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Inductive Projection Planning: Putting CSP in the Picture

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Abstract. The progressive contribution of renewables is key to decarbonize electricity systems. However, high shares of intermittent renewables remain a worldwide concern. Least Cost Capacity Expansion models are heavily led by short-sighted cost criteria and they do not take into account the feedback on the hourly electricity markets influencing investments. Their outcomes are often unrealistic and cannot come true with the current market rules, as they would require huge hidden subsidies because the captured price by non-dispatchable renewables would be often below the market price. Inductive approaches – based on actual hourly production from renewables and assigning the expected cost trends to each one of the technologies – would yield more realistic, actionable solutions. The aim of this paper is to present a planning approach for the new installed capacity, Inductive Projection Planning (IPP), an advanced tool that optimizes with respect to multiple objectives, has been developed using the Spanish case as an example. The necessity of CSP for a true energy transition in shown, avoiding excessive fossil-fueled backup generation.

INTRODUCTION

Decarbonization of human activities is the main and urgent challenge that we face today. Decarbonizing the electrical sector with renewables is becoming more and more urgent as reducing CO_2 emissions in the other two energy sectors, heat and transportation, are not as easy to accomplish using current technologies. Moreover, renewable electrical technologies are currently cheaper than fossil fuel plants.

High penetration of cheap but non-dispatchable renewable generation technologies, like wind and photovoltaics (PV), along with the progressive decommissioning of conventional power plants cause fundamental concerns to arise on security of supply to policy makers and electrical system operators. In addition, a generation fleet consisting mostly of variable renewables will create other important concerns in terms of grid stability and affordable ramps for the backup plants.

The main issue is whether the fleet of renewable generation units will be able to respond to the demand needs, particularly at the times of peak demand. New large-storage concepts that can seasonally decouple the collection and the delivery of energy is a kind of never-ending economic utopia. Besides, new dams seem to be more and more difficult to deploy. There are only two mature renewable technologies that are dispatchable in real-time settings: hydro and biomass, but their possibilities to significantly increase their shares are rather limited.

Natural complementary of renewable energy sources along with proactive management of demand and interconnections could mostly solve the supply concerns in renewable based generation fleets. The primary role of the new generation of Solar Thermal Electricity (STE) plants would be to contribute – contribute to the bulk of solar electricity production in sunny countries by complementing PV production – to the bulk of the solar electricity generation in sunny countries. STE/CSP plants can provide synchronous and absolutely firm supply, with no deviations for the day-ahead program from sunset until sunrise next day.

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Considering the issues and additional investments that dysfunctionalities of a large penetration of non-dispatchable renewables will cause, the services that the thermal storage of Solar Thermal Electricity (STE) plants can provide to the system – strategic reserve, curtailments collection, price arbitrage – should constitute additional relevant reasons to push the deployment of STE plants in a more balanced share with PV when planning the generation fleet in the Energy Transition process.

THE STARTING POINT: PROTERMOSOLAR TRANSITION REPORT

Renewable generation technologies are quite different from each other. Policy Makers must understand their differences to achieve an optimum generation structure with the minimum fossil backup, as markets and expansion models cannot do it. In June 2018, Protermosolar presented a report (1) comparing the advantages of using Inductive Projection Planning (IPP). IPP projects, on hourly basis, the historical production data from all renewables, with some fine tuning to take into account the improved performances of new equipment's, implementing the dispatch flexibility of STE and Biomass plants through a rational dispatch criteria to reduce emissions (see Figure 1).

FIGURE 1. Rational of the Protermosolar Report (the proposed fleet could have been modified to achieve better results)

Meeting the demand at any time is about programming the dispatch of available and feasible generation units (see Figure 2). Wind and sun will be the pillars of electricity generation in the future. Large hydro and biomass will also contribute with their dispatch flexibility. But wind parks and PV plants generate only when the resource is available, therefore the appropriate generation pieces should be put together to meet the demand avoiding as much CO_2 emissions as possible.

