of such account to be considered as inputs for the predictive GPR model.

Table.1. Developed tree structure

Child node 1	2		
Child node 2	3		
Size of node	16	6	10
Node mean	0.417328	0.167671	0.750203
Node variance	0.092337	0.015568	0.000785
Split variable	GDP		
Split constant	0.439649		
Standard error (test)		0.0052	
Standard error (train)		0.0069	

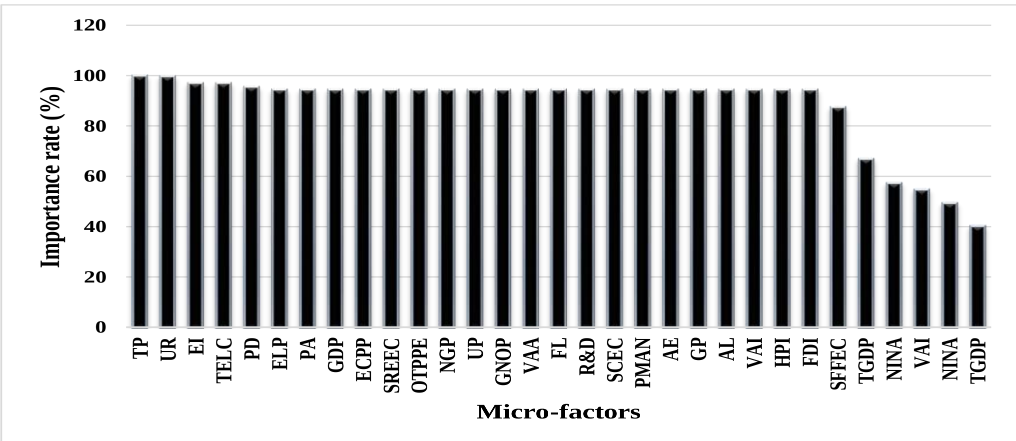

Fig. 4. Importance rate of influential factors of CO_2 emission in Iran

Forecasting Scenario

Two main scenarios were designed to speculate on the technologies, renewables, or the CHP-CCS, capable of letting Iran fulfill its commitments to the Intended Nationally Determined Contributions (INDCs). Since OS assumes that all SDP policies are fulfilled by the end of the plan period, the identified micro factors were forecasted based on the SDP targets. Sometimes the SDP lacked any policy regarding the identified micro-factors, in which cases results from BAU were used as an assumption that the government would not put forward a strong plan on this matter by 2030. FS, the second scenario, assumes that the SDP's encompassing policies like the previous development plans are insignificantly fulfilled by the end of the plan period. As a result, the micro-factors in this scenario got forecasted based on their historical trend, using univariate GPR models. Table 2 provides forecasted values for the identified micro-factors, based on the designed scenarios.

Table 2. Information and assumptions in the designed scenarios

Micro factor	Information	Forecasted values					
		OS			FS		
		2020	2025	2030	2020	2025	2030
AL	OS: AL should increase by 18% by the end of the plan period. FS: AL follows a slightly increasing trend between 2018 and 2030, based on an exponential GPR model: RMSE: 1.4412 R^2: 0.94	30.83	35.74	41.43	29.37	30.77	31.72
SCEC	OS: the SDP contains no clause on the coal industry in Iran. FS: SCEC follows a slightly constant trend between 2018 and 2030, based on a rational quadratic GPR model: RMSE: 0.04384 R^2: 0.6	0.236	0.247	0.247	0.236	0.247	0.247
SREEC	OS: SREEC should increase by 5% by the end of the plan period. FS: SREEC follows a slightly constant trend between 2018 and 2030, based on an exponential GPR model: RMSE: 0.01759 R^2: 0.61	1.055	1.1088	1.165	1.0046	0.9969	0.9957
SFFEC	OS: The share of natural gas in the final energy consumption of all sectors should be maximized by the end of the plan period. FS: SFFEC follows a slightly increasing trend between 2018 and 2030, based on an exponential GPR model: RMSE: 0.15587 R^2: 0.73	99.124	99.373	99.621	99.081	99.130	99.138
VAA	OS: VAA will increase by 8% each year by the end of the SDP. FS: VAA follows a slightly increasing trend, based on an exponential GPR model: RMSE: 0.90409 R^2: 0.83	11.967	17.583	25.835	9.575	9.636	9.667
FDI	OS: FDI rises by four folds by the end of the SDP period. PS: FDI follows a decreasing trend between 2018 and 2030, based on an exponential GPR model: RMSE: 7.2162 R^2: 0.82	115.435	462.603	1856.886	41.910	32.855	27.551
GNOP	OS: the SDP contains no clause on GNOP; however, based on the World Bank forecasts, GNOP will reach to the level of 70 US$ per barrel by 2030. PS:	65	67.45	70	42.95	41.211	40.423
CPI	OS: CPI will reduce by 10% by the end of the SDP period. PS: CPI will dramatically drop, based on a Matern 5/2 GPR model: RMSE: 2.169 R^2: 1	94.12	85.076	76.902	85.277	55.795	41.150
UP	OS: development of small cities around larger ones will reduce the population living in slums by 10% till the end of the SDP period and reduce the population development in large cities. PS: UP will increase substantially by the end of 2030, based on a Matern 5/2 GPR model: RMSE: 0.0357 R^2: 1	75.642	75.526	75.916	63.726	68.916	76.818

