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Research Article

Fuzzy multi-objective optimization of the energy transition towards renewable energies with a mixed methodology

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Abstract

Paper aims: the combination of the quality indices, a novel model called “Dynamic Growth Allocation Model (DGAM)”, Fuzzy Decision Making Theory (FDM), Analytical Hierarchy Process (AHP) and the Evolutive Particle Swarm Optimization (EPSO) is proposed.

Originality: the multi-objective optimization (with uncertainty) of the Argentine energy transition is not sufficiently studied. This combined methodology in this problem was not published and it had good, relatively easy and fast results.

Research method: the optimization indices (EROI, CO2, IC and RP), the methodology used (DGAM, FDM, AHP and EPSO) and its results are analyzed.

Main findings: (i) the nuclear energy allowed the renewable transition; (ii) the fossil dismantling and the investment in biomass and wind are needed; (iii) the EROI depends on the good load factor, useful life and performance.

Implications for theory and practice: It is sought a minimum Renewable Participation (RP) of 20% of Argentina with a sustainable energy matrix.

Keywords

Multiobjective Optimization with Energy Scenarios. Energy Return Returned On Investment (EROI). Investment Cost and Emissions. Fuzzy Decision Making Theory. Evolutive Particle Swarm Optimization (EPSO).

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1. Introduction

The urgency of making a transition from fossil-based sources to renewable sources arises for a variety of reasons. Firstly, environmental sustainability as the sustained growth of carbon dioxide (CO_2) emissions would lead to irreversible climatic changes. Secondly, energy sustainability as the depletion of non-renewable resources would lead to an energy crisis. In this context, the improvement of ‘Energy Efficiency’ is the one with the greatest impact. This involves progressive improvements in manufacturing technologies, efficient use of resources (mainly scarce or polluting resources), ensuring the longest possible lifetime and improvements in efficiencies. In this sense, the Energy Returned on Investment (EROI) measures the ratio of Benefit/energy cost (not economic). Energy transitions are necessary to obtain a better systemic EROI, which is not easy to solve. There is no common agreement between these disciplines in measurement, definition and evaluation criteria, since some of them are contrary (for example, economics vs. environmental regulations). Second, formulating these problems requires expensive and complex software. Finally, this is because these attributes are not subject to the conventional laws of market equilibrium and, consequently, are not directly and objectively monetizable.

This paper is a novel proposal of the present author to solve the problem of energy and environmental sustainability of an energy power system. Nobel sustainability indices were formulated, some of them per unit of power (this is to make it independent of the installed power). A novel iterative method is proposed to estimate the impact of the expansion of the renewable production capacity. This problem is complex and it cannot be solved satisfactorily using linear or dynamic programming methods due to the number of objectives, non-linearity of the attributes and the presence of uncertainty. It is sought to optimize and analyze the energy transition seeking to optimize the Argentine energy system regarding several novel indexes and dynamic models of renewable penetration scenarios. A minimum participation of 20% in renewable energy power is searched. Additionally, the improvement of technical, economic and environmental quality indices is sought, carrying out investment plans in generation equipment that involves the attributes related to economic (Cost), energy (EROI and renewable participation) and environmental quality (emissions expressed as equivalent in CO_2). The indices that are proposed are: Energy Return On Energy Investment (EROI), CO_2 emissions, Investment Cost (IC) and Renewable Proportion (RP). Second, the formulation of the fitness function by extension to the fuzzy domain.

A multiobjective model was extended to the fuzzy domain, by means of the convergence of the different optimization criteria by the use of the t-norm called 'Algebraic Product' (according to the 'Fuzzy Decision Making in Fuzzy Environments') is proposed. Fuzzy models are based on the reasoning and perception of the human being and allow change of domain to the variables or functions studied. Within the 'Fuzzy Decision Making Theory', the uncertainty associated with the desired result obtained is called as 'Fundamental Uncertainty'. In this way there are degrees of acceptance of a certain variable to a given set. This mean, the certainty or risk of accepting a given alternative is possible to be modelled using fuzzy sets. In the present work, the algebraic product t-norm is used, which is simpler and less drastic than Einstein's product. Regarding the solution method, the metaheuristics qualities are exploited as flexible methods of problem solving. In this aspect, the Evolutive Particle Swarm Optimization (EPSO) metaheuristic was applied. Through the analysis of results, it is expected that the dynamic indices will improve in the stages analyzed. This work will serve to deepen the proposed models in future works.

This work is organized as follows: in Section 3, the state of the art is presented. In Section 4. the material and methods are presented and the index formulation and methodology are developed: EROI (Section 4.1), CO2 Emissions (Section 4.2), Investment Cost (Section 4.3) and Renewable Participation (Section 4.4). The Dynamic Growth Allocation Model (DGAM) is developed in Section 4.5. In Section 5, a simulation of the Argentinean Electric Matrix based scenario-based is presented: the main parameters (Section 5.1), transition energy (Section 5.2), fuzzy indices (Section 5.3) and Evolutive Particle Swarm Optimization (Section 5.4). The conclusions are described in Section 6. The Annex presents the Mathematical modelling (Annex 1), Fuzzy Decision Making (Annex 2), Evolutionary Particle Swarm Optimization EPSO (Annex 3) and Energy transition proposed in the state of the art (Annex 4).

2. Nomenclature

2.1. Acronyms

DGAM Dynamic Growth Allocation Model
EPSO Evolutionary Particle Swarm Optimization
EROI Energy Returned On Investment
EO Energy Obtained
EI Energy Invested
LCA Life Cycle Assessment
RP Renewable Participation

Symbols

$\mathrm{EW_m}$ Exponential Weight of Criteria m.
μ_m Generic Membership Function of Criteria m.
$\mathrm{U_m}$ Generic Variable of Criteria m.
$\mathrm{U_m^{[Up,\ Low]}}$ Limit Value of Criteria m, (Up: Upper Limit; Low: Lower Limit).

UL_{gi} Useful Life of each type of each power source gi.
P_{gi} Installed Power Invested of each power source gi.
LF_{gi} Load Factor of each power source gi.
$EROI_{gi}$ Energy Returned On Energy Investment (EROI) of each power source gi.
η_{gi} Performance of each of each power source gi.

3. State of the art

Energy efficiency (EE) is defined as that between the Useful Energy (UE) of an energy system and the Energy Invested (EI); EE is divided in Supply Side Management (SSM) and Demand Side Management (DSM). SSM refers to the technological improvement of devices and their efficiency and DSM refers to change in consumer demand behavior (Lovins, 2017). Within the electric power supply chain, an indicator of EE mentioned in the state of the art is the Energy Returned On Investment (EROI). The EROI is the relationship between the Energy Obtained (EO) by the generation source and the Energy Invested (EI). The EO is relatively easy to obtain, while the EI requires complex analysis of the production chain, measuring the associated expenses and waste (Arvesen & Hertwich, 2015). This problem exceeds the scope of economic theory and involve decision theory and computational economics and it is a matter of discussion in the state of the art. The Life Cycle Assessment (LCA) allows the design, research and evaluation of a production process and the associated environmental impact during the exploitation of the energy resource in question (Brundage et al., 2019). If the Energy Invested is reduced, the EE improves.

The Energy Transition (ET) describes either the change in the composition or the structure of the primary energy supply, the gradual change of a specific model of energy supply in a new stage of the energy system, and changes in the economic activities of a country in a long-term horizon based on the passage from some energy sources to others (Isoaho & Karhunmaa, 2019; Falcone et al., 2019). ET includes the gradual diffusion of new devices, such as engines that replace the workforce of animals and people, and are characterized by changes in: energy use patterns, energy quantities, the characteristics of energy resources or the dynamics of energy demand. ET usually takes decades to be partially or completely performed. The solution to this problem is complex, since multiple criteria must be considered: environmental, economic, technical and quality indices. There is no agreement on which scenario design criteria is the most appropriate, since it depends on the energy, political, economic and social context. The scenarios currently studied for Adaptation to Climate Change are: 'Business as Usual' (BAU) and 'Collective Responsibility' (CR). BAU refers to planning according to current criteria and CR implies a significant change that will reorient current patterns in a significant way. In recent decades, energy from renewable sources has gained momentum worldwide, motivated by different factors. A first factor was the economic incentives that promote its penetration. A second factor was the growing economy of scale and the consequent decrease in costs.

The ET must satisfy certain conditions: satisfaction of requirements with respect to costs, regulations regarding environmental impact, standards and standard procedures, speed of solution, etc. The simultaneous satisfaction of these criteria is difficult and arises from applying compromise solutions between them (optimization) and according to the needs (hierarchy). They should be organized through categories that present different importance, being attributed to the hierarchical criteria different relevance and values. This procedure is referred to as Analytic Hierarchy Process (AHP). The decision maker provides (or not) subjective evaluations (a priori or posteriori) regarding the relative importance of each of the criteria and he must specify their preference with respect to each of the decision alternatives (Hwang et al., 1993; Kosheleva & Kreinovich, 2018). The result of the AHP is a hierarchy with priorities that show the global preference for each of the decision alternatives. The weights obtained must meet a set of minimum conditions to be coherent, called consistency criteria. One of the fuzzy logic characteristics, besides incorporating the AHP, is the use of ordinary language as a description language in a computer, thus incorporating the knowledge of an expert in a given task. It introduces the imprecision and subjectivity proper to human activity in an automated procedure. Fuzzy models emulate one of the "intelligent" functionalities of human beings: reasoning with uncertainty (Shahzadi et al., 2020).

Several works were already presented in the literature that relied the renewable energy transition. Here, a part of them are reviewed.

Emilia Ruggeri & Santiago Garrido (Ruggeri & Garrido, 2021) have analyzed the energy and socio-economic variables of the renewable energy incentive plans carried out in Argentina. The equity of the impact of such long-term planning was analyzed.

Soonho Hwangbo et al. (2021) have developed a mathematical model of electricity based on renewable energy and large-scale utility networks to achieve a low-carbon economy in South Korea.

Wang et al. (2018) have proposed an optimal planning method, with a mixed-integer linear programming problem based on graph theory, for a community level multiple energy systems that jointly determines the optimal generation.

Zhao & You (2021) have proposed a renewable ET planning under uncertainty using a data-driven multistage adaptive robust optimization approach with machine-learning. The proposal is interesting, although it has limitations in the uncertainties of the considered data, multiple and complex restrictions and the need for supervised learning.

Other works to mention are the following. Kokkinos et al. (2020) have proposed a circular bio-economy via ET supported by Fuzzy Cognitive Map modeling towards sustainable low-carbon environment. Capellán-Pérez et al. (2019) have proposed a dynamic EROI and material requirements in scenarios of global transition to renewable energies. Navas-Anguita et al. (2019) have proposed a Simulation and LCA of synthetic fuels produced via biogas dry reforming and Fischer-Tropsch synthesis. Bogdanov et al. (2021) have proposed a Low-cost renewable electricity as the key driver of the global ET towards sustainability. Adesanya et al. (2020) have proposed a transition of US with 100% renewable electricity. Ligus & Peternek (2018) have proposed the determination of most suitable low-emission energy technologies development in Poland using integrated fuzzy AHP-TOPSIS method.

