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Optimising the insertion of renewables in the Colombian power sector

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ABSTRACT

While most of Colombia's power comes from large-scale hydroelectricity generation, it still depends on fossil-fuel-based technologies. Alternative cleaner energy sources have been largely neglected despite their abundance and the likely complementarities between different renewable resources. This limited mix of energy sources has made the system vulnerable to unpredictable and recurrent drought conditions (El Niño) occurring every 4–5 years. In the past, El Niño brought high energy costs and power supply losses. This paper proposes an optimisation model to study the insertion of renewable energy systems (RES) into the Colombian electricity sector. The model considers a cost-based generation competition between conventional technologies (hydro and thermal) and alternative RES (solar photovoltaic (PV) and wind). It aims at minimising system costs, CO_2 emissions, and the number of blackout events. The model is solved by following two procedures known as Implicit Stochastic Optimisation (ISO) and Robust Optimisation (RO), and the results indicate that alternative renewables should replace all fossil-fuel-based technologies for economic and environmental reasons. Solar PV seems particularly promising to expand system capacity, as it contributes to both the reduction of the overall system costs and to the ability of the system to cope with extreme dry weather conditions.

1. Introduction

The continuous worldwide growth in energy demand, and its impacts on CO_2 emissions, have prompted changes in the traditional energy production practices, moving from those based on fossil fuels to technologies based on renewables [1]. Undoubtedly, renewable energy has been one of the best strategies to reduce greenhouse gas emissions and, consequently, to mitigate global warming. Thus far, the focus of this change has mainly been on the installation of power-generation facilities, particularly solar PV and wind technologies [4,5].

In 2015, solar PV and wind power accounted for 77% of all the new power installations in the world and hydropower accounted for most of the remainder [4]. It was the first year that the power capacity added into the world came primarily from renewables, rather than from all the fossil-fuel-based technologies combined. Looking at the total power in place, renewables supply at least 23.7% of the world's demand, with 16.6% coming from hydropower installations [5].

This growing trend towards renewables has sped up the learning curve, prompting greater technology efficiency and lower costs [6]. Solar PV and onshore wind technologies have experienced the most remarkable cost reductions in the past seven years, and forecasts predict that costs will continue to fall in the near future until they are even cheaper than conventional technologies [7,8]. It is expected that renewable energy systems (RES) will become the cheapest options in most countries around the world by 2030, and that by 2040 the costs of wind and solar PV would fall by up to 41% and 60% respectively [9].

Colombia has important coal, water, wind and solar irradiation resources (but limited established gas and oil reserves) for electricity generation. However, at present, large hydropower facilities satisfy the primary electricity demand (about 65%) and gas- and coal-fired plants contribute with the rest (about 35%). There is a small wind farm with a capacity of about 19 MW along the north coast of the country and a 10 MW solar farm in the south-western, which together contribute to less than 0.02% of the total demand. Apart from that, alternative renewables, such as wind and solar, have been largely neglected despite their abundance and their apparent complementarities with hydropower.

The limited mix of energy resources has created considerable vulnerability in the Colombian power system, particularly in extreme dry weather conditions such as El Niño events. El Niño has exposed the vulnerabilities of the power system in the past, as the

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system largely depends on hydropower; therefore, dry conditions may lead to power supply losses, high production costs, and loss of the overall competitiveness for the country. In the business-as-usual scenario, it is still expected that the contribution of hydroelectricity and fossil-fuel-based technologies will increase in the coming years. In practice, expansion plans only consider renewables marginally and there is significant uncertainty on what may happen to the system in the mid-to long-term. Furthermore, there are over a dozen indicative expansion-plan scenarios, but no real commitment or goals set for renewables at the large scale [10,11].

Within this context, this paper analyses the optimal power system expansion for Colombia until 2030, in terms of the appropriate combination of energy sources in time. This is particularly important given that the demand for electricity will continue to grow over time and that the government appears to continue incentivising conventional technologies. Cost-based generation competition between conventional energy technologies and alternative RES (solar PV and wind power) is considered, as well as the economic, environmental (CO_2 emissions), and technical implications of different combinations of technologies.

It is important to note that a comprehensive life-cycle (or environmental analysis) for the conventional and RES technologies is not reported here, as this goes beyond the scope of the paper. Nevertheless, the paper acknowledges the existence of some negative impacts of RES. For example, the literature has estimated that the CO_2-eq emissions of PVs and wind technologies are between 14 and 45 gr and 10 to 18 per kWh, respectively. These values are significantly lower than the emissions calculated for fossil-based technologies, which could vary from 100 to 1000 depending on the type of technology assessed (see, [12–14]).

In addition, other negative impacts of RES on the environment have been identified and amply reported elsewhere (see e.g., [15–17]). For instance, during the construction of RES projects habitat loss, land fragmentation and the increase of contaminant concentrations in air-borne dust due to soil disturbances may occur. Also, while in operation, utility-scale RES may affect wildlife and make noise (wind turbines), consume fresh water (PV panels), use large extensions of land and disturb the visual landscape. Finally, at the end of their life, the components of solar PVs must be recycled in order to avoid the spill of the toxic materials contained within them. Interest readers are encouraged to look at references such as, Saidur, et al. [16] and Hernandez et al. [17]; for further information about the negative impacts of RES on the environment.

In terms of methodology, the literature offers a wide range of long-term (e.g., [18,19]); and short-term [20–22] electricity modelling approaches that could be considered for finding the optimal mix of energy sources for the Colombian case. Optimisation and simulation techniques are the two most common approaches employed (e.g., [21,23]), and various cases of application have been undertaken, but mainly in the industrialised world – for example in Greece [24], Italy [25], Australia [26], and Brazil [18].

The stochastic nature of the variables required for modelling electricity production (e.g., solar irradiance, wind speed and precipitation) demands the use of innovative algorithmic approaches to simulate weather-related variables and to find optimal configurations or solutions (e.g., [27,20,26,28]). Some of the procedures most commonly employed include stochastic optimisation with simulation of random variables, implicit stochastic optimisation and robust optimisation with scenarios, scenario trees, genetic algorithms and fuzzy sets, among others (e.g., [2,23,29,20,28]). Implicit stochastic optimisation and robust optimisation are commonly employed in the electricity sector, because they are simple to use, require few computational resources, and enable the explicit consideration of uncertain parameters via synthetic data or interval data.

Most models aim to minimise the total investment and operation costs of the system, the amount of CO_2 emitted, and the number of potential blackout events (e.g., [21,30,18,20]). Constraints are usually associated with the operation of the system as a whole (plant management, electricity generation, and meeting demand, among others) and very few consider transmission-related constraints [20,28]. Short-term planning models are usually concerned with simulating the operation of the system node-by-node and hourly, whereas long-term planning models are more concerned with identifying the optimal combination of energy sources within an established planning horizon.

The rest of this paper is organised as follows: first, a brief description of the Colombian power sector is presented in Section 2. Section 3 proposes an optimisation model for the Colombian case, as well as the data fed into the model and the modelling process itself. Section 4 presents the results and conducts the corresponding sensitivity analysis. The article discusses findings in Section 5 and concludes with some remarks in Section 6.

2. The Colombian power sector

Colombia, located in the northwest corner of South America, is a country rich in natural resources. Water is particularly important for power generation and approximately 65% of the power sector's capacity comes from large hydropower stations, while the remaining is produced using fossil-fuel-based technologies (mostly gas and coal). In 2015, the electricity demand of the country was 66.174 GWh and the national grid had a net effective power capacity of 16.420 MW installed [31].