Table 2. Information and assumptions in the designed scenarios (continius)

Micro factor	Information	Forecasted values					
		OS			FS		
		2020	2025	2030	2020	2025	2030
PD	OS: Decentralization of urban population through developing small cities around larger ones, particularly, Tehran; development of Andisheh city to lower the PD in Tehran city and stabilize it in the coming years. PS: PD will follow a growing trend, based on a Matern 5/2 GPR model: RMSE: 0.0469 R^2: 1	49.546	49.570	49.595	51.604	55.048	58.172
TELC	OS: Detection and modification of electricity consumption patterns in all sectors will stabilize the level of TELC by the end of the SDP period. PS: TELC will increase substantially by the end of SDP, based on a Matern 5/2 GPR model: RMSE: 2.6132 R^2: 1	252.345	265.217	178.746	279.292	324.540	351.460
PA	OS: the SDP contains no clause on GNOP. PS: PA will reduce slightly by the end of the SDP, based on a Matern 5/2 GPR model: RMSE: 0.0386 R^2: 1	68.6230	66.792	65.169	68.630	66.792	65.169
GDP	OS: GDP will grow by 36% till the end of the SDP period. PS: GDP will decrease slightly by the end of the SDP, based on an exponential GPR model: RMSE: 13.151 R^2: 0.98	706.548	1038.152	1525.386	555.998	548.250	540.875
ECPP	OS: Detection and modification of energy consumption patterns in the residential area will reduce the rate of energy consumption there by 5% until the end of the SDP period. PS: ECPP will follow a slightly decreasing trend by 2030, based on an exponential GPR model: RMSE: 72.229 R^2: 0.99	3105.375	2901.345	2710.721	3215.300	3184.100	3154.000
TP	OS: The fertility rate will increase from 1.66 in 2017 to 2.5 by the end of the SDP. PS: TP will follow a growing trend by the end of 2030, based on a rational quadratic GPR model: RMSE: 0.070935 R^2: 1	85.827	94.204	103.398	83.932	88.343	90.287
FA	OS: a forest conservation policy will be put in action, and FA will change insignificantly until the end of the SDP. PS: FA will decrease slightly by the end of 2030, based on a squared exponential GPR model: RMSE: 0.023121 R^2: 1	6.564	6.564	6.564	6.457	6.170	6.111
AE	OS: The rate of AE remains 100% until the end of the SDP. PS: AE will slightly decrease by the end of 2030, based on an exponential GPR model: RMSE: 0.0984 R^2: 1	100	100	100	99.957	99.888	99.820
OTPPE	OS: conversion of gas-burning power plants to CHP-CCS power plants and installation of CHP-CCS power plants with an efficiency rate between 50-70% will enhance the OTPPE by 7% till the end of the SDP. PS: OTPPE will increase slightly by the end of 2030 based on a Matern 5/2 GPR model: RMSE: 0.34396 R^2: 0.97	39.618	42.471	45.528	38.221	38.786	39.154
ELP	OS: according to the “Iranian targeted subsidy plan”, all energy prices will increase by 20% annually. PS: ELP will reduce slightly by the end of 2030, based on an exponential GPR model: RMSE: 25.573 R^2: 0.99	876.023	939.086	1006.688	697.352	677.303	658.378
GP	OS: according to the “Iranian targeted subsidy plan”, all energy prices will increase by 20% annually. FS: GP will remain slightly constant, based on a squared GPR model.	1728	4299.816	10699.321	1174.1	1267.7	1267.9