Table 1 shows a summary of the present proposals with: country of analysis, sources analyzed, linear or non-linear modeling, type of uncertainty, resolution methodology and limitations. Most of the important published works are carried out using deterministic models, or in the best of cases, mixed with stochastic models. That is, they use classical models of mathematical programming, which have limitations in their formulation and quality of the results obtained. No important studies were found on the energy transition applying the EPSO metaheuristic. It is also observed that there are few studies that involve all the different types of generation sources.

Table 1. Search results in the Scopus database (conducted in November 2021).

Author/Year	Country of study	Source	Modeling	Indices	Objective and Constraints	Resolution method	Limitation
Ruggeri & Garrido (2021)	Argentina	All types	Deterministic	Socio-economic Indices	Linear	Statistic	Analysis from statistical records
Hwangbo et al. (2021)	South Korea	Fossil	Mixed: deterministic and stochastic	Economic cost, emissions and energy	Linear	Mathematical Programming	Linearization removes accuracy from the solution
Wang et al. (2018)	Beijing	Fossil			Linear	MILP model based on graph theory	
Zhao & You (2021)	New York	All types			Multiple and non Linear	Machine Learning	Supervised learning is needed
Kokkinos et al. (2020)	Greek	Biofuel	Fuzzy Cognitive Map (FCM)	Environmental social, economic and political impacts	Non Linear	Heuristics	It requires interactive methodologies
Capellán-Pérez et al. (2019)	Global	All types	Deterministic	EROI and material requirements	Non Linear	Heuristics	Economic costs or emissions are not considered
Navas-Anguita et al. (2019)	Spain	Biogas and fossil		Energy and emissions	Linear	life cycle assessment	
Bogdanov et al. (2021)	Global	All types		Economic cost, emissions and energy			Does not consider uncertainty
Adesanya et al. (2020)	United States	All types				Statistic	Analysis from statistical records
Ligus & Peternek (2018)	Poland	All types	Fuzzy	Environmental socioeconomic and political impacts		AHP-TOPSIS method	

Source: The Author.

Proposals based on linear programming have the disadvantage that they require the objective functions and constraints to be linear or, if they are non-linear, to be linearized. This can produce that the solution obtained is not the most satisfactory and there are many solutions of better quality. Those models that are only deterministic and probabilistic (not fuzzy) do not take into account value uncertainties. This is a problem in a context where there is uncertainty that affects the decision maker. These proposals do not take into account hierarchy criteria either or, in the best of cases, they make linear weightings. The latter is an inconvenience due to metric compatibility (same measurement units) and the presence of subjectivity and uncertainty in the assessment of each index (Camargo et al., 2018). The complexity and breadth of the search space makes these proposals unsuitable. For these reasons, dynamic programming is also not possible. Proposals based on fuzzy models are not optimization models but assessment and ranking models. Lastly, there is no common agreement on how the EROI and LCA should be calculated, this is because the state-of-the-art estimates (usually) do not consider the production chain and waste management. There is also no agreement on how to assess and prioritize environmental variables. Finally, there are no important studies for the Argentine electricity matrix or agreement to solve the energy crisis and transition to renewables.

The present work is a novel mixed multi-objective optimization method that considers the presence of uncertainty in the valuation of the indices, ranking/assessment of the optimization criteria and the use of the EPSO metaheuristic. This has the advantage of being able to solve any problem in a relatively simple way and without the need to linearize the objectives or restrictions.

A novel interactive life cycle analysis model is also proposed that contemplates the expansion of the productive capacity, production times and the calculation of the EROI. In this work, the EROI considers all the expenses of the production chain (including all waste) and the operation y maintenance of the generator and power system. Additionally, this proposal does not restrict investment in nuclear energy given its technical advantages.

The contributions are the following: a novel dynamic model of productive chain and its EROI, a novel formulation of indices, use of the EPSO experimental metaheuristic in continuous search space, use of fuzzy decision theory and the combination of all these techniques.

4. Material and methods

In order to determine the energy invested of the power sources (wind, photovoltaic, hydraulic, biomass, fossil and nuclear), a LCA is carried out where the essential sectors for obtaining the generator and the fuel necessary for its operation are divided. The sectors are extraction, processing, manufacturing, construction, transport and waste treatments, the latter is distributed throughout the entire system. The transport sector is considered concentrated; this is like one more stage of the life cycle. This life cycle is carried out for two inputs: materials used and fuel required. Regarding the latter, the cost of the generator fuel and the fuel required for transportation are considered. In this way, energy costs are obtained, which are referred to in Tons of Oil Equivalent (toe).

The parameters were mainly processed and the complete model was validated from the information of the public reports prepared by the Argentine Chamber of Renewable Energies (Argentina, 2021a) and the public database available from the Ministry of Energy and Mining (Argentina, 2021b).

Figure 1 shows the schematic diagram related to the operation to determine the most satisfactory scenario of investment allocation of power energy. A computation of materials necessary to build the generation source is carried out, including the generator, infrastructure and complementary equipment. In turn, the type of fuel (fossil, nuclear, organic, etc.) and its quantity are determined. From there, the energy calculations of each stage considered of the life cycle are made. Each stage has a certain performance, associated time, energy cost and waste. Waste contemplates the production chain of materials and fuel. Nuclear waste is considered in the production chain and, therefore, the necessary energy. The transport sector is distributed in the production chain, however, and for simplicity, it was drawn as another stage.

The present work seeks to propose a growth model of this productive chain (Annex 1), which allows to produce and expand the installed capacity in generators (Figure 2). Then, this model will assign the expansion of this productive capacity, according to each generation and through the interest indices. This allocation will be in proportion to the estimated growth of the expansion of productive capacity. This growth in productive capacity will be transferred in the expansion of the installed capacity of each generation source and its infrastructure. The proportion of this assignment will be determined by the state variable, which defines the search space of the problem to be optimized. To model the expansion of installed power and energy demand over time, auxiliary functions are used. These functions are affected by growth factors, which depend on the aforementioned growth allocation. In this way, the evolution of the electricity matrix and percentage proportion of each generation source are determined.

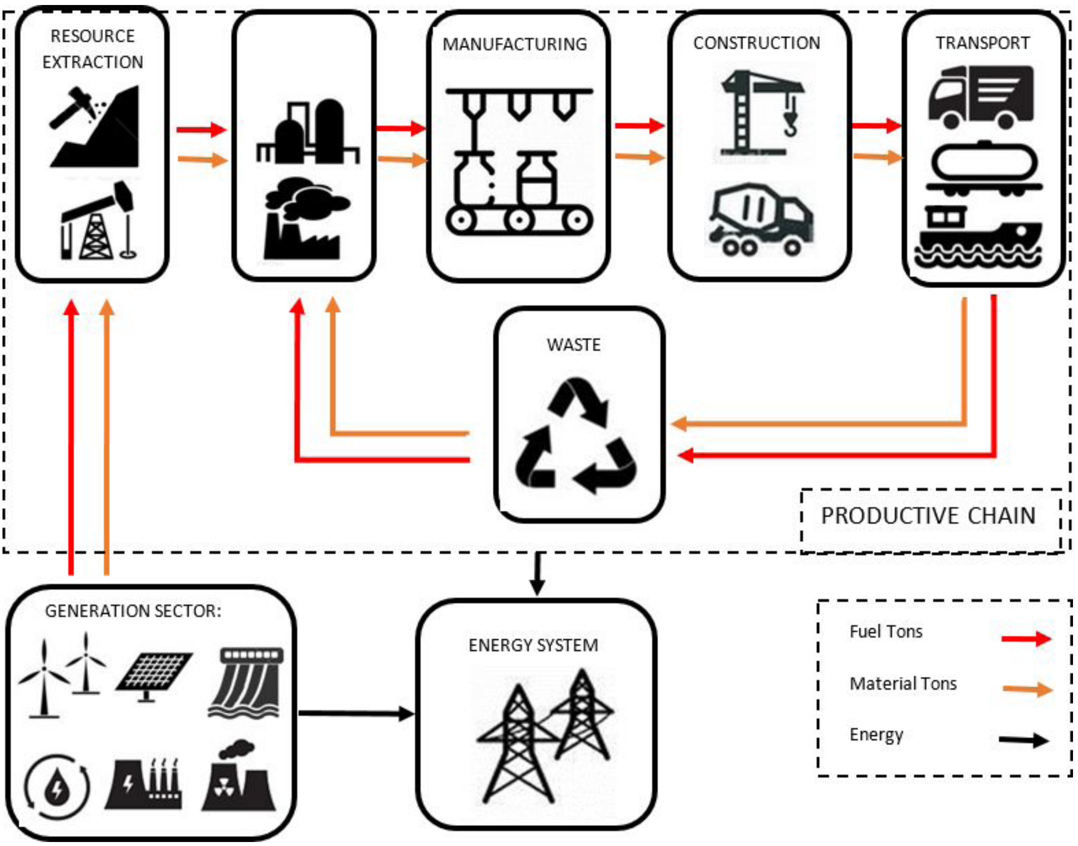

Figure 1. Life Cycle Analysis (LCA) model applied in the present work. Source: The Author.

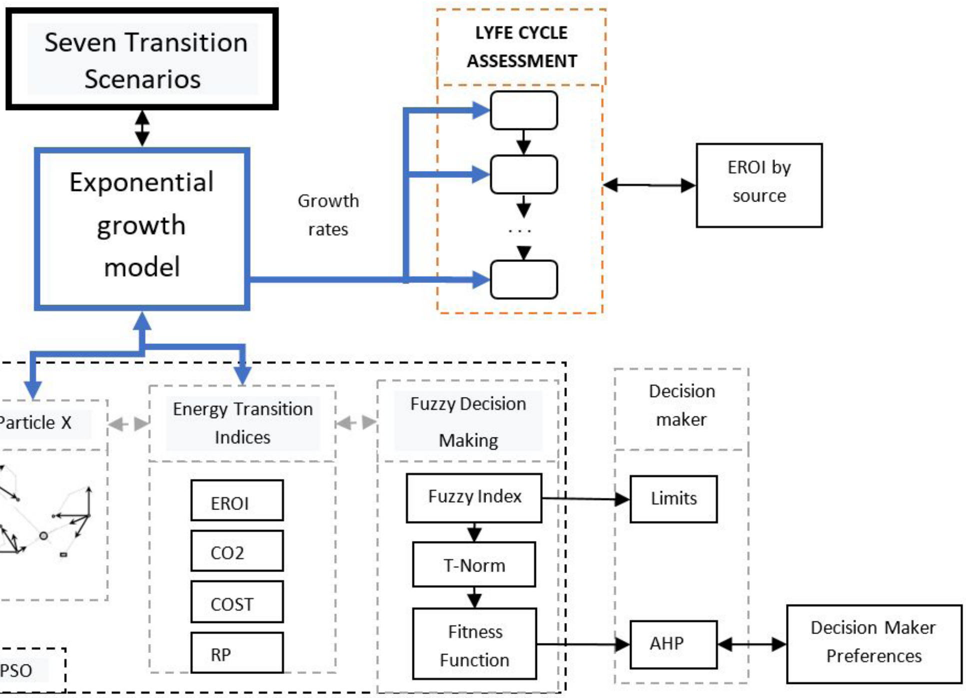

Figure 2. Dynamic growth model and its interaction with fuzzy modeling and the metaheuristic EPSO. Source: The Author.