Demand has been continuously growing over the years and thermoelectricity has been gaining a share in power generation. Fig. 1 depicts the growing trend of demand and the share of hydropower and thermal power sectors, for 2000 to 2015. It is important to note that the share of the thermal sector increased sharply during drought periods (El Niño years 2009–2010) and especially during El Niño 2015, which, according to the National Oceanic and Atmospheric Administration (NOAA), was the strongest of its type over the past 65 years [32].

In 1992, El Niño caused a profound crisis in the national power sector that lead to the reform and subsequent liberalisation of the market, which was aimed at encouraging investment and competition in electricity generation and trading. At present, under a liberalised market, companies compete making short- and long-term transactions in the spot market and on bilateral financial contracts. Power generation companies, in particular, make daily price offers and declare the next day's power generation. Thus, the National Dispatch Centre (XM) dispatches plants according to a merit-order criterion in order to meet demand; the last unit dispatched sets the spot price for system [33]. Under rainy conditions,

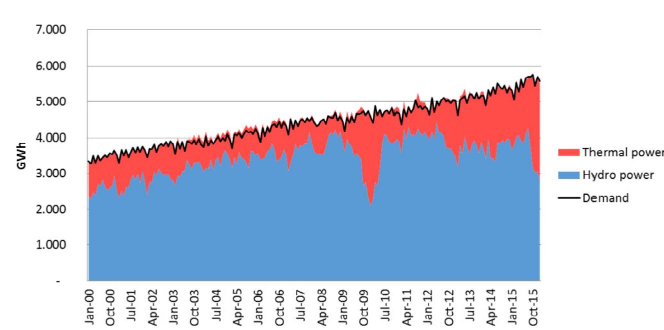


Fig. 1. Monthly electricity demand and hydropower and thermal power generation (Data source: [31]).

hydropower usually sets the spot price, but during El Niño, thermal units, which are more expensive to operate, set the price.

The Colombian Commission for the Regulation of Energy and Gas (CREG) created a capacity mechanism in 2006, aiming at reducing the financial risk for companies and at encouraging future investments in order to improve system reliability and to better confront droughts [34]. However, as shown in Fig. 2, the spot price skyrocketed during El Niño 2015–2016, reaching average prices of about 25 US dollar cents per kWh, from May 2015 to May 2016.

El Niño events in 2015–2016 led to the realisation that this capacity mechanism was expensive, insufficient, and inefficient, as companies that benefited from it for the past ten years were unable to meet their obligations. It is estimated that around 8 billion US dollars were spent in the scheme from 2006 to 2016. Consequently, analysts have called for a shift towards demand participation and renewables [35,36]. However, the Planning Office of the Colombian Ministry of Energy and Mines (UPME) remains partial to hydro-thermal technologies in its plan to expand the country's power capabilities in the next 15 years [10,11].

Despite the above, on May 2014, the Colombian government enacted Law 1715, which incentivizes the insertion of RES into its energy matrix and promotes RES for off-grid rural areas. The aim of the law is to reduce greenhouse gases emissions, secure energy supply, and promote energy efficiency. The law relieves up to 50% of capital costs, charges no VAT on all RES-related equipment, and reduces the importing tariffs on RES equipment and materials. It also created a fund called FENOGE that supports financially RES projects for sparse poor off-grid rural areas, where around 2 million people live (4% of the population) [37,38]. The focus of this paper is on assessing the insertion of RES into the grid, and for that reason, a more detailed analysis of RES for off-grid areas is not performed here.

Law 1715 is therefore an important RES policy instrument for Colombia and it should contribute to the diffusion of RES throughout the territory. The idea would be to find alternative clean energy resources that would be able to complement the country's hydropower sector [39]. In this sense, Rodriguez et al. [40] identify locations in Colombia that have the potential for power generation based on the complementarities between renewables. Their results point out some negative complementarities between renewables, in the order of 50%. This indicates that alternative renewable technologies could be considered during droughts and increase water saving during rainy or normal conditions. Fig. 3 shows some of the complementarities between precipitation and solar radiation for different areas in Colombia.

In conclusion, there are clear advantages in diversifying the portfolio of electricity resources for the Colombian power sector, so as to be better prepared to face future El Niño events. This paper progresses in this direction by working on the optimal insertion path of various renewables. The next section presents an optimisation model that evaluates the insertion of alternative RES (solar PV and wind power) into the Colombian electricity sector and assesses their economic, environmental, and technical implications.

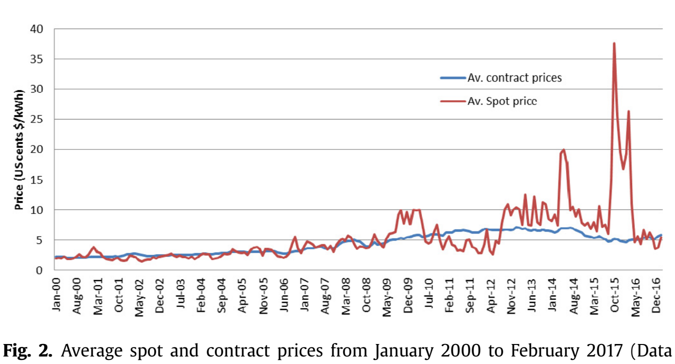


Fig. 2. Average spot and contract prices from January 2000 to February 2017 (Data source: [31].

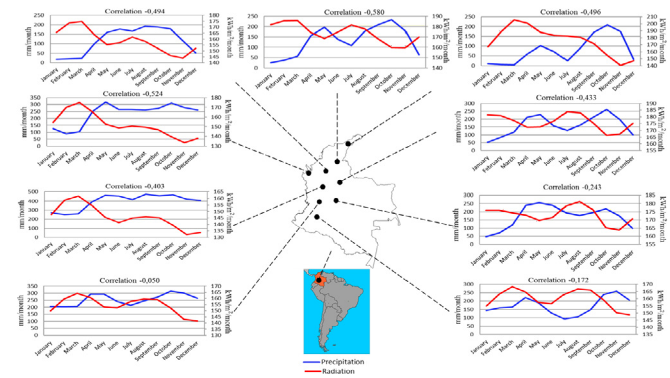


Fig. 3. Complementarity between solar radiation and precipitation at different locations in Colombia. (Data source: NOAA's reanalysis database, years July 1948 and December 2015).

3. Model formulation, data and process

This section presents an optimisation model to evaluate the insertion of RES into the Colombian power sector. First, the model or problem formulation is presented. Then, the data fed into the model is shown. Finally, the data processing and the solving procedures that were followed, are discussed.

3.1. The optimisation model

The model seeks to optimise the corresponding mix of resources necessary to meet electricity demand as it evolves over time and to establish an optimal capacity-expansion plan. For this purpose, alternative renewable technologies – solar PV and wind power – compete in economic and environmental terms with conventional technologies – hydropower and thermal power (coal and gas). The model identifies the resources that minimise overall system costs. The details of the model (decision variables, objective function and constrains) are provided below.

3.1.1. Decision variables

The decision variables used in the optimisation model are classified according to the following categories: *i)* electricity production, referring to decisions regarding the amount of electricity produced at time t by different resources i (E_t^i: E_t^{Hydro}, E_t^{Gas}, E_t^{Coal}, E_t^{Solar}, E_t^{Wind}); *ii)* capacity investment, referring to decisions regarding power capacity expansion or the addition of different types of resources (X_t^i: X_t^{Hydro}, X_t^{Gas}, X_t^{Coal}, X_t^{Solar}, X_t^{Wind}); *iii)* blackouts, referring to the unmet demand at time t ($E_t^{Blackout}$); and *iv)* decisions about reservoir discharges at time t (DD_t).