Table 2. Information and assumptions in the designed scenarios (continius)

Micro factor	Information	Forecasted values					
		OS			FS		
		2020	2025	2030	2020	2025	2030
NGP	OS: according to the "Iranian targeted subsidy plan", all energy prices will increase by 20% annually. FS: NGP will follow a declining trend by the end of 2030, based on an exponential GPR model: RMSE: 149.14 R^2: 0.85	1382.4	3439.853	8559.456	632.063	471.632	392.938
UR	OS: the SDP contains no clause on UR. FS: UR will increase slightly by the end of 2030, based on a Matern 5/2 GPR model: RMSE: 0.0993 R^2: 0.96	2.179	2.360	2.556	2.179	2.360	2.556
EI	OS: EI will reduce by 3% annually until the end of the SDP. FS: FS will follow a slightly increasing trend during early 2020s, thence to fall into a declining trend by the end of 2030, based on a squared exponential GPR model: RMSE: 0.33188 R^2: 0.84	7.511	6.450	5.539	8.593	8.657	8.021
PMAN	OS: there is no clause on PMAN in the SDP. PS: PMAN will remain slightly constant till the end of 2030, based on an exponential GPR model: RMSE: 0.40024 R^2: 0.63	38.461	38.244	38.203	38.461	38.244	38.203
R&D	OS: R&D will reach 4% until the end of the SDP. FS: R&D will slightly increase between 2018 and 2030, based on an exponential GPR model: RMSE: 0.0649 R^2: 0.8	1.072	2.532	4	0.2601	0.3156	0.342
VAI	OS: VAI will increase by 9.3% annually until the end of the SDP. FS: VAI follows an increasing trend by the end of 2030, based on a squared exponential GPR model: RMSE: 2.2613 R^2: 0.79	38.431	45.106	52.941	39.320	40.271	40.265

With the exception of 26 univariate GPR models, developed for forecasting the identified micro-factors, a multivariate GPR model was developed as well in order to forecast the annual CO_2 emission of Iran by 2030. Diverse kernel functions got used to find the most accurate predictive model for this purpose. The dataset was split according to 70/30 rule, meaning that 70% of the dataset was used for the training set and 30% for the validation one. Table 3 provides the performance indicators for the developed multivariate GPR models.

Table 3. Performance of the GPR models in terms of accuracy

Model	RMSE	R^2
Exponential GPR	17546	0.99
Matern 5/2 GPR	18378	0.99
Squared Exponential GPR	18617	0.99
Rational Quadratic GPR	18750	0.99

Iran is ranked seventh in terms of CO_2 emission globally. As previously shown in Figure 1, the CO_2 emission process in Iran is on the rise. Also, the country has not yet made a firm decision to accept the Intended Nationally Determined Contributions (INDCs), given the possible sanctions. Although Iran is not currently legally bound by the Intended Nationally Determined Contributions (INDCs), it is committed to lower its annual CO_2 emission by 4%, in comparison to 2010. Meanwhile, relevant officials have remarked that there is a potentiality of a 12% reduction in case of obtaining international aids and not being exposed to any further sanctions.

In any case, in its national development plan, Iran is obliged to implement programs to reduce the level of greenhouse gas emission and ultimately protect the environment.

Nonetheless, past research has shown that Iran has failed to achieve the goals of the Fourth and Fifth National Development Programs.