The evaluation function to be used by EPSO are determined by the Fuzzy Decision Theory (Annex 2). The EPSO metaheuristics (Annex 3) will explore the search space and look for the best alternatives. By means of heuristic rules it will determine a more satisfactory solution to the problem which correspond to rules of communication between particles (alternatives), comparison and movement (alteration of the proposed solution in the direction where it is believed that there are good solutions). EPSO is an experimental metaheuristic product of combining the functioning of PSO (Kadkol, 2021) and genetic algorithms. Mutations are made in the parameters using standard normal functions, to model the probability of mutation and its effect. This feature gives it a good capacity for exploration and robustness in the search for good solutions. Additionally, in the present research it had a good functioning for this type of problem, where the search space is continuous.

Indices are constructed from the proposed mathematical growth model. These indices correspond to the systemic EROI, which is calculated from the EROI of each generator, CO2 emissions, Investment Cost (COST) and the proportion in renewable energy (RP). These indices are transformed to the fuzzy domain and weighted by exponential weights, which are obtained from the AHP. Additionally, for the assembly of these indices, limits of dis/acceptance of the same are needed. These are obtained from extremely unfavorable scenarios. Finally, the intersection of these fuzzy indices are carried out by means of the t-norm. This operator allows to build an aptitude function obtaining (at most) the worst diffuse index obtained. Algebraic product is used, which is one of the t-norms that is continuous and, additionally, it is one of the less strict (this can be developed in future work).

In the transport sector, three types are considered: trucks, trains and ships. A constant ratio between imports and exports was also considered. Growth factors only affect national production and it is considered that there is no restriction on access to imported products. For simplicity, this proposal considers invariable energy costs and oil prices and it also does not consider technological improvements in generators and the production chain. However, these aspects can easily be incorporated. Additionally, variations and logistical changes are not considered.

4.1. Energy returned on investment

Firstly, the energy obtained in each stage s analyzed and for each sector of generation gi (wind, solar, photovoltaic, biomass, fossil and nuclear) is expressed in the Equation 1. In this expression the necessary parameters for each generation sector are: efficiency η_{gi}, installed power $P_{gi}^{[s]}$, useful life UL_{gi} and load factor LF_{gi}.

From the installed power of each sector, the total installed power is calculated (Equation 2).

$$EO_{gi}^{[s]} = P_{gi}^{[s]} \cdot UL_{gi} \cdot \eta_{gi} \cdot LF_{gi} \tag{1}$$

$$P_T^{[S]} = \sum_{1}^{6} P_{gi}^{[S]} \tag{2}$$

Secondly, the EROI (Arvesen & Hertwich, 2015) is defined in each stage s for each sector of generation gi (Equation 3).

$$EROI_{gi}^{[s]} = \frac{EO_{gi}^{[s]}}{EI_{gi}^{[s]}} \tag{3}$$

Equation 1 is replaced in Equation 3 and the Equation 4 and Equation 5 are obtained in the present research.

$$EROI_{gi}^{[s]} = \frac{P_{gi}^{[s]} \cdot UL_{gi} \cdot \eta_{gi} \cdot LF_{gi}}{EI_{gi}^{[s]}} \tag{4}$$

$$EI_{gi}^{[s]} = \frac{P_{gi}^{[s]} \cdot UL_{gi} \cdot \eta_{gi} \cdot LF_{gi}}{EROI_{gi}^{[s]}} \tag{5}$$

From Equation 4 and Equation 5 the systemic (total) EROI is obtained (Equation 6 and Equation 7).

$$EROI_T^{[s]} = \frac{\sum\left(P_{gi}^{[s]} \cdot UL_{gi}^{[s]} \cdot \eta_{gi} \cdot LF_{gi}\right)}{\sum\left(EI_{gi}^{[s]}\right)} \tag{6}$$

$$EROI_T^{[s]} = \frac{\sum\left(P_{gi}^{[s]} \cdot UL_{gi} \cdot \eta_{gi} \cdot LF_{gi}\right)}{\sum\left(\frac{P_{gi}^{[s]} \cdot UL_{gi} \cdot \eta_{gi} \cdot LF_{gi}}{EROI_{gi}^{[s]}}\right)} \tag{7}$$

Dividing by the total installed power $P_T^{[S]}$ the Equation 8 is obtained in this research:

$$EROI_T^{[s]} = \frac{\frac{\sum\left(P_{gi}^{[s]} \cdot UL_{gi} \cdot \eta_{gi} \cdot LF_{gi}\right)}{P_T^{[s]}}}{\sum\left(\frac{P_{gi}^{[s]}}{P_T^{[s]}} \cdot \frac{UL_{gi}}{EROI_{gi}^{[s]}} \cdot \eta_{gi} \cdot LF_{gi}\right)} = \frac{\sum\left(AP_{gi}^{[s]} \cdot UL_{gi} \cdot \eta_{gi} \cdot LF_{gi}\right)}{\sum\left(AP_{gi}^{[s]} \cdot RT_{gi}^{[s]} \cdot \eta_{gi} \cdot LF_{gi}\right)} \tag{8}$$

Where two terms of importance are defined: $RT_{gi}^{[s]}$ is the energy recovery time of the generator gi (Equation 9) and $AP_{gi}^{[s]}$ is the proportion of the electrical matrix that is had in each type of generation gi (Equation 10). In other words, of each total power installed, a total percentage corresponds to each type of generation gi.

$$RT_{gi}^{[s]} = \frac{UL_{gi}}{EROI_{gi}^{[s]}} \tag{9}$$

$$AP_{gi}^{[s]} = \frac{P_{gi}^{[s]}}{P_T^{[s]}} \tag{10}$$

It is observed that the systemic EROI depends on the EROI of each generation source and therefore on the recovery time RT. Then, when the EROI increases, the systemic EROI also increases.

4.2. Carbon dioxide emissions

Defining the CO_2 emissions for each type of generation, the Equation 11, Equation 12 and Equation 13 are obtained in this research:

$$CO_{2gi}^{[s]}\left[\frac{CO_2EQ}{MW}\right] = ef_{gi} \cdot \frac{\left(EO_{gi}^{[s]} + EI_{gi}^{[s]}\right)}{P_T^{[s]}} \tag{11}$$

$$CO_{2gi}^{[s]}\left[\frac{CO_2EQ}{MW}\right] = \frac{ef_{gi}}{P_T^{[s]}} \cdot \left(EO_{gi}^{[s]} + \frac{EO_{gi}^{[s]}}{EROI_{gi}^{[s]}}\right) \tag{12}$$

$$CO_{2gi}^{[s]}\left[\frac{CO_2EQ}{MW}\right] = ef_{gi} \cdot \frac{EO_{gi}^{[s]}}{P_T^{[s]}} \cdot \left(1 + \frac{1}{EROI_{gi}^{[s]}}\right) \tag{13}$$

Then, the energy obtained is replaced and the Equation 14 is obtained.

$$CO_{2gi}^{[s]}\left[\frac{CO_2EQ}{MW}\right] = 720 \cdot ef_{gi} \cdot LF_{gi} \cdot \eta_{gi} \cdot AP_{gi}^{[s]} \cdot \left(1+\frac{1}{EROI_{gi}^{[s]}}\right) \tag{14}$$

Then, the monthly emissions of all power sources gi are added and the Equation 15 is obtained. The power sources are: wind, photovoltaic, hydraulic, biomass, fossil and nuclear.

$$CO_{2T}^{[s]}\left[\frac{CO_2EQ}{MW}\right] = 720 \cdot \sum_{gi=1}^{gi=6}\left(ef_{gi} \cdot \eta_{gi} \cdot LF_{gi} \cdot AP_{gi}^{[s]} \cdot \left(1+\frac{1}{EROI_{gi}^{[S]}}\right)\right) \tag{15}$$

It is observed in Equation 15 that: as there is an increase in the EROI, the CO_2 emissions are lower, since there is a greater energy and economic profitability. Therefore, the sources that have a better EROI will have a lower associated investment cost.

4.3. Economic cost

The monthly cost is taken, instead of taking the total cost, since the energy matrix is in permanent change (investing and disinvesting in generation permanently). The cost is referred to the total installed power, to make it independent of it. The Discounted Cash Flow (DCF) method was used (Camargo et al., 2018; Bogdanov et al, 2021) which is showed in Equation 16.

$$\text{Value}^{[s]} = -\text{Initial Investment} + \sum_{s=1}^{n}\frac{\text{Cash Flow}^{[s]}}{(t_d+1)^S} \tag{16}$$

DCF consists of estimating foreseeable earnings Cash Flow and discount, using a discount rate t_d, the present value. t_d corresponds to the discount rate of the project studied which depends on various factors: country risk, US rate, and project risk. In renewable energy and electrical projects, the rate is usually around 10% (Camargo et al., 2018). Defining the investment cost for each type of generation below, the Equation 17 is obtained:

$$C_{gi}^{[s]} = K\left[\frac{\text{USD}}{\text{MWh}}\right] \cdot EI_{gi}^{[s]}\left[\text{MWh}\right] \tag{17}$$

Where K is a constant to calculate the cost equivalent of the energy balance made. To do this, the hours in a month, the ETO units and the oil price are considered. The K value is obtained as:

$$K = 30\left[day\right] \cdot 24\left[\frac{h}{day}\right] \cdot \frac{1}{1.7}\left[\frac{\text{ETO}}{MWh}\right] \cdot 75\left[\frac{USD}{barrel}\right] \cdot 7.6\left[\frac{barrel}{ETO}\right] = 2.3 \cdot 10^5\left[\frac{USD}{MWh}\right] \tag{18}$$

A capital recovery factor CRF_{gi} is defined, in order to obtain the cost corresponding to stage s considered (Camargo et al., 2018; Bogdanov et al., 2021).