3.1.2. Objective function

The objective function (Eq. (1)) represents the overall costs of the system during the entire planning horizon T, with all five types of technologies i. These include: operational expenditure (OPEX - C); capital expenditure (CAPEX - IC); reliability charge costs (RC) for the technologies that can guaranty firm energy; environmental costs (EC), measured as the cost of CO_2 emitted by fossil-fuel-based technologies; and the penalties associated with potential blackout events (BC).

$$Min\sum_t\sum_i\left(C_t^i\cdot E_t^i+IC_t^i\cdot X_t^i+RC_t\cdot X_t^i+EC_t\cdot PCO2_t^i+BC_t\cdot E_t^{BlackOut}\right) \quad (1)$$

3.1.3. Demand constraint

Eq. (2) balances electricity demand at each time period *(D_t)* with electricity generation via each resource (*i*: hydro, gas, coal, solar PV and wind). It also takes into account the blackouts that occur when there are insufficient generation resources. As already discussed, blackouts are penalised in the objective function, according to the established electricity rationing costs.

$$\sum_{i=1}^{5}E_t^i+E_t^{BlackOut}=D_t[GWh],\quad \forall t=1,\dots,T \quad (2)$$

3.1.4. Hydropower constraints

Hydropower production is modelled here as an aggregated reservoir of the system. The constraints (Eq. (3), Eq. (4), and Eq. (5)) simulate the changing conditions of the reservoir from time *t* to *t+1*. Eq. (3) updates the amount of water within the reservoir by balancing the water inflows and outflows; water inflows (WI_t) result based on projected precipitations, whereas outflows result from electricity production (E_t^H) and dam discharges (DD_t). The level of the reservoir is maintained between its minimum and maximum technical volumes. Water discharges are greater than zero when the level of the reservoir exceeds its maximum technical volume (RV_t^{max}); otherwise, they are set to zero (Eq. (4)). Finally, when new capacity is added to the system (e.g., a new plant is built), Eq. (5) updates the maximum capacity of the aggregated reservoir and takes into consideration the average capacity factor for hydropower plants (δ^H).

$$RV_{t+1}=RV_t+WI_t-E_t^H-DD_t,\quad \forall t \quad (3)$$

$$RV_t^{min}\le RV_t\le RV_t^{max},\quad \forall t \quad (4)$$

$$RV_{t+1}^{max}=RV_t^{max}+720\cdot\delta^H X_t^H,\quad \forall t \quad (5)$$

3.1.5. Thermal power constraints

The amount of electricity produced by both, gas and coal plants, is limited by the maximum installed capacity of each resource at time *t* (Eq. (6)), which is updated for time *t+1* when new capacity is added to the system (Eqs. (7) and (8)). δ^G and δ^C indicate the average capacity factors for both technologies, gas and coal plants, respectively. Finally, the average amount of CO_2 emitted by gas and coal when producing 1 GWh of electricity is assumed to be 553 and 984 ton CO_2/GWh respectively [45]. The overall pollution at time *t* is presented in Eq. (9).

$$E_t^G\le E_t^{G\_max};E_t^C\le E_t^{C\_max},\quad \forall t \quad (6)$$

$$E_{t+1}^{G\_max}=E_t^{G\_max}+\delta^G\cdot X_t^G,\quad \forall t \quad (7)$$

$$E_{t+1}^{C\_max}=E_t^{C\_max}+\delta^C\cdot X_t^C,\quad \forall t \quad (8)$$

$$PCO2_t=553{*}E_t^G+984E_t^C,\quad \forall t \quad (9)$$

3.1.6. Solar PV constraints

The electricity output of a solar farm is determined by the amount of solar irradiation (G_t) that falls on the farm, the exposition time (Δt), the total area of the panels (A_t^S), and the efficiency (η^S) and capacity factors (δ^S) associated with the type of technology employed (see Eq. (10)). Similarly, as in Section 3.1.5, the maximum capacity is updated if additional capacity is added to the system. Thus, capacity additions increase the total area of solar farms in Eq. (11).

$$E_t^S=\eta^S\delta^S G_t A_t^S\Delta t,\quad \forall t \quad (10)$$

$$A_{t+1}^S=A_t^S+\delta^S\cdot X_t^S,\quad \forall t \quad (11)$$

3.1.7. Wind power constraints

Electricity production by a wind farm, in a given location, depends on the characteristics of the location and the technical features of the turbines installed [46,47]. Wind speed data is normally collected at a 10 m height (h_0). In order to use such data, they need to be recalculated for the average height of current pylons' (as indicated in Eq. (12)). *h* is the height at which wind speed is calculated, V_t^h is the wind speed at height *h*, V_t^o is the wind speed at height h_o (10 m) and α represents the roughness of the terrain on which the wind farm lies – typical values for well-exposed areas with low roughness are around 1/7 [48]. Thus, electricity generated by wind farms can be calculated following Eq. (13), where E_t^W is the electricity output at *t*, ρ is the air density in kg/m^3, A^W is the swept area of a typical turbine, *N* is the number of turbines installed, η^W is the capacity factor and Δt is the exposition time (e.g. Ref. [20]. Finally, Eq. (14) updates the number of turbines whenever further capacity is added to the system.

$$V_t^h=V_t^o\left(\frac{h}{h_o}\right)^{\alpha}[m/s] \quad (12)$$

$$E_t^W=\left(\frac{1}{2}\rho A^W V_t^{h3}\right)N_t\eta^W\Delta t\ [GWh] \quad (13)$$

$$N_{t+1}=N_t+\delta^W\cdot X_t^W \quad (14)$$

3.2. Data gathering and processing

The model described above aims at optimising the expansion and operation of the Colombian power sector for a planning horizon of 15 years using monthly cost, electricity demand, water input, solar radiation, and wind speed data. This section describes the data gathered and processed to feed the model.

3.2.1. Data gathering

15 years of historical data (2000–2015) of water inputs and electricity demands were retrieved from the system operator XM [31]. Solar irradiation and wind speed data were obtained from the NOAA's Earth System Research Laboratory Reanalysis database [49]. The data were gridded (1° × 1°), corresponding to La Guajira (12 N, 71.5 W), assuming that solar and wind farms were located there.

La Guajira, on the northern coast of Colombia, is an arid area of more than 20,000 km^2 that has some of the greater solar and wind resources in the country, making it one of the best locations for alternative renewable technologies [46]. The average wind speed is 5–7 m/s and the average solar radiation is 6 kWh/m^2 [50]; [3]. The data retrieved were validated using the governmental reports *Wind Atlas and Wind Energy in Colombia* [51] and *Solar Radiation Atlas of Colombia* [52].

3.2.2. Data processing

Data were used for model parameter estimations and for the generation of synthetic time-series of hydro-meteorological scenarios. The aim was to simulate plausible future climatic scenarios for the years to be optimised. This research used the Castalia software to generate scenarios of water inputs, solar irradiation and wind speed, under El Niño, La Niña and normal conditions. This software was selected because it preserves the statistical characteristics of the hydro-meteorological data as well as their periodicity, intermittency and long-term persistence (Hurst-Kolmogorov behaviour) [53]. This was fundamental for recreating the uncertainty imbedded in the problem and for preserving the natural climate behaviour, e.g., the inter-annual variability and the auto- and cross-correlations of and between the parameters.

Simultaneously, an ARIMA(2,1,1) x SARIMA(1,12,1) model, with two lagged periods and a seasonality of 12 months, was applied in order to estimate future electricity demands during the planning horizon (Fig. 4). The values generated were statistically validated with high-demand projections reported by UPME [11] and Macías and Andrade [10].

Finally, one of the novelties in this paper is the inclusion of the concept of learning curves [6], within the optimisation model, to estimate plausible future trends of the costs of the technologies over the course of the planning horizon. Learning curves establish how technology prices decrease over time as a result of the knowledge and experience gained by technology production, installation and use [6].