Using the following two perspectives, this article tries to discuss Iran's potentiality to possibly accept the Intended Nationally Determined Contributions (INDCs) and select high-yield technologies to achieve the goals of the Sixth Development Plan:

1. Deploy a decision model to select a high-yield technology to reduce annual CO_2 emission (for which, the present article discussed the use of CHP-CCS technology and renewable energy technology)
2. Examine optimistic and pessimistic scenarios in order to achieve the goals of the Sixth Development Plan.

Fig. 5 shows the predicted values for CO_2 emission in Iran, based on the designed scenarios. Table 4 also checks whether Iran can meet its commitments to the Intended Nationally Determined Contributions (INDCs), based on the designed scenarios. The findings suggest that Iran will not be able to fulfill its commitment based on the FS at all. Extending the share of renewables in the energy mix, or converting the gas-burning power plants to CHP-CCS plants, will not help Iran honor its commitment to the Intended Nationally Determined Contributions (INDCs). However, retrofitting gas-burning power plants with CHP-CCS technology and installing new energy-efficient CHP-CCS power plants are seemingly more influential to reduce or, at least, stabilize CO_2 emission in this country, in comparison to renewable technologies.

Iran will be able to honor both targets, the 4% reduction and the 12% one, based on OS, even without considering renewables or the CHP-CCS development in the SDP. However, just like the FS, the CHP-CCS technologies are of more importance in comparison to the renewables as Iran can sooner achieve its targets through these technologies. Under the FS assumptions, Iran can touch the 4%-reduction target with or without consideration of the CHP-CCS and renewables by the end of 2023. This is while there is more potential for the reduction of CO_2 emission in this country if the development of the CHP-CCS technologies is taken into consideration in the SDP. According to the FS with the development of the CHP-CCS, CO_2 emission of Iran will reduce by 5.7% in comparison to the 2010's level. However, the figure for renewables is 5.15%.

Considering FS without renewables and the CHP-CCS development, Iran still can meet the 12%-reduction target by the end of 2028. Development of renewables or the CHP-CCS technologies will help the country achieve the goal by the end of 2027. Yet, under the renewable development scenario, the CO_2 emission of Iran may reduce by 12.51% till the end of 2027. The figure for the development of the CHP-CCS is about 13.12%.

Keeping the abovementioned facts in mind, development of CHP-CCS technologies in Iran is seemingly a more effective way for the country to achieve its goal, with regard to the Intended Nationally Determined Contributions (INDCs) in comparison to the renewable energies. Regardless of the Intended Nationally Determined Contributions (INDCs), the strategy is more helpful for this country to stabilize the level of its emission in the coming years by comparison, at least from an environmental point of view.

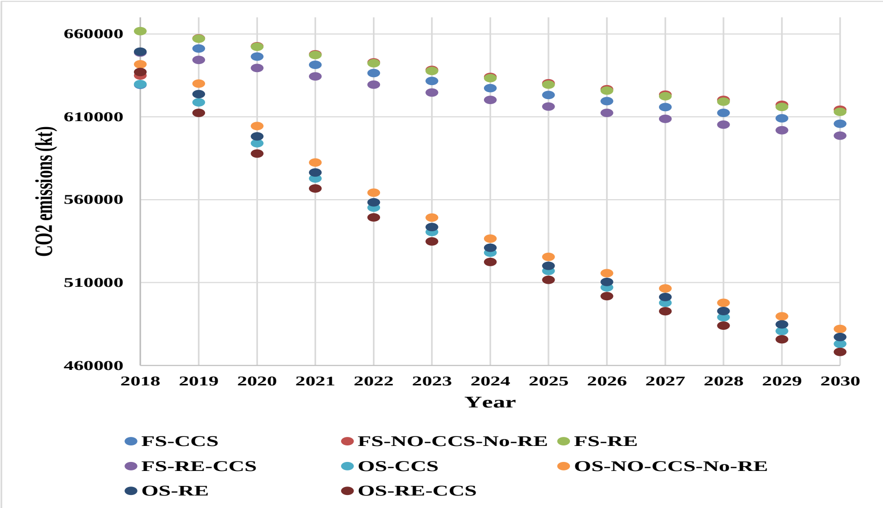

Fig.5. Predicted values for CO_2 emission of Iran, based on the designed scenarios

Table 4. State of Iran's commitments to the Intended Nationally Determined Contributions (INDCs), based on the designed scenarios.