$$CRF_{gi} = \frac{t_d \cdot (1+t_d)^{UL_{gi}}}{(1+t_d)^{UL_{gi}} - 1} \tag{19}$$

There is a permanent investment and this is considered in the cash flow. The monthly cost is given by Equation 20.

$$C^{[s]}\left[USD\right] = \frac{Cash\ Flow^{[s]}}{(t_d+1)^S} = \frac{2.3 \cdot 10^5}{(1+t_d)^s} \cdot \sum_{1}^{6}\left(CRF_{gi} \cdot \frac{P_{gi}^{[s]} \cdot UL_{gi}^{[s]} \cdot \eta_{gi} \cdot LF_{gi}}{EROI_{gi}}\right) \tag{20}$$

Dividing the cost by the total installed power $P_T^{[s]}$ the Equation 21 is obtained:

$$C^{[s]}\left[\frac{USD}{MW}\right]=\frac{2.3\cdot 10^5}{(1+t_d)^s}\cdot\sum_1^6\left(CRF_{gi}\cdot\frac{P_{gi}^{[s]}\cdot UL_{gi}^{[s]}\cdot\eta_{gi}\cdot LF_{gi}}{EROI_{gi}\cdot P_T^{[s]}}\right) \tag{21}$$

$AP_{gi}^{[k]}$ is replaced in Equation 21 and the Equation 22 is obtained.

$$C^{[s]}\left[\frac{USD}{MW}\right]=\frac{2.3\cdot 10^5}{(1+t_d)^s}\cdot\sum_1^6\left(CRF_{gi}\cdot\frac{AP_{gi}^{[k]}\cdot UL_{gi}^{[s]}\cdot\eta_{gi}\cdot LF_{gi}}{EROI_{gi}}\right) \tag{22}$$

Equation 22 shows that: as there is an increase in the EROI, the investment cost is lower, since there is a greater economic profitability. Therefore, the sources that have a better EROI will have a lower associated investment cost.

4.4. Restriction on renewable generation

According to the indices studied, the methodology should choose the sources that have the highest EROI (renewable or non-renewable), which would be an inconvenient. Therefore, a restriction on investment in renewables is added, which must be maximized (Equation 23). This expression calculates the total proportion of renewable generation with respect to the total installed power.

$$\mathrm{RP}^{[s]}=\sum_{gi\grave{o}\{Renewable\}}\left(A_{P_{gi}}^{[s]}\right) \tag{23}$$

4.5. Dynamic Growth Allocation Model (DGAM)

The allocation or assigned proportion of the growth in installed power the Equation 24 is defined, corresponding to each type of generation. In case of being the unit, it means that all the investment was allocated in that type of generation gi and stage s. Then, it is presented mathematically the power growth allocation per generator the Equation 25 is defined, power growth per generator Equation 26 is defined and total power growth Equation 27 is defined as follows below:

$$A\Delta P_{gi}^{[s]}=\frac{\Delta P_{gi}^{[s]}}{\Delta P^{[s]}} \tag{24}$$

$$A\Delta P_{gi}^{[s]}=\frac{\Delta P_{gi}^{[s]}}{\Delta P^{[s]}} \tag{25}$$

$$Cr_{gi}^{[s]}=\frac{\Delta P_{gi}^{[s]}}{P_{gi}^{[s]}} \tag{26}$$

$$Cr^{[s]}=\frac{\Delta P^{[s]}}{P_T^{[s]}} \tag{27}$$

From the expressions of Equation 24, Equation 25, Equation 26 and Equation 27, the Equation 28 and Equation 29 are obtained as follows below:

$$\frac{A\Delta P_{gi}^{[s]}}{AP_{gi}^{[s]}}=\frac{\Delta P_{gi}^{[s]}/\Delta P^{[s]}}{P_{gi}^{[s]}/P_T^{[s]}}=\frac{\Delta P_{gi}^{[s]}}{\Delta P^{[s]}}\cdot\frac{P_T^{[s]}}{P_{gi}^{[s]}} \tag{28}$$

$$\frac{A\Delta P_{gi}^{[s]}}{AP_{gi}^{[s]}} = \frac{\Delta P_{gi}^{[s]} / P_{gi}^{[s]}}{\Delta P^{[s]} / P_{T}^{[s]}} = \frac{Cr_{gi}^{[s]}}{Cr^{[s]}} \tag{29}$$

From this expression, the assignment or search variable $\mathrm{X}_{\mathrm{gi}}^{[\mathrm{s}]}$ (EPSO search vector) used for optimization is:

$$X_{gi}^{[s]} = A\Delta P_{gi}^{[s]} \tag{30}$$

Then the growth by generation sector is given by Equation 31.

$$\mathrm{Cr}_{\mathrm{gi}}^{[\mathrm{s}]} = \frac{\mathrm{X}_{\mathrm{gi}}^{[\mathrm{s}]}}{\mathrm{AP}_{\mathrm{gi}}^{[\mathrm{s}]}} \cdot \mathrm{Cr}^{[\mathrm{s}]} \tag{31}$$

It is to be noted that the Equation 32 and Equation 33 must be satisfied.

$$\sum_{gi=1}^{6} \left(X_{gi}^{[s]} \right) = \sum_{gi=1}^{6} \left(\Delta P_{gi}^{[s]} \right) \cdot \frac{1}{\Delta P^{[s]}} \tag{32}$$

$$\sum_{\mathrm{gi}=1}^{6} \left(\mathrm{X}_{\mathrm{gi}}^{[\mathrm{s}]} \right) = 1 \tag{33}$$

Since $\mathrm{X}_{\mathrm{gi}}^{[\mathrm{s}]}$ is a random variable, it is normalized Equation 44, which allows a proportional distribution of the expected investment.

5. Simulation of a Real Energy Matrix

5.1. Parameters

Table 2 presents the main parameters of the generators: EROI, useful life, charge, efficiency emissions and recovery factor. The nuclear source has the best EROI, while the Photovoltaic Solar Energy hast the worst EROI. This is due in part to service life, load factors, and energy expenditures in the life cycle. From these results, it is observed that the most convenient source is nuclear. This would be the case if the restriction of renewable energy and the times associated with the production chain did not exist. However, this is an important aspect that will explain the results analyzed in the next subsections.

Table 2. Parameters associated with each type of generation used (Wind, Solar photovoltaic, Hydraulic, Biomass, Fossil and Nuclear).

Power Source	EROI [u]	Useful life [y]	Load factor [u]	Efficiency [u]	Emissions factor $\left[\frac{t\,CO_2\,EQ}{MW}\right]$
Wind Energy	4.11	25	0.37	0.8	0.162
Photovoltaic Energy	3.59	25	0.24	0.65	0.3807
Hydraulic Energy	6.63	60	0.69	0.8	0.0405
Biomass Energy	4.54	15	0.71	0.32	0.081
Fossil Energy	4.30	15	0.89	0.35	0.81
Nuclear Energy	9.61	40	0.72	0.3	0.0405

Source: The Author.

5.2. Energy transition

Different (optimized) scenarios were proposed that favor each type of generation used (Wind, Solar photovoltaic, Hydraulic, Biomass, Fossil and Nuclear). Each of these scenarios were optimized using the methodology proposed in this article. The most satisfactory scenario was obtained based on the best of the six scenarios based on each renewable source.

Table 3 presents the initial and final composition (for each scenario) of the electrical matrix according to the sources used. Each of them was optimized using the same procedure, limiting the search space in order to favor their assignment. In their respective favorable scenarios, the following variations are observed: Wind Energy (from 4% to 14%), Photovoltaic Energy (from 1% to 9%), Hydraulic Energy (from 31% to 27%), Biomass Energy (from 1% to 14%), Fossil Energy (from 31% to 36%) and Nuclear Energy (from 6% to 31%). Additionally, Wind, Photovoltaic and Biomass Energy grow considerably in their favorable scenarios.

Table 3. Composition of the Argentine electricity matrix, according to the scenarios proposed.

Power Source	Initial Scenario	Wind Scenario	Photovoltaic Scenario	Hydraulic Scenario	Biomass Scenario	Fossil Scenario	Nuclear Scenario	Optimal Scenario
Wind Energy	4%	14%	3%	10%	9%	12%	9%	9%
Photovoltaic Energy	1%	1%	9%	2%	1%	2%	2%	2%
Hydraulic Energy	31%	26%	26%	27%	26%	18%	18%	18%
Biomass Energy	1%	6%	7%	9%	14%	3%	8%	9%
Fossil Energy	58%	30%	30%	30%	30%	36%	31%	31%
Nuclear Energy	6%	22%	17%	15%	17%	20%	31%	30%
Total Energy	100%	100%	100%	100%	100%	100%	100%	100%

Source: The Authors.

Biomass has high increases since it has a good EROI and the fact that the emitted emissions are offset. A decrease in the proportion of the composition in Hydraulic and Fossil generation in the electrical matrix is observed in all scenarios: they fall between a third and a quarter of their value, approximately. This is justified by the economic and environmental inconvenience, as will be seen in the analysis of the scenarios. The final Nuclear composition in all scenarios is high, first of all, because Nuclear Energy have a good EROI, which is at least two times that of the remaining sources. Second, its levels of costs and resulting emissions are lower. Since the optimal scenario was obtained from the nuclear scenario, both bear some similarity in the final electrical matrix.

Figure 3 presents the electrical matrix in [%] of the Optimal Scenario. A bar graph shows how the proportion of each generation source in the Argentine electricity matrix varies over the 15 years studied. Figure 3 shows the progressive growth of nuclear and renewable energy, and the disinvestment in fossil energy. Given that

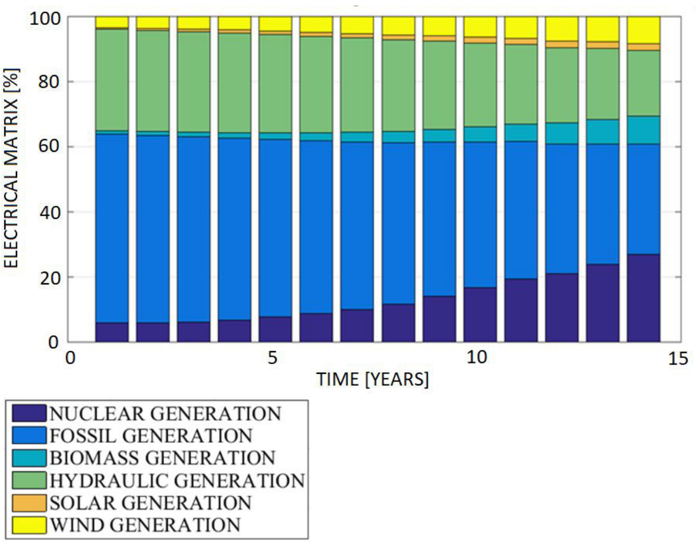

Figure 3. Electrical matrix (%) vs. time in years for the Optimal Scenario. Source: The author.

nuclear power plants take many years to build, their growth in installed power has a certain inertia. In contrast, renewable generation has shorter life cycle times. The investment in nuclear energy is due to its good EROI, which contributes to a good systemic EROI, low cost and emissions. For this reason, at the beginning of 15 years, they invest in other types of generation. In this sense, the generation source that is promoted in the short and medium term is wind energy and biomass. Wind power have less construction time and a high or intermediate EROI, depending on the location.