To calculate the cost of each technology over time, it is first necessary to empirically estimate parameter b of the learning rate equation ($LR = 1 - 2^{-b}$). This allows for the computation of the costs of a technology over time, by applying the learning curve equation$C(y_t) = C(y_0)\left(\frac{y_t}{y_0}\right)^{-b}$, where (y_t/y_0) represents the percentage change of the installed capacity from time *0* to time *t*, $C(y_t)$ represents the cost at time *t*, and $C(y_0)$ are historical data of costs at time $t=0$ [54]; [6]. For the five technology options considered in this work (see Fig. 5), we computed their CAPEX, OPEX, and levelised costs of electricity (LCOE) using data from IRENA [55] and IEA [56]; and validated estimates from Tidball et al. [8].

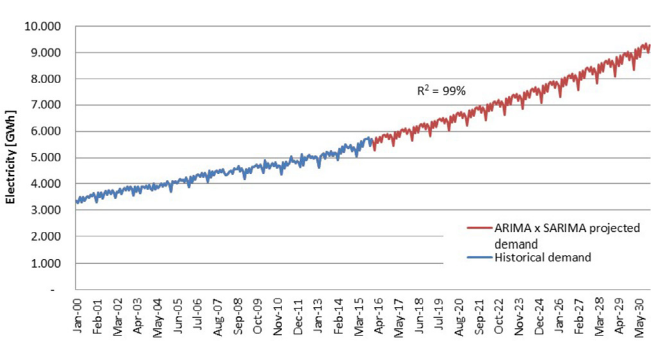


Fig. 4. Historical and projected electricity demand with a ARIMA(2,1,1) x SARIMA(1,12,1) model.

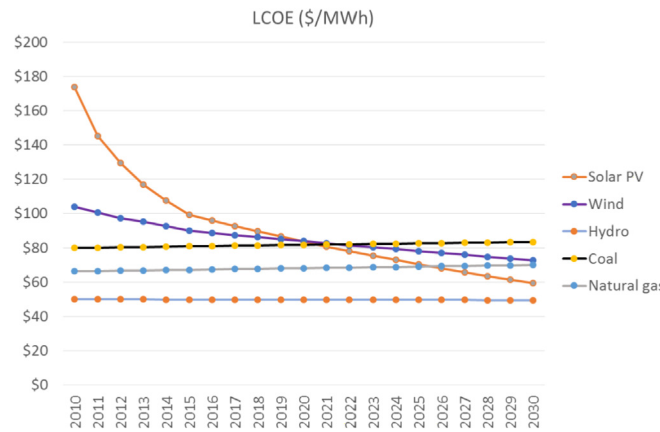


Fig. 5. Historical and projected LCOE for the various technologies considered (2010–2030).

Lastly, to estimate future environmental costs of electricity production based on fossil-fuel-based technologies, historical prices for CO_2 were retrieved from Bloomberg [57] database and the future predictions are taken from Luckow et al. [58].

3.3. Optimisation process and sensitivity analysis

This section provides a brief description of the procedures that were followed to solve the model above and to perform the sensitivity analysis of the proposed solutions. The optimisation model was solved by following two different procedures known as Implicit Stochastic Optimisation (ISO) and Robust Optimisation (RO). Implicit Stochastic Optimisation (ISO) is an approach that facilitates optimisation of a model under uncertainty using synthetic datasets (with $\overline{\Omega}$ representing the entire universe). As previously discussed, synthetic data facilitate the representation of uncertainty because they can contain several plausible realisations or climate condition scenarios. By solving the optimisation problem in a deterministic fashion, ISO finds an optimal solution for each of the scenarios $\omega \in \overline{\Omega}$ considered [59]. Thus, for each realisation of uncertainty, a different optimal solution is found. Statistical analyses (e.g., descriptive statistics, multiple regression analysis) are then applied to draw some general conclusions from the different results obtained [59]. ISO is a popular and widely accepted procedure to address optimisation problems under uncertainty (i.e., when some parameters are not fully known), because it is simple to use, demands few computational resources, and enables the explicit consideration of the stochastic components of the model while preserving the natural behaviour of the variables (i.e., their inter-annual variability and auto- and cross-correlations). Furthermore, it is deterministic, which reduces the time to obtain a solution.

Eq. (15) shows the general form of the ISO formulation within the context of the model presented in Section 3.1. Here, $\overrightarrow{X}$ represents the decisions regarding power capacity additions, while $\overrightarrow{E}$ represents the decisions regarding the electricity production with the capacity available at time t, and $\omega \in \overline{\Omega}$ is a particular climate realisation.

$$O^*_\omega = \left\{ \begin{array}{c} Min\ Z^*\left(\overrightarrow{X_\omega}, \overrightarrow{E_\omega}\right) = \left\{ f\left(\overrightarrow{X_\omega}, \overrightarrow{E_\omega}\right)\right\} \\ st.\ g_i\left(\overrightarrow{X_\omega}, \overrightarrow{E_\omega}\right) \le 0; \quad \forall i \\ X \in \overline{X}, E \in \overline{E} \end{array} \right\} \forall \omega \tag{15}$$

The second procedure employed to solve the optimisation model described in Section 3.1 is known as Robust Optimisation (RO). RO is another approach to address problems under uncertainty and allows the use of synthetic datasets or ranges of values (if historical data are not available) to represent the unknown parameters of the model [60]; [2]. In contrast to ISO, RO aims at finding a unique solution that would be optimal for the worst-case realisation in $\overline{\Omega}$ and feasible for any other realisation ω of the uncertain parameters [61].

Eq. (16) shows the general formulation of RO within the context of the model presented in Section 3.1. Note that the conceptual difference between ISO and RO is that RO (Eq. (16)) seeks for a unique solution for the entire dataset ($\omega \in \overline{\Omega}$) and not a solution for every realisation (ω). Consequently, the outcome is only one optimal plan for the worst-case scenario of the dataset, which is also feasible for any other realisation.

$$O^* = \left\{ \begin{array}{c} Min\, Z^*\left(\overrightarrow{X}, \overrightarrow{E_\omega}\right) = \left\{ f\left(\overrightarrow{X}, \overrightarrow{E_1}\right), f\left(\overrightarrow{X}, \overrightarrow{E_2}\right), \ldots, f\left(\overrightarrow{X}, \overrightarrow{E_\omega}\right) \right\} \\ st.\, g_i\left(\overrightarrow{X}, \overrightarrow{E_\omega}\right) \le 0; \quad \forall i \\ X \in \overline{X}, E \in \overline{E} \end{array} \right\} \tag{16}$$

After obtaining the optimal solutions via ISO and RO, alternative analyses were conducted in order to assess the robustness of the optimal installations suggested. To do so, different datasets, with 200 scenarios, were created for each of the uncertain parameters in the model. Then the ISO and RO optimal investment solutions (X_t^*) were taken as given and the operation or dispatch of the system (E_t^*) was optimised under the new scenarios. The model was left to decide how to meet the demand at each period of time t (E_t^*) with the available resources (i.e., fixed technology capacity and climate-related variables). The changes that occurred with the objective function and the electricity production mix, including blackouts, were then noted. This enabled us to assess how robust and reliable the optimal installations suggested by ISO and RO were; a solution was considered robust if the value of the objective function remained unchanged for a different set of scenarios and reliable if no blackout events occurred.