Year	2030	Reduction % in comparison to the 2010's level (%)	4%-reduction target	12%-reduction target
BAU-CCS	605840.4	-5.72	Not satisfied	Not satisfied
BAU-NO-CCS-NO-RE	614250	-7.19	Not satisfied	Not satisfied
BAU-RE	612980	-6.97	Not satisfied	Not satisfied
BAU-RE-CCS	598623.2	-4.46	Not satisfied	Not satisfied
OS-CCS	472972.5	17.46	Satisfied	Satisfied
OS-NO-CCS-NO-RE	481972	15.89	Satisfied	Satisfied
OS-RE	477150	16.73	Satisfied	Satisfied
OS-RE-CCS	468155.8	18.30	Satisfied	Satisfied

Since CO_2 emission on a national level is a sophisticated matter, with many factors affecting the issue, this paper firstly conducted a TA to identify the possible influential factors of CO_2 emission. The analysis resulted in 26 micro-factors, classified under five different macro-factors. The identified micro-factors were then introduced to the GBDT model to find the most decisive micro-factors particular of Iran. Except for NINA and TGDP, the other micro-factors, topped by TP, UR, and EI were found influential by the GBDT model and were, therefore, considered for scenario analysis in this study. Two scenarios were taken into consideration: 1) The OS assumes that the SDP will be fully accomplished and accordingly forecasts CO_2 emission of Iran with the adoption of renewable policies and CHP-CCS policies by 2030. 2) The FS assumes that the SDP's policies are partially fulfilled and by 2030 Iran will remain the same as it is currently. While the micro-factors have been forecasted mainly based on the SDP's policies in the OS, they have been forecasted based on their historical trends using univariate GPR models. The forecasted values have been then put in a multivariate GPR model, and CO_2 emission of Iran by 2030 have been predicted accordingly.

CONCLUSION

Between 2007 and 2012, under the Kyoto Protocol, industrialized nations pledged to reduce their greenhouse gas emission. However, some countries, such as the United States and Russia, abandoned the treaty and withdrew. Because Kyoto did not have an executive obligation, it did not live up to its commitments. Countries across the globe adopted an historic international climate agreement at the U.N. Framework Convention on Climate Change (UNFCCC) Conference of the Parties (COP21) in Paris in December 2015. In anticipation of this moment, countries publicly outlined what post-2020 climate actions they intended to take under the new international agreement, known as their Intended Nationally Determined Contributions (INDCs). The climate actions communicated in these INDCs largely determine whether the world achieves the long-term goals of the Intended Nationally Determined Contributions (INDCs): to hold the increasing trend of global average temperature to well below 2°C, to make efforts to limit the increase to 1.5°C, and to achieve net zero emission in the second half of this century. On the other hand, Iran is ranked seventh in terms of global CO_2 emission and has been following an increasing trend during the recent years.

The electricity sector is the major contributor to CO_2 emission of this country, in spite of the several CDMs the government adopted in the last three decades. On the other hand, the country is committed to lower its annual CO_2 emission by 4% by the end of 2030according to INDC, in comparison to its level in 2010. As a result, this paper tried to find an early-yielding solution for the issue by adopting scenario analysis.

Results suggest that investment in CHP-CCS technologies is a better alternative than renewables for Iran if it intends to fulfill its commitments to the Intended Nationally Determined Contributions (INDCs) sooner and more efficiently. Additionally, it is seemingly a better solution for stabilization of CO_2 emission in case of faulty implementation of SDP's policies. However, this paper goes through the issue from an environmental viewpoint, and techno-economic analysis, or a life cycle assessment, is needed to grasp a better understanding over the nature of the issue. For this, future studies need to take an economic viewpoint and analyze the total investment required for implementation of these scenarios. More importantly, it would be preferable for future studies to assess the impact of implementing such policies on electricity price in the future.

ACKNOWLEDGEMENTS

This work is part of a PhD dissertation. The authors would like to thank Islamic Azad University Roudehen Branch and Saba three-megawatt CHP power plant for their scientific support in this research.

GRANT SUPPORT DETAILS

The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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