Figure 4, Figure 5, Figure 6 and Figure 7 show the EROI, Emissions and Economic cost vs. time, respectively. In these graphs, the upper and lower limits that build the fuzzy indices are shown. In cases where the indices must be maximized (EROI and RP), the upper limit constitutes the values of full satisfaction and vice versa for the lower limit. In cases where the indices must be minimized (CO2 and COST), the lower limit constitutes the values of full satisfaction and vice versa for the upper limit. This case is valid for any assigned weight. The intermediate values correspond to a level of satisfaction intermediate between zero and one, depending on the assigned exponential weight.

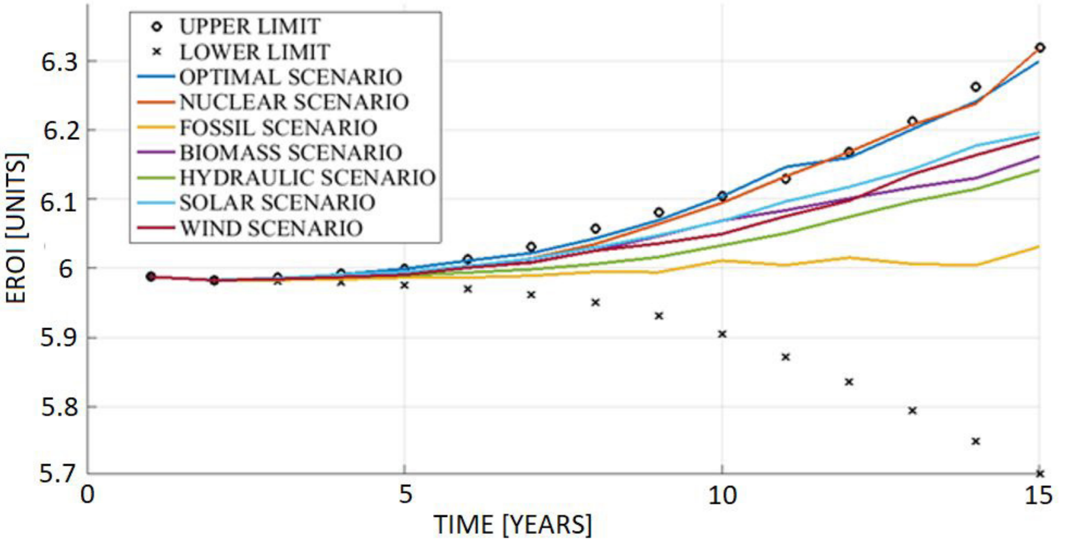

Figure 4. Energy Returned On Investment (EROI) vs. time [years] for the Optimal Scenario. Source: The Authors.

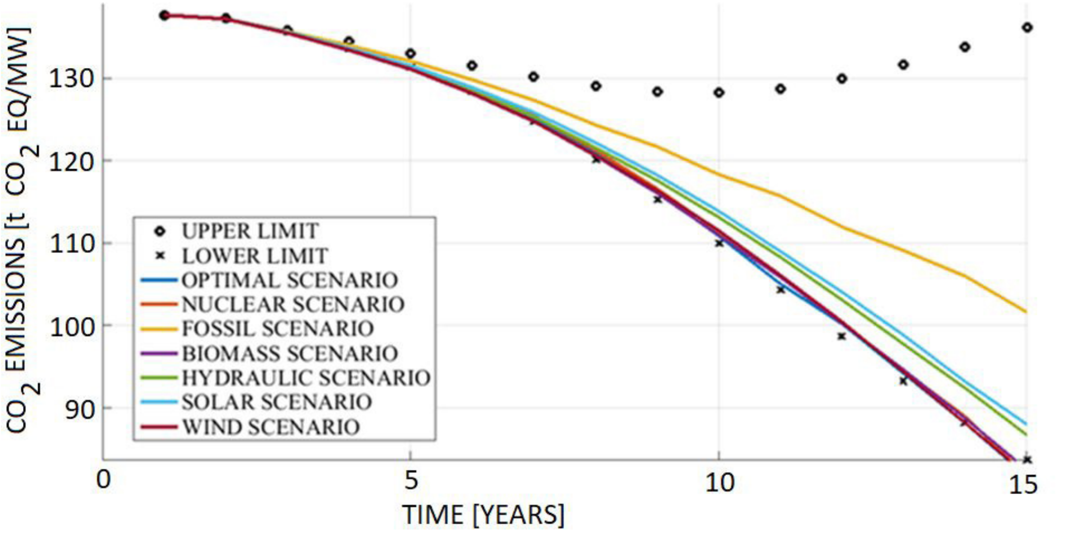

Figure 5. Emission $CO_2\left[t\,CO_2\ EQ/MW\right]$ vs. time $\left[years\right]$, for the Optimal Scenario. Source: The Author.

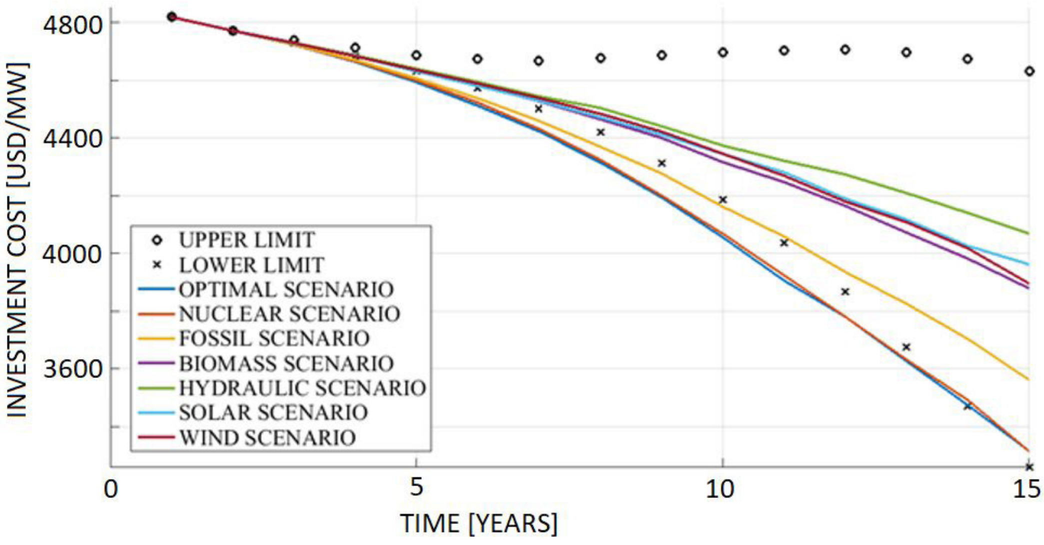

Figure 6. Investment Cost [USD/MW] vs. time in years, for the Optimal Scenario. Source: The Author.

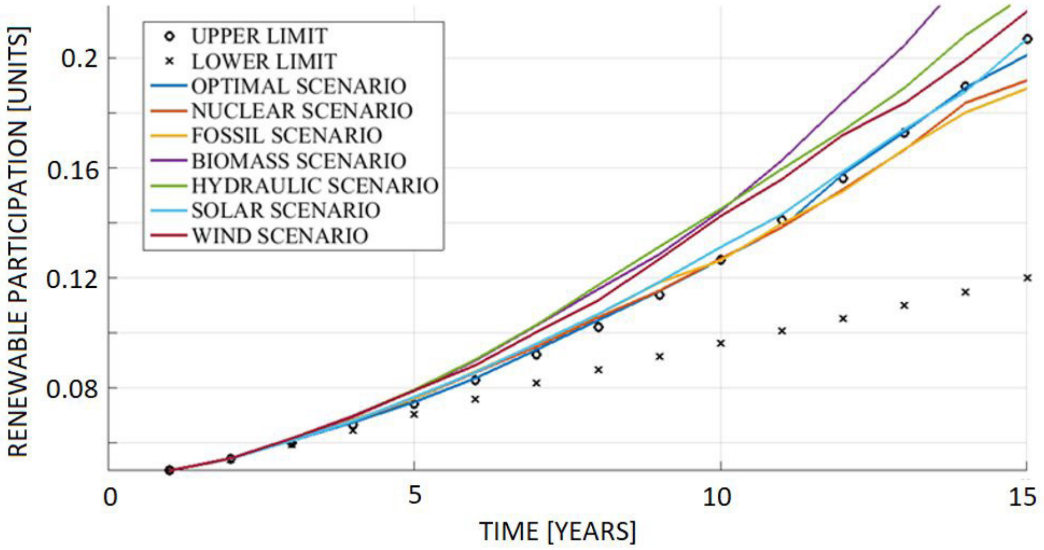

Figure 7. Investment Cost [USD/MW] vs. time in years, for the Optimal Scenario. Source: The Author.

Figure 4 shows the EROI graph for each type of scenario studied and the upper and lower limits used for fuzzy functions. It is observed that the scenario with the lowest global energy profitability corresponds to that of Fossil Scenario, which remains approximately constant. Additionally, in this scenario the best EROI was obtained by building nuclear generators. Biomass generation has interesting characteristics, such as security of supply, provided that the availability of the input is guaranteed and an intermediate EROI. It is observed that the most favorable in the very long term (10 to 15 years) is the transition towards nuclear energy which have the best EROI and service safety.

Figure 5 shows the monthly emission levels in tons of CO_2 equivalent for the studied scenarios. Logically, it was obtained that the scenario that produced the greatest amount of emissions is the Fossil Scenario, and the one with the least emissions is Optimal Scenario. The other scenarios obtained similar levels. All the proposed scenarios are closer to the lower limit than the upper limit, which makes the results promising. This implies that the methodology seeks to offset emissions that are produced by sources with poor EROI and/or a high emissions factor. It does this by searching for complementary sources that have a low emission factor and/or a high EROI. The source that meets these conditions and was chosen for all scenarios is nuclear (see Table 3). Nuclear generation has an EROI greater than 9 units (see Table 1), that is, the systemic EROI could grow by 50% if only nuclear power plants were installed and all other generation sources were dismantled. This is not allowed due to the restriction of renewable generation and given that any alternative that results in better indices than the desired ones are indifferent for the proposed fuzzy modeling.