Finally, sensitivity analyses of the costs of the technologies, particularly those associated with the new renewables (solar PV and wind), were performed by assuming variations in their costs and seeing their effect on the optimal solutions (capacity installations X_t^* and energy production mix E_t^*). One of the analyses consisted of increasing the costs associated with the new renewables by 10% and seeing the effect on the optimal solutions. Additionally, during a separate analysis, the ISO and RO models were run ignoring the environmental costs associated with CO_2 production and the changes in the optimal solutions were observed. The next section provides a detailed description of the results found.

4. Results

4.1. Implicit stochastic optimisation

Fig. 6 shows the average results of the ISO over 200 scenarios. The model indicates that the electricity demand in the country over the next 15 years could be supplied as follows: about 52% by hydropower (coefficient of variation (C.V.) 9%), 34% by wind power (C.V. 25%), and 14% by solar PV (C.V. 76%). To achieve this, the model suggests installing, on average, about 13.2 GW of solar power (C.V. 60%), 10.73 GW of wind power (C.V. 30%), and 53.3 MW of

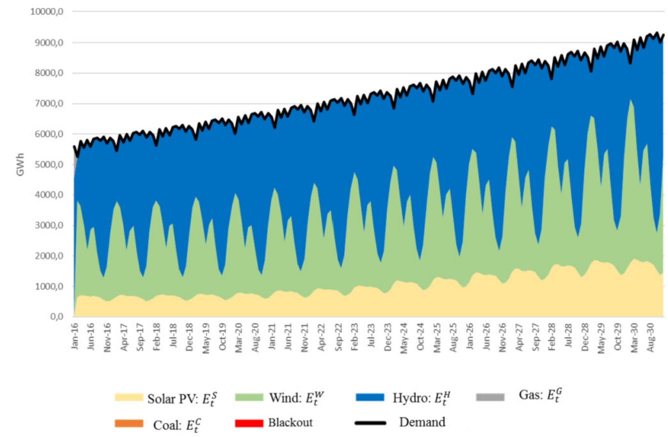
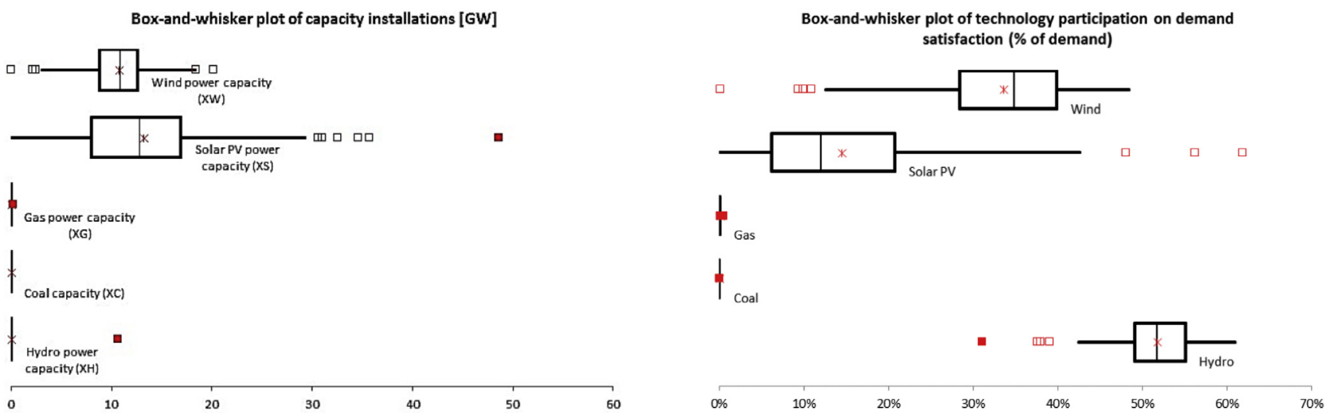


Fig. 6. Average optimal ISO results on electricity production through different resources (E_t^*).

hydropower. Fig. 7 shows the box-and-whisker plots for both the new capacity installations (X_t^*) and the electricity generation through the five different sources considered (E_t^*). The results indicate no new installations of coal, gas, and hydropower for almost all scenarios (Fig. 7a), which means that any future hydroelectricity production should come from the existing plants or reservoirs. It also indicates that current gas and coal facilities should stop operating altogether for environmental and cost reasons. It is therefore implied that the current gas and coal facilities should be replaced by new solar and wind plants (Fig. 7b).

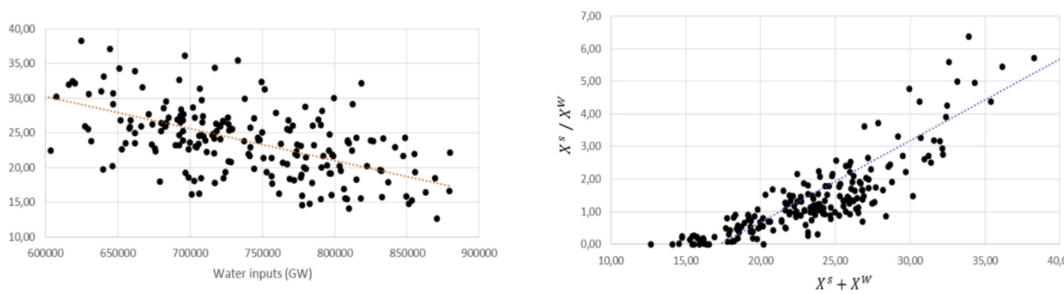
The aforementioned results suggest that regardless of the hydrological conditions of the scenario to be optimised, the model always seeks to fulfil almost half of the demand by installing new solar and wind power facilities, and discards other conventional options based on costs and environmental reasons. Be that as it may, the model gives differing priorities to solar PV over wind power, depending on the hydrological conditions of the scenario to be optimised. Fig. 8a shows the total amount of water input within the synthetic scenarios (x-axis) and its relation to the results of the optimisation regarding power capacity additions in solar and wind (X_t^S and X_t^W in the y-axis). It shows that as water inputs increase, lower capacities in alternative renewables are necessary due to the larger share of hydroelectricity in satisfying the demand. On the contrary, if water inputs are low, the necessity for new capacity installations is larger. Fig. 8b shows that the more power capacity in alternative renewables is required (x-axis), the larger is the capacity size recommended for solar PV over wind power (y-axis). Hence, the model tends to give larger priority to solar PV over wind power when the dependency on new renewables is expected to be larger (see Fig. 8b).

Wind power outperforms solar PV only when less than 20 GW of new capacity in alternative renewables is necessary. Wind power is preferred over solar PV in the scenarios where water inputs are large, because hydropower can then satisfy a large portion of the demand. However, the opposite situation is observed in scenarios where water inputs are low and the share of hydroelectricity in satisfying demand is not as desired. In those situations, solar PV is preferable to wind power because solar radiation is more stable and reliable than wind speeds in La Guajira (the C.V. for solar radiation is 1% and 9% for wind speeds in La Guajira; see Fig. 9). Therefore, a system relying on the expected outputs of solar farms would be more reliable than when relying on wind farms in la Guajira. Otherwise, if the solar PV capacity is insufficient and wind power cannot deliver the necessary electricity, the thermal plants, particularly gas-based ones, would need to operate and produce