The investment cost in USD/MW is presented in Figure 6. Likewise, the investment in nuclear energy (to a greater or lesser extent) in all the scenarios offset the increase in cost by opting for less profitable sources.

There are three scenarios that obtained costs totally or partially lower than the desired cost: Fossil, Nuclear and optimal. The other scenarios, which correspond to renewable sources, have intermediate costs. It is observed that the transition with the lowest cost corresponds to the Nuclear Scenario, and the one with the highest cost is the Hydraulic Scenario. Fossil and Photovoltaic Scenario are among the lowest cost scenarios.

Figure 7 shows the attribute associated with the percentage of participation of renewable sought, which is increasing from the starting point to that obtained. Except for the fossil and nuclear scenario, the scenarios exceed the desired upper limit (20% renewable target). The optimal scenario sought to be as close to it as possible, with the objective of relying on other sources and minimizing the investment cost.

5.3. Fuzzy Functions

Figure 8 shows the Fuzzy Function associated with the attributes to be optimized (EROI, CO2, Investment Cost and Renewable Participation) and their confluence, for the optimal scenario and the confluence of these fuzzy functions.

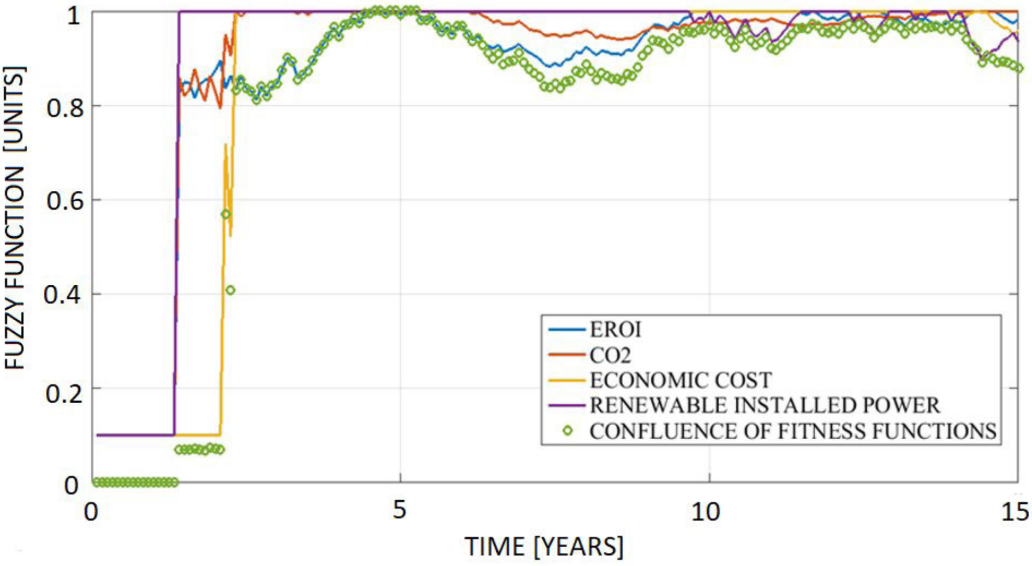

Figure 8. Fuzzy Function associated with the attributes to be optimized and their confluence. Source: The Author.

When the value is one unit it means that the index has reached or even improved the established limits (upper or lower). The limit wanted depends on whether the decision-maker wants to maximize or minimize the index in question. If the value is null it means that the corresponding index reached the opposite limit and that it is unwanted by the decision maker. In turn, this level of satisfaction is influenced by the weights used, which produces an over/undervaluation of the indices (expansion or contraction). It is observed that all the proposed optimization indices have a good level of acceptance. The renewable generation restriction was almost fully satisfied, while the index with the lowest level of satisfaction was the EROI. This is logical according to what was analyzed in Section 4. The effect of the algebraic product t-norm is observed which is stricter than the t-min. The graphed values correspond to the level of acceptance of each optimized index by the decision maker.

The graphs of confluence function that were obtained by the different scenarios studied are presented in Figure 9. That is, the final curves are plotted in a similar way to that shown in Figure 8, this is for each

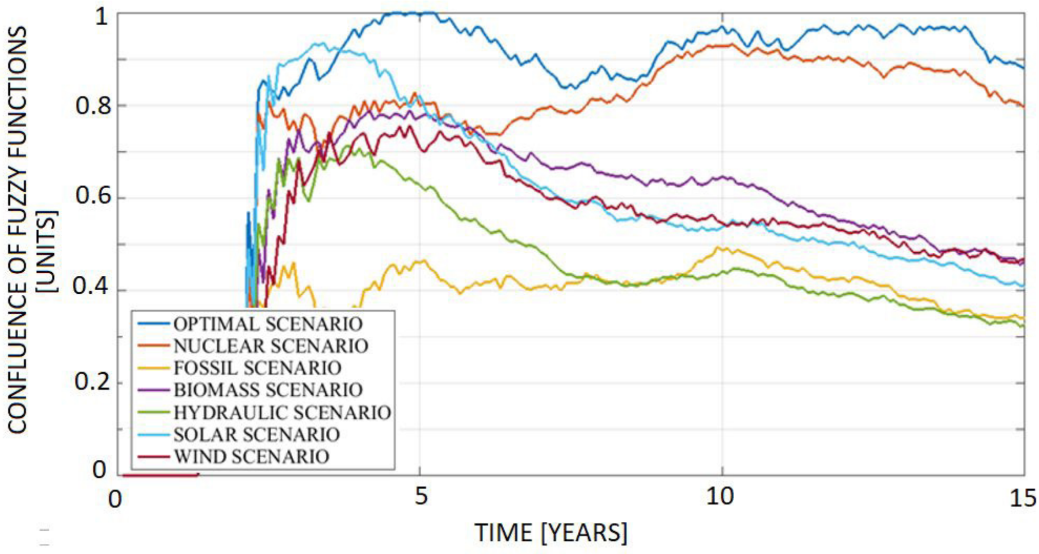

Figure 9. Confluence of the fuzzy functions for each scenario. Source: The Author.

proposed scenario. The optimal scenario has a better fitness function per stage than the other scenarios. The Nuclear Scenario begins with low fitness values, due to inertia in its growth, however its final value is higher than all other scenarios. The Optimal and Nuclear based scenarios are the ones with the best fuzzy functions, because to the high emission levels and in the second to the high levels of investment cost. The Biomass Scenario possesses an aptitude in third place with respect to the Optimal and Nuclear Scenario, because to its good load factor, low emission factor and intermediate EROI. The Optimal Scenario has a good aptitude in most of the stages, only surpassed in the final stage by the Photovoltaic scenario, which has a final aptitude superior to the other generation sources. In second place, the nuclear scenarios have the best confluences of the analyzed attributes. This is because the optimal scenario was obtained using the nuclear scenario as a starting point. Both scenarios have a high presence of nuclear energy and an adequate combination of the other resources.

5.4. Evolutive Particle Swarm Optimization (EPSO)

The EPSO metaheuristic was applied with 50 particles and 100 iterations to each scenario. Figure 10 shows the executions for this model for the transition scenarios. The total fitness function is shown, which corresponds to the confluence considering three stages for each scenario.

The number of particles and iterations were adjusted ad hoc, performing a large number of simulations and analyzing the execution time and quality of the solution obtained. Additionally, it is important to note that two mutations are made for each particle, therefore the total number of particles is 150. Also, from this analysis it was seen that there are no considerable improvements after 100 iterations. This can be developed in depth in future publications. The total time was 950 seconds, that is, 15 minutes and 40 seconds. That is, each optimization was done in about 2 minutes and 15 seconds. The EPSO operating mechanism obtained good results, although substantial improvements are obtained in the first 50 iterations. This is because PSO-based metaheuristics have difficulty finding better solutions in advanced iterations.

The Optimal Scenario was obtained from the scenario with the best fitness function (Figure 10). It is observed that the order of scenarios according to the fitness function obtained was the following (from the best to the worst): Optimal, Nuclear, Biomass, Wind, Solar photovoltaic and Fossil. It is observed how the optimal and nuclear scenarios stand out notably from the rest, since both scenarios are similar. In them, considerable investment is made in nuclear, wind and biomass energy. This makes sense according to what was analyzed in the previous sections, due to the EROI, CO_2 emissions, cost and Proportion in renewable.

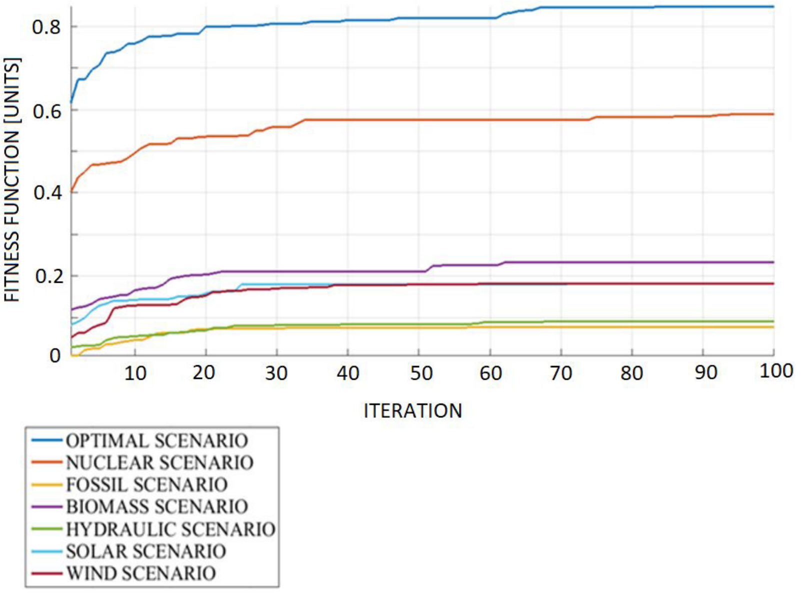

Figure 10. Confluence of the fuzzy functions for each analyzed scenario. Source: The Author.

6. Conclusions

The problem of energy transition is extensive, complex and multidisciplinary, and it cannot be resolved using conventional methods, due to the existence of multiple optimization objectives (which are also non-linear) and the presence of uncertainty in their valuation. To obtain the optimal alternative that maximizes the fuzzy fitness function, "Evolutionary Particle Swarm Optimization" (EPSO) was applied in each scenario. It would not be possible to easily solve this problem with mathematical programming techniques. The search space of the present problem is continuous and the modeling is non-linear, dynamic and multi-objective. This makes linear, mixed, and dynamic programming unsuitable. The fact that the search space is continuous requires that it be discretized or transformed into another simpler search space for these alternatives to be valid. This can cause good solutions to be lost. The fact that there are multiple objectives complicates metric compatibility, so the subjective assessment of each optimized index must be used. This makes the optimal solution up to the decision maker.

The present proposal does not need to resort to linearizing, discretizing and a priori evaluations of the objectives, it only the weights produced by the AHP. A novel dynamic model of allocation DGAM, sustainability indices and fuzzy decision model were used in the present work. It was observed that a necessary time was required for the expansion of the existing production, according to the investment allocation model. The methodology proposed in this paper produces good results for the problem of finding the best investment alternative in each generation source. The main practical implications of this combination are:

- The EROI is a good indicator of energy efficiency and sustainability, since it encompasses the energy cost-benefit and can be used to estimate the economic cost and emissions. These are determined by installed power, load factor, useful life, performance, emissions factor, and discount rate;
- The proportion of nuclear, wind and biomass generation favors a sustainable electricity matrix. The scenarios based on nuclear generation were those that obtained the best results, followed by wind and biomass generation. The investment in hydraulics has high associated investment costs, together with its associated time, makes it inconvenient. The scenario with investment in Fossil was the least satisfactory regarding CO_2 emissions, which is logical. The optimal composition of renewable energies (Solar, Wind and Biomass) reaches the target of 20%, and considering the hydraulic energy, this reaches the third part of the Electrical Matrix;
- Total installed power follows the growth trend of the Argentine Energy System, and the composition of the final Electrical Matrix requires strong state policies, broad consensus with the different sectors of society, and awareness campaigns. The time required for the energy transition depends on the energy source (more time is required for nuclear generation);

- The EPSO metaheuristic works very well for these types of problems, with almost continuous search space. Its good exploration capacity allowed finding solutions with a high function of aptitude, precision and robustness. The fuzzy decision model allows the construction of an objective function, without the needing of define linear functions and constraints or economically value the attributes. The decision maker must determine only the exponential weights according to the AHP. The fuzzy functions allowed to guide the metaheuristic to the improvement of the proposed solution. The optimal solution in some indices achieved the desired maximum or minimum values;
- Novel environmental assessment mechanisms can be made from this work.

The work was validated by comparing with BAU and CR scenarios (Annex 4). Additionally, the results were analyzed using expert knowledge and international standards. In this way, it was verified that the results were consistent. However, variations in the price of oil or in energy costs are not considered. Variations in the production chain or technological improvements that seek to reduce energy consumption are not considered either. Changes in energy demand were also not considered, since it requires cultural changes. Future work may take these aspects into account, as well as the inclusion of uncertainty in the life cycle analysis and this would allow detailing the procedure used.

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Annex 1. Mathematical modelling.

The model of this research is based on the characteristics of energy consumption in extraction and production in the time (15 years or 180 months). s' consider the moment when the life cycle begins. Helper functions are used (exponential and normal functions) and auxiliary functions ($f_1(s,s')$, $f_2(s,s')$ and $f_3(s,s')$). Using this algorithm, from the data obtained from the LCA, the growth of installed power, energy obtained and invested can be modelled.

BEGIN /* Exponential growth model for the evolution of installed power */

Input: LCA and Generator technical data, Stage s and energy power sector gi.

Outputs: Total installed power $P_{gi}^{[s]}$ and assignment $AP_{gi}^{[s]}$.

Step 1: Calculate auxiliary functions $f_1(s,s')$, $f_2(s,s')$ and $f_3(s,s')$

$$f_1(s,s') = \begin{cases} 0, & s \in \left[0\ ,\ s'+T_{inv}+T_{pr}\right] \\ E_1, & s \in \left[s'+T_{inv}+T_{pr}\ ,\ s'+T_{inv}+T_{pr}+UL\right] \\ 0, & s \in \left[s'+T_{inv}+T_{pr}+UL\ ,\ 180\right] \end{cases} \tag{34}$$

$$f_2(s,s') = \begin{cases} 0 & s \in \left[0\ ,\ s'+T_{pr}\right] \\ E_2 \cdot N\left(s'+\frac{Tinv}{2}+T_{pr}, \frac{T_{inv}}{6}\right) & s \in \left[s'+T_{pr}\ ,\ s'+T_{pr}+T_{inv}\right] \\ 0 & s \in \left[s'+T_{pr}+T_{inv}\ ,\ 180\right] \end{cases} \tag{35}$$

$$f_3(s,s') = \begin{cases} 0, & s \in \left[0\ ,s'\right] \\ E_3 \cdot e^{-r\cdot(s-s')} & s \in \left[s'\ ,\ s'+T_{pr}\right] \\ 0, & s \in \left[s'+T_{pr}\ ,\ 180\right] \end{cases} \tag{36}$$

Step 2: Calculate the growth factor.

$$f_{gi}^{[s+1]} = f_{gi}^{[s]} \cdot \left(1 + cr \cdot \frac{X_{gi}^{[s]} Norm}{\Delta P_{gi}^{[s]}}\right) \tag{37}$$

WHILE $(\boldsymbol{min}\left(\mathrm{AP}^{[s]} - \mathrm{AP}^{[s-1]}\right) > tolerance)$ DO

Step 3: Calculate the power invested $PO_{gi}^{[s]}$ and power obtained $PI_{gi}^{[s]}$ per stage s.

$$PO_{gi}^{[s]} = \sum_{s'=2}^{180} f_1(s,s') \cdot f_{gi}^{s+1} \tag{38}$$

$$PI_{gi}^{[s]} = \sum_{s'=2}^{180} \left(f_1(s,s') + f_2(s,s') + f_3(s,s')\right) \cdot f_{gi}^{s+1} \tag{39}$$

Step 4: Calculate the total installed power of the system with the depreciation f_{dep} of installed power.

$$P_{gi}^{[s]} = P_{gi}^{s-1} \cdot \left(1 - f_{dep}\right) + PO_{gi}^{[s]} \tag{40}$$

Step 5: Calculate the proportion of the electrical matrix, according to each generation source gi.

$$AP_{gi}^{[s]} = \frac{P_{gi}^{[s]}}{P_T^{[s]}} \tag{41}$$

END WHILE

END PROGRAM

The time $s' + T_{inv} + T_{pr}$ (months) represents the time elapsed between the start of the generator's manufacturing life cycle, until it comes into operation (contemplating extraction, production and installation).

The time $s' + T_{inv} + T_{pr} + UL$ (months) considers the time elapsed until the generator reaches its useful life.

The interval $\left[s' + T_{pr},\ s' + T_{pr} + T_{inv}\right]$ (months) considers the time that must elapse between when the extraction of the mineral begins and when it ends, where the energy E_2 is invested. The mining extraction and processing process is modelled by a normal function with mean equal to $s' + \frac{T_{inv}}{2} + T_{pr}$ and standard deviation equal to $\frac{T_{inv}}{6}$.

The interval $\left[s',\ s' + T_{pr}\right]$ considers the time between when the manufacturing process starts and when the Life Cycle ends, where the energy E_3 is invested. The exponential function, whit growth rate r, considers the energy expenditure in manufacturing, being of a high value at the beginning and progressively decreasing. Future publications will detail this algorithm in greater depth.

BEGIN /* Algorithm of Objective Functions and Constraints */

Data: Power and technical data for each generation source gi.

Input: Particle X_i corresponding to swarm X (investment allocation), for each generation source studied.

Output: Objective and Restriction Functions by stage during the period analyzed S.

FOR $s = 1:S$ and $gi = 1:6$ **DO**

Step 1: Normalization of the search vector X_i used to assign the generated power:

$$X_{gi}^{[s]}{}_{Norm} = \frac{X_{gi}^{[s]}}{\Sigma X_{gi}^{[s]}} \tag{42}$$

BEGIN /* Iterative Electric Matrix Correction Model */

Step 2: Start program Dynamic Growth Allocation Model (DGAM).

END

Step 3: calculate the Energy Returned On Investment (EROI) of the System.

$$U_1^{[s]} = EROI_T^{[s]} = \frac{\Sigma\left(A_{P_{gi}}^{[s]} \cdot UL_{gi}^{[s]} \cdot \eta_{gi}^{[s]} \cdot LF_{gi}^{[s]}\right)}{\Sigma\left(A_{P_{gi}}^{[s]} \cdot RT_{gi}^{[s]} \cdot \eta_{gi}^{[s]} \cdot LF_{gi}\right)} \tag{43}$$

Step 4: calculate total emissions of CO_2 of the System.

$$U_2^{[s]} = CO_{2T}^{[s]}\left[\frac{t\,CO_2EQ}{MW}\right] = 720 \cdot \sum_{gi=1}^{gn}\left(ef_{gi} \cdot AP_{gi}^{[k]} \cdot \eta_{gi} \cdot LF_{gi} \cdot \left(1 + \frac{1}{EROI_{gi}^{[k]}}\right)\right) \tag{44}$$

Step 5: calculate total cost of the System.

$$U_3^{[s]} = C_s\left[\frac{USD}{MW}\right] = \frac{2.3 \cdot 10^5}{\left(1 + t_d\right)^s} \cdot \sum_{1}^{gn}\left(FRC \cdot \frac{AP_{gi}^{[k]} \cdot UL_{gi}^{[k]} \cdot \eta_{gi} \cdot LF_{gi}}{EROI_{gi}}\right) \tag{45}$$

Step 6: calculate the proportion of the electrical matrix in renewable.

$$U_4^{[s]} = \sum_{gi \,/\, \{\mathrm{Re}newable\}}\left(A_{P_{gi}}^{[s]}\right) \tag{46}$$

END FOR

END PROGRAM

Annex 2. Fuzzy Decision Making.

The transformation algorithm to the fuzzy domain and confluence is presented, according to the FDM. In Equation 48 and Equation 49, the EW_m are exponential weights (for each criteria m), whose effect is to expand ($EW_m < 1$) and contract ($EW_m > 1$) the fuzzy functions (Camargo et al., 2018). If the objective is to be maximized, the function has a positive slope, which causes the upper limit to be sought (and vice versa for the case of minimization). The exponential weights are obtained from the AHP. The attributes associated with EROI and CO2 (Annex 1) will have a dilation in their fuzzy functions ($EW = 0.57$ for both), while the others will have no effect ($EW = 1$). The limits and fuzzy functions are dynamic and they are calculated taking into account extreme energy scenarios. To simplify the algorithm, an auxiliary variable is added to establish the preference values in the fuzzy limits, depending on whether it is maximization or minimization.

BEGIN /* Fuzzy Decision Making */

Data: Objective and Constraints U_m, Exponential Weights EW_m (AHP), Lower U_m^{Low} and Upper U_m^{Up} Limits.

FOR ($m = 1:4$ and $s = 1:S$) DO

Step 1: Calculate the auxiliary variable a.