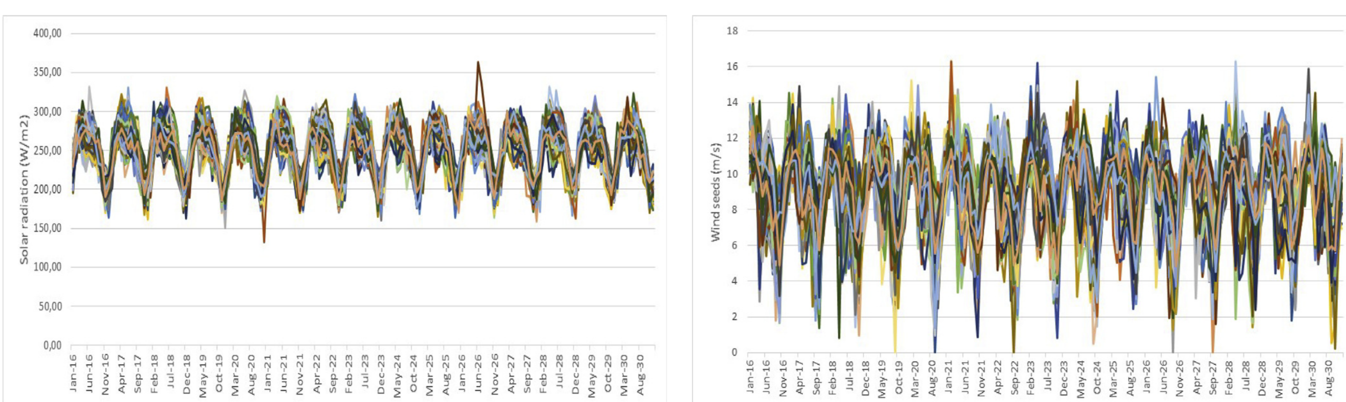
(a) (b)

Fig. 7. (a) Mean power capacity installations by technology option (X_t^*); and (b) mean electricity generation by type of source (E_t^*).



(a) (b)

Fig. 8. (a) Water inputs vs. capacity installations recommended in alternative renewables (solar PV plus wind power); and (b) capacity installation in alternative renewables vs. solar PV capacity over wind capacity (an indication of technology priority).



(a) (b)

Fig. 9. Synthetic time series of solar radiation (a) and wind speeds (b) in La Guajira (12 N, 71.5 W). With 1% of C·V., solar radiation is more stable and predictable than wind speeds, which have a C.V. of 9%.

the demand that is left unattended. In the long run, this would be costlier than having a larger facility with solar PV from the start (see below).

A robustness analysis of some of the optimal combinations in solar and wind capacity installations (X_t^S and X_t^W) was performed by optimising the operation of the system under 200 different scenarios. The model was left to decide how to meet the demand under the new hydro-meteorological scenarios, with fixed power capacities (i.e., considering what technological resources would be necessary to produce the cheapest electricity needed for the system, E_t^*).

The optimal combinations of solar (X_t^S) and wind (X_t^W) capacity installations were plotted, and from there, four different combinations that lie over the regression line of the sample of

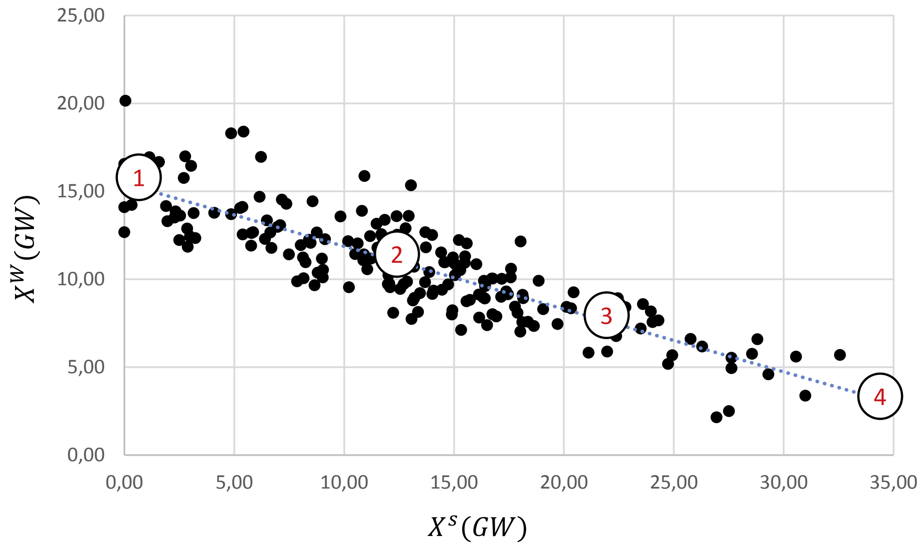


Fig. 10. Four different optimal recommendations given by the ISO model regarding combinations of solar PV (X_t^S) and wind power (X_t^W) capacity installations. Point 1 (0, 15.44), point 2 (13.2, 10.73), point 3 (22.5, 7.41), point 4 (35, 2.95).

observations were selected for the analysis. Fig. 10 shows the ISO results with regard to the installations capacity in solar PV and wind, as well as the regression line. Four combinations of X_t^S and X_t^W are highlighted, selected to sufficiently represent the entire range of combinations of the different policy recommendations (points 1 to 4). Points 1 and 4 represent the extremes of the range, while point 2 represents the average of the ISO's results and point 3 was selected to fill the gap between points 2 and 4 equidistantly.

Fig. 11 shows the optimal generation mix (E_t^*) with the combinations of solar PV and wind capacity installations defined above. It is evident that if lower solar PV capacity is installed, greater participation would be required from gas and coal in order to satisfy the increasing demand. As already mentioned, although wind is cheaper than solar PV it is also less reliable because wind speeds fluctuate more than solar radiation in la Guajira, creating periods where wind farms are not able to respond sufficiently and, consequently, thermal plants would have to produce the necessary portion to meet demand. Fig. 12 summarises these results, and also depicts the overall costs of the system for each of the four evaluation points. The figure shows how the share of gas and coal diminishes as the solar PV capacity increases, which contributes to the reduction of the overall costs of the system. The next section presents the results of the RO modelling, which are contrasted with the ISO results discussed above.

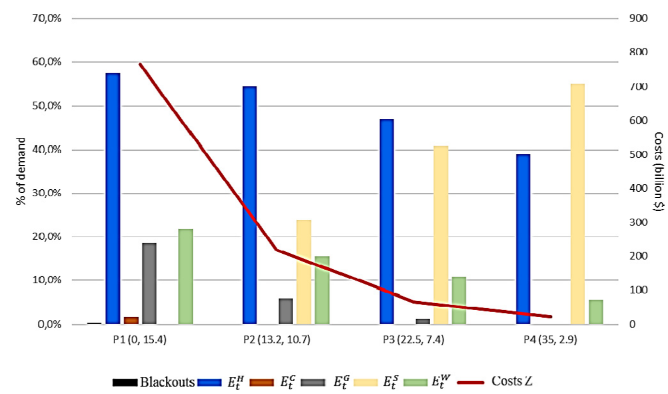


Fig. 12. Average production of different resources and overall system cost for different combinations of solar PV and wind power capacity installations. P1, P2, P3, and P4 stand for points 1 to 4 equivalently.

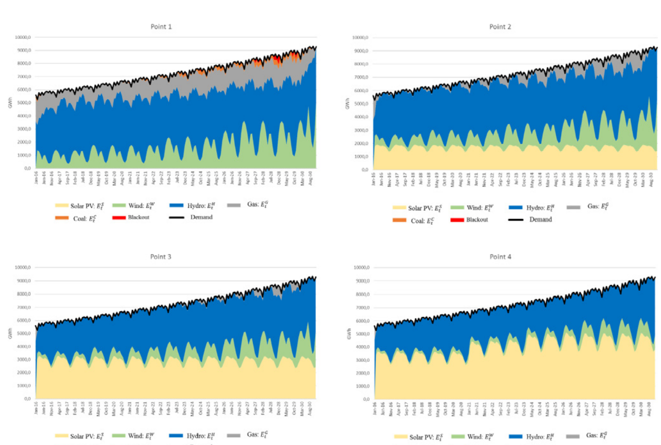
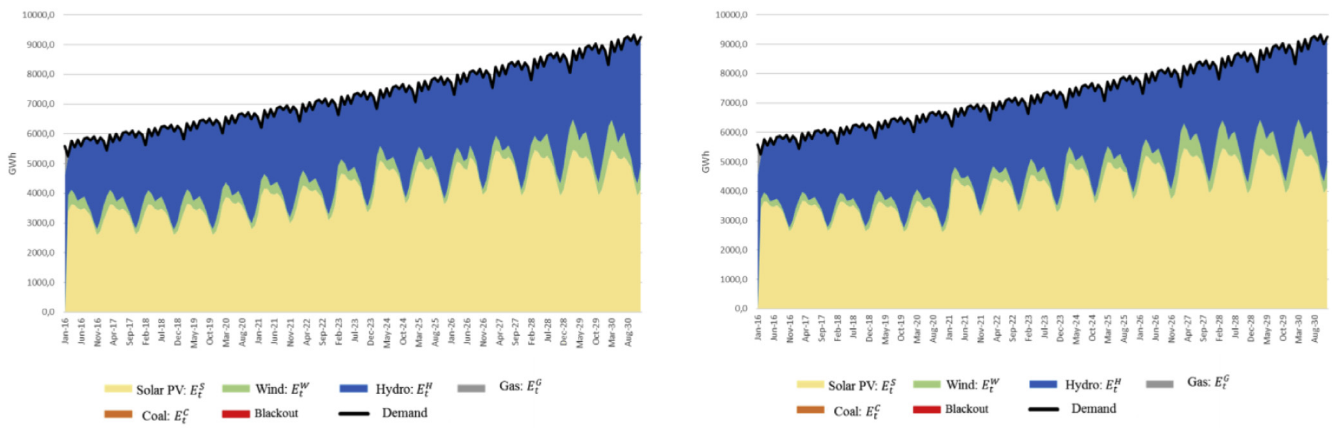


Fig. 11. Optimal generation mix (E_t^*) for four different ISO combinations of solar PV and wind power capacity installations under different scenarios.

4.2. Robust optimisation

Fig. 13 shows the results of the RO approach with 200 scenarios (Fig. 13a), as well as the robustness assessment of its results (Fig. 13b).

As mentioned earlier, RO is a type of stochastic optimisation formulation that seeks to find the optimal solution for the worst-case scenario within a dataset of several potential realisations of uncertain parameters ($\omega \in \overline{\Omega}$), that is also feasible for any other realisation in $\overline{\Omega}$. In this case, the results show that by installing 37.84 GW of solar PV and 2.13 GW of wind power in la Guajira, Colombia would be able to meet its power demand for the next fifteen years, at minimum costs and even under adverse hydro-meteorological conditions. This capacity mix would allow, on average, the supply of 38.28% of the total demand through hydropower (C.V. 2%), 56.31% through solar PV (C.V. 1%) and 5.26% through wind power (C.V. 6%), as well as result in 0% of blackout events. These results are in the vicinity of point 4, chosen in Fig. 10,



(a) (b)

Fig. 13. (a) RO's optimal generation results (E_t^*); and (b) its validation assessment.

but with a lower cost ($24.6 billion).

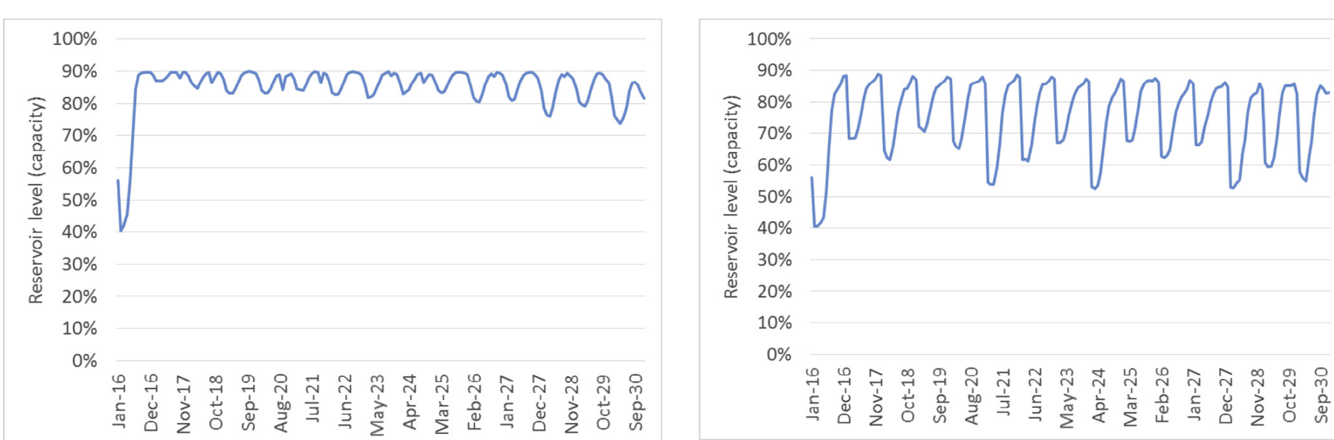
RO's optimal solution was also analysed in terms of its robustness. Similar to the previously conducted optimisation, RO's optimal solutions regarding installations (X_t^*) were fixed and the operation of the system was simulated using 200 different scenarios. The model was left to decide how to meet the demand (E_t^*) with the available resources (i.e. capacities installed and hydro-meteorological conditions). The assessment shows no significant differences with the optimal results originally obtained with the RO, suggesting similar production participation levels for all the five technology options, no blackout events and the same value of objective function. This indicates that the optimal solution found with RO was also optimal for other datasets with different realisations of uncertain parameters.

Fig. 14 shows the average behaviour of the system's reservoir during the entire planning horizon, for both the original RO optimisation results and the RO reliability assessment (assuming RO as being the best solution). There, it can be seen that the system's reservoir maintains above 70% of its maximum capacity on average under the original optimisation scenarios and above 50% under the validation scenarios. This suggests that the solution would enable the power system to respond well to extreme climatic events, maintaining the level of the reservoirs significantly above critical low levels. This is a highly desirable outcome for the Colombian power sector.

4.3. Sensitivity analysis

Besides the validation of the aforementioned results, sensitivity analyses of some of the costs in the objective function were also performed. First, the costs associated with the alternative renewables (solar PV and wind) were increased by 10%, while those associated with the conventional technologies held constant. Also, in a separate analysis, both ISO and RO were run ignoring the environmental costs associated with CO_2 emissions, which negatively affect the fossil-fuel-based technologies. Table 1 shows the results of the sensitivity analyses. The values in bold highlight significant differences when contrasted to the original (ISO and RO) solutions.

The results indicate that the optimal solutions originally identified with the ISO and the RO are not sensitive to small variations in the costs of the new renewables (see the columns entitled *original*



(a) (b)

Fig. 14. The system's reservoir level as a percentage of its max capacity throughout the planning horizon for: (a) the original RO's optimisation and (b) RO's validation assessment.

Table 1
Sensitivity analysis results of ISO (left tables) and RO (right tables). The tables on top show the values with capacity installations (X_t^*) and those in the bottom show the electricity production mix (E_t^*).