IF Minimization of attribute m THEN

$$a = 1 \tag{47}$$

ELSE IF Maximization of attribute m THEN

$$a = 0 \tag{48}$$

END IF

Step 2: Calculate the states μ_m using the next function.

$$\mu_m^{[s]} = \begin{cases} a & , U_m^{Low} \geq U_m \\ \left(\dfrac{U_m^{Up} - U_m}{U_m^{Up} - U_m^{Low}} \right)^{EW_m} & , U_m^{Low} \leq U_m \leq U_m^{Up} \\ 1 - a & , U_m^{Up} \leq U_m \end{cases} \tag{49}$$

Step 3: Calculate the weights between stages s, using the t-norm used (Algebraic Product).

$$\mu_t^{[s]} = t\left(\mu^{[s]}, \mu_t^{[s-1]} \right) = \mu^{[s]} \cdot \mu_t^{[s-1]} \tag{50}$$

END

END PROGRAM

Annex 3. Evolutionary Particle Swarm Optimization EPSO

EPSO takes the equation of motion of the PSO (Kadkol, 2021) and adapts it in a similar way to the method of genetic algorithms (Equation 53 and Equation 54). In each k-iteration, the evolutionary operators of mutation (*), selection and combination are applied them to the parameters (Equation 51) and global optimum (Equation 52) (Miranda et al., 2019). $N(0,1)$ is a random variable with Gaussian Distribution of mean equal to zero and standard deviation equal to the unity, the comma is to separate the two said parameters. Section 2 describes each variable and parameter used in the EPSO metaheuristics.

BEGIN /* Evolutionary Particle Swarm Optimization EPSO*/

Step 1: Initialize $X_i^{[k]}$, $b_G^{[k]}$, $b_i^{[k]}$ at zero, random values or a good value according to the designer's criteria.

Step 2: Calculate fitness functions (Annex 1): $f\left(X_i^{[k]}\right)$ and $f\left(b_i^{[k]}\right)$.

FOR (($k = 1:100$) and ($i = 1:50$)) DO

Step 3: Mutate parameters (two mutations per particle): $w_{Ii}^{*[k]}$, $w_{Ii}^{*[k]}$, $w_{Si}^{*[k]}$. A normal function with mean equal to zero and standard deviation equal to unity is used, both parameters of the Gaussian Distribution are separated by a comma.

$$w_{i[I,C,S]}^{*[k+1]} = w_{i[I,C,S]}^{*[k]} \cdot \left[1 + \sigma \cdot N(0,1)\right] \tag{51}$$

Step 4: Mutate better position of the swarm (two mutations per particle): $b_G^{*[k]}$.

$$b_G^{*[k+1]} = b_G^{*[k]} + w_{iN}^{*[k]} \cdot N(0,1) \tag{52}$$

Step 5: Equation and rule of motion, respectively:

$$V_i^{[k+1]} = w_{Ii}^{*[k]} \cdot V_i^{[k]} + w_{Ci}^{*[k]} \cdot \left(b_i^{[k]} - X_i^{[k]}\right) + w_{Si}^{*[k]} \cdot \left(b_G^{*[k]} - X_i^{[k]}\right) \tag{53}$$

$$X_i^{[k+1]} = X_i^{[k]} + V_i^{[k+1]} \tag{54}$$

Step 6: Limit position $X_i^{[k+1]}$ and speed $V_i^{[k+1]}$.

Step 7: Stochastic tournament: looking for the best particle or its mutation $b_G^{*[k]}$. In the process, the fitness functions $f\left(X_i^{[k]}\right)$, $f\left(b_G^{*[k]}\right)$ are calculated.

Step 8: Compare and update the best positions seen by the particles $b_i^{[k]}$ and by the swarm $b_G^{[k]}$.

$$f\left(X_i^{[k]}\right) > f\left(b_i^{[k]}\right) \Rightarrow b_i^{[k+1]} = X_i^{[k+1]} \tag{55}$$

$$f\left(X_i^{[k]}\right) > f\left(b_G^{*[k]}\right) \Rightarrow b_G^{*[k]} = X_i^{[k]} \tag{56}$$

END FOR

END PROGRAM

Annex 4. Energy transition proposed in the state of the art

The scenarios, graphed again in this work, of the Argentine Chamber of Renewable Energies (CADER) are presented in Figure A1, Figure A2 and Figure A3.

The main criteria to consider in the BAU scenario (Figure A1) are the following:

➢ The percentages of contribution of each source to the consumption of each sector demanded remains constant over time.

➢ The electricity balance remains constant over time.

➢ Electricity generation occurs with an average yield of generation according to 2015 data.

➢ The contribution of nuclear energy remains constant depending on the data from 2015, since the installed power cannot be increased.

➢ The increase that nuclear power should provide is allocated to renewables.

The main criteria to consider in the CR scenario (Figure A2) are the following:

➢ Changes in consumption habits are proposed, which causes the demand for energy to decrease.

➢ Electricity generation occurs with an average yield of generation according to 2015 data.

➢ The contribution of nuclear energy remains constant depending on the data from 2015, since the installed power cannot be increased.

➢ The increase that nuclear power should provide is allocated to renewables.

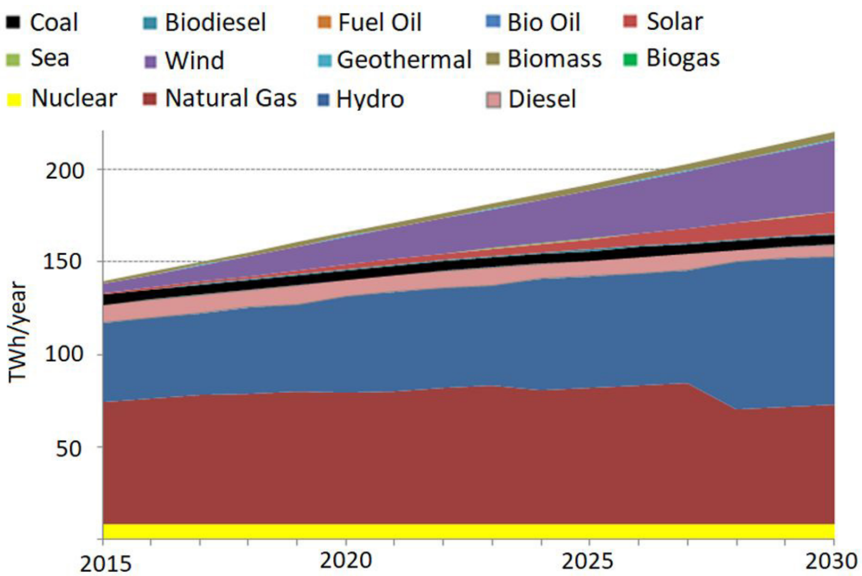

Figure A1. Electrical matrix, for the Business as usual (BAU). Source: The Authors.

Figure A3 shows the composition of the electrical matrix in the BAU and CR scenarios. Currently, the Argentine Primary Energy Matrix is predominantly composed of fossil fuels (see Figure A3) and presents two peculiarities: the high contribution of natural gas (54%) and the very low participation of mineral coal (less than 1%). There is a high and growing dependence on fuels, as a result of generation dispatch with a growing fossil predominance and high inefficiency in transportation systems. The current construction of gas turbine plants, combined cycles, etc., decreases the import of electrical energy, but increases the import of these fuels, and therefore the total balance is not improved. The CR (see Figure A3) scenario seeks a more drastic reduction in fossil fuels than the BAU scenario. However, neither of the two scenarios contemplates a growth in nuclear energy.

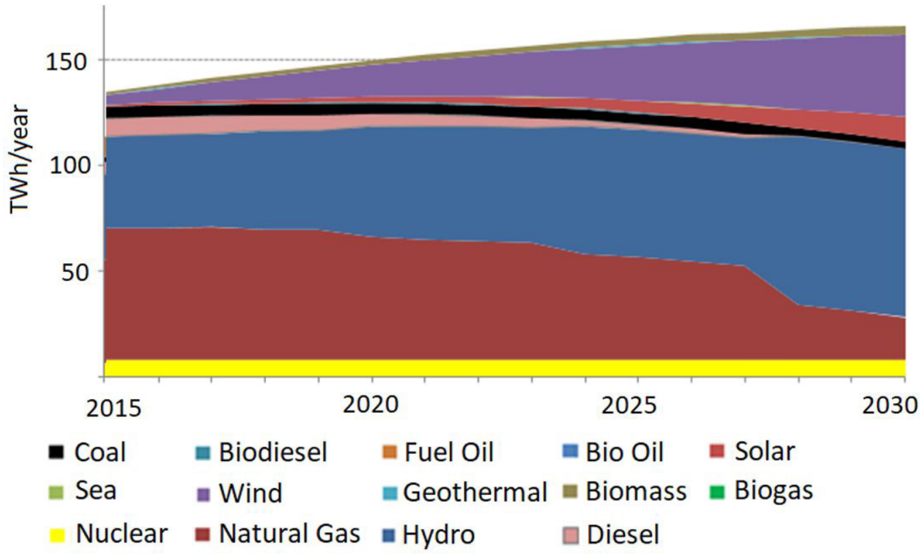

Figure A2. Electrical matrix, for the Business as usual (BAU). Source: The Authors.

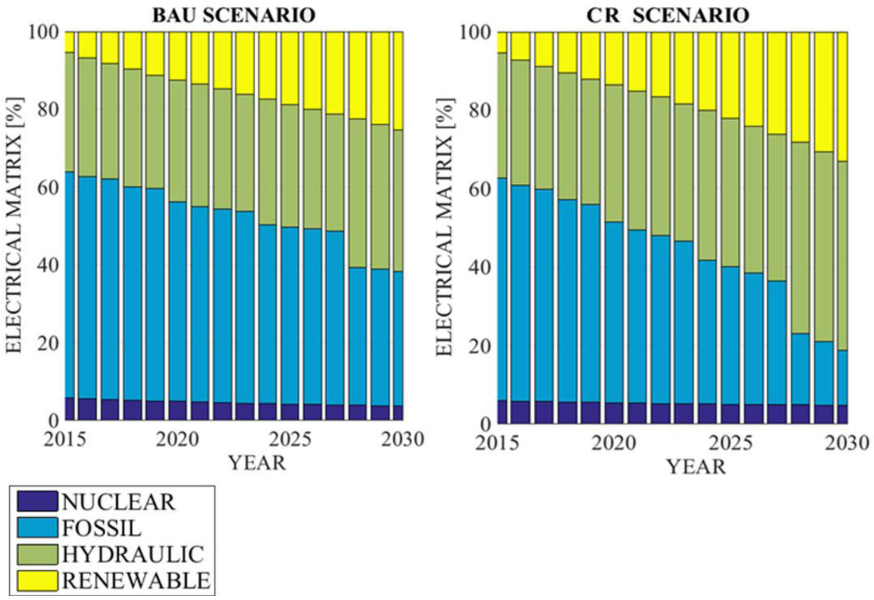

Figure A3. Electrical matrix for the Business as usual (BAU) and Collective Responsibility (CR). Source: The Authors.