Capacity installations $\boldsymbol{X_t^*}$				Capacity installations $\boldsymbol{X_t^*}$			
ISO	Original results	+10% renewable costs	No environmental costs (CO_2)	RO	Original results	+10% renewable costs	No environmental costs (CO_2)
Solar	13,2	13,3	**0,0**	Solar	37,8	37,5	**0,0**
Wind	10,7	10,6	**7,2**	Wind	2,1	2,2	**5,0**
Hydro	0,1	0,1	0,0	Hydro	0,0	0,0	0,0
Gas	0,0	0,0	0,4	Gas	0,0	0,0	**4,0**
Coal	0,0	0,0	0,0	Coal	0,0	0,0	0,0
Average electricity production $\boldsymbol{E_t^*}$(% Demand)				Average electricity production $\boldsymbol{E_t^*}$(% Demand)			
ISO	Original results	+10% renewable costs	No environmental costs (CO_2)	RO	Original results	+10% renewable costs	No environmental costs (CO_2)
Blackouts	0,0%	0,0%	0,0%	Blackouts	0,0%	0,0%	0,0%
Hydro	52,1%	52,2%	56,8%	Hydro	38,4%	38,9%	**57,3%**
Coal	0,0%	0,0%	**5,4%**	Coal	0,0%	0,0%	**7,9%**
Gas	0,1%	0,1%	**7,0%**	Gas	0,1%	0,1%	**15,0%**
Solar	14,1%	14,0%	**0,0%**	Solar	56,1%	55,4%	**0,0%**
Wind	33,7%	33,7%	30,8%	Wind	5,4%	5,5%	**19,8%**

results and + *10% renewable costs*). This suggests that the general recommendation of installing new renewables to replace the old fossil-fuel-based technologies holds even for a less favourable economic scenario for the renewables. In both cases, the general recommendation is to install solar PV and wind power (in a larger proportion in the case of RO, as already discussed) and almost no installations are recommended for hydro, gas and coal. The electricity production mix also remains unchanged.

Nonetheless, the results vary significantly when the optimisation models are run without considering the environmental costs associated with CO_2 pollution. When the pollution costs are ignored, the models suggest fewer capacity additions in general (7.5 GW for ISO and 9 GW for RO). Wind installations remain necessary, but on a smaller scale, and no solar PV installations are recommended at all due to their cost and overall efficiency. Furthermore, gas installations appear on the map, particularly in RO, but hydro and coal are still not recommended. Consequently, the energy production mix changes, given that gas and coal fulfil a larger share of the demand and no portion of the demand is fulfilled by solar PV. Although fossil-fuel-based technologies see their share reduced significantly in relation to today's figures (about 35%), the system remains highly dependent on hydropower. In addition, the share of wind production satisfying demand reaches values between 20 and 30%.

The next section provides a more elaborate discussion on all the results and on their implications for policy.

5. Discussion

The aforementioned results indicate that alternative RES, solar PV and wind power, currently largely ignored in Colombia, are the most promising options to continue the expansion of the Colombian power system. Hydrothermal power (i.e., hydro, gas and coal) are almost never part of the optimal expansion plans identified within the analysed scenarios, except when environmental pollution costs are ignored. In such cases, wind energy remains an optimal solution due to its costs, as does gas. These findings contrast with the business-as-usual situation in Colombia, where the share of hydroelectricity and fossil fuel-based technologies is expected to increase over the next fifteen years.

Similar economic and environmental results have been obtained in various places where new renewables have been suggested to replace conventional technologies, e.g. Brazil [18], South Korea [62], Bangladesh [63], Ontario Canada [64], and the west coast area of Saudi Arabia [65]. Undoubtedly, the use of renewables has a positive effect on the environment, e.g., they can make grids less dependable on fossil fuels and therefore make them more sustainable environmentally [25,18]. In addition, they also have positive economic impacts. For example, Vithayasrichareon et al. [26] found that, for the Australian Electricity Market, even though renewable energy sources may increase the average energy cost by $0.2/MWh, they would reduce the risk of having higher costs (i.e., its standard deviation) due to the uncertainties associated with gas and carbon prices. McInerney and Bunn [66] also argue in favour of over-installing wind power facilities to take advantage of low wind speeds, which may in turn increase revenues.

Conventional energy technologies, such as hydro, gas, and coal, have reached a maturity point that makes any significant reduction to their costs unlikely [6]. The costs associated with these technologies may even increase in the future due to mechanisms such as reliability charges, environmental taxation, reductions in gas and oil reserves, and depletions in available land and fresh water. In contrast, the learning curves of RES are still on the rise, suggesting that in the future, cheaper and more efficient renewable technologies are likely to be developed [6].

In terms of electricity production, almost all the analyses conducted suggest that, in the short-to mid-term, all gas and coal generation should cease in Colombia and be replaced by the output of the new renewables. Hydroelectricity with storage capacity in the form of reservoirs will remain a central component of the country's electricity mix, but the level of dependency on hydroelectricity could be reduced from the current levels of 65% to levels below 40%. In the long term, from 2030 and beyond, alternative energy sources might be necessary, as reservoirs may be insufficient to regulate the power system. This issue however, goes beyond the scope of this research.

Less dependency on hydroelectricity and a richer mix of energy sources are fundamental for reducing power system vulnerabilities. When environmental considerations are ignored and emission costs are negligible, the optimal solutions still incorporate few fossil-fuel-based technologies but remain largely dependent on hydroelectricity. Despite the dependence on hydroelectricity, this is still a positive scenario from the environmental and economic points of view, but it may not be a robust solution during critical dry times.

Results also indicate that there is a trade-off between the capacities to be installed in solar PV and wind power. Wind power is an abundant resource and the cheapest new renewable option to complement a hydroelectricity-driven country with an abundance of water inputs in the short run. However, if water inputs are low, such as during El Niño, the environmental costs increase due to the increased share of gas production. Solar PV appears to be a more expensive option in the short run, but also a more robust and a cheaper option in the long term, as it reduces the possibility of future participation of fossil-fuel-based technologies – even during critical dry times.

Finally, it is important to note that this paper makes some assumptions and simplifications regarding the dispatch mechanisms and the Colombian power system. One of these assumptions is that we did not take into account storage facilities for solar PV, as this function is largely met by reservoirs in this country (see Ref. [27]. The model also disregards hourly behaviour as the focus is on long-term planning. Furthermore, the model does not take any transmission issues into consideration as this goes beyond the scope of the paper. Nevertheless, as the results suggest that solar PV is the most appropriate option to expand system capacity, and solar radiation is a resource that is not spatially concentrated (in contrast to other technologies), the paper assumes that small PV plants could be located near sites of demand or near currently available transmission lines, or that public policies are developed to incentivise distributed generation (see for example [18].

The paper concludes in the next section, summarising some of the most relevant conclusions acquired throughout the analyses presented above.

6. Conclusions

An optimisation model to evaluate the insertion of new renewables into the Colombian power sector was developed. The model considers cost-based generation competition between conventional technologies (hydro, gas and coal) and alternative renewables (solar PV and wind). Two stochastic approaches were used to provide solutions to the problem of concern – ISO and RO. These two approaches were selected because they are simple to implement, require few computational resources, facilitate the consideration of uncertain parameters while preserving their natural behaviour, and their results, although conceptually different, offer an ample perspective of the problem at hand.

The results suggest that Colombia is ready for renewable energy sources and that these should be carefully considered when expanding the capacity of the system within the next fifteen years. Priority should be given to solar PV over wind power, and together they should replace the current gas and coal thermal plants in Colombia. The main reasons to support this shift are economic and technical, as well as environmental. The apparent complementarities between solar radiation and wind speeds, together with the hydrological water inputs in Colombia, make alternative renewables (particularly solar PV) optimal options to strengthen the power system by making it less vulnerable to future El Niño events. Although hydroelectricity is a renewable source, it is also costly and a high dependency on it has made the system vulnerable to El Niño and to other potential long-term climatic changes.

In terms of further research, as already mentioned, we are also working on some final elements of the complementarities between hydro, solar and wind power for the Colombian case, which should help in informing decisions regarding the placement of renewable facilities in the country.

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