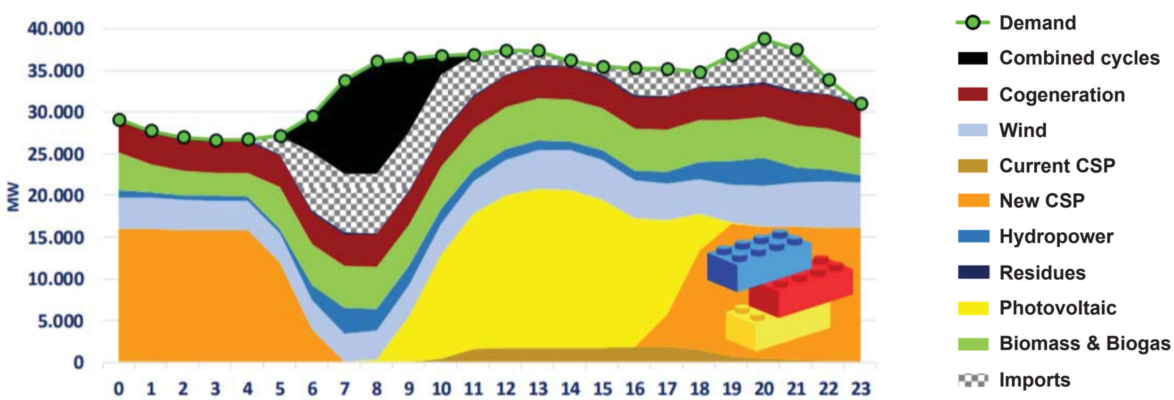


FIGURE 2. Example of how the demand will be hourly covered on a particular day with the available generation units (1)

The goal of planning is to decarbonize the generation system, ensure quality of supply and grid stability at an affordable cost. Until now, Planners and Policy Makers relied on the results of Least Cost Capacity Expansion (LCCE) models and they were right when mostly conventional power plants were considered. But these models don't understand properly neither the value and constraints of the different renewable technologies nor the impact on investment decisions caused by the low market prices that would result in their so called least cost generation fleets. Understanding the complementary among renewables allows for a much more "common sense" fleets and associated dispatch strategy, which can be conceived to achieve a stronger emission reduction. That's why we recommend an inductive bottom-up approach for planning rather than a deductive one. Thus, a sound combination of technologies allowing for an advanced decarbonization can be proposed.

LCCE models (typical agnostic approach) results in never ending fossil backup and emissions, unrealistic business development, high curtailments and high hidden system's overall costs while using common sense inductive approaches the achievement of decarbonization goals with higher renewable contribution, reduced curtailments and also lower overall system's cost can be reached. LCCE models focus exclusively on price forgetting many other aspects, which finally impact on the total system cost. They do not take advantage of the operational complementarity among different renewable technologies, which can be done through a rational inductive planning.

Using the actual data of renewable production on the past years one can demonstrate that the demand can be satisfied by a proper fleet with a large share of renewable plants and that grid stability requirements can be also accomplished. As the price for most of the new capacity is going to be awarded through auctions, we have assumed that the proper way to deploy new STE plants will be through auctions as well, but requesting a dispatch profile that complements the PV production.

The results in the first attempt – just by proposing a common sense and more balanced mix with complementary dispatch profile between PV and CSP – were very impressive: much lower emissions, much lower curtailments and exports, no need of nuclear and coal by 2030 and, surprisingly, lower cost than the official mix. The results of our study were highly influential in the current Spanish Energy and Climate Plan, which included 5 GW of new STE plants by 2030 (2).

CIEMAT OPTIMIZATION TOOL APPLYING ARTIFICIAL INTELLIGENCE

Researchers at CIEMAT – Plataforma Solar de Almería – were encouraged by this inductive approach and applied artificial intelligence techniques to perform an automatic optimization using genetic algorithms. The optimization estimates the optimum new power to be installed for PV (P_{pv}), wind (P_{wind}) and CSP (P_{csp}) power plants that at least satisfy the demand and minimize the curtailments (curtailments) at the lowest possible cost (cost). The first results were presented at GENERA 2020 fair in Madrid (3).

Among the different possibilities to couple cost with any other variable to find the optimum fleets we have selected "curtailments" as the second most important criteria to be considered. The curtailment level is the best indicator regarding impacts on investment motivations, hidden cost of grids etc., which can't be modeled but that have to seriously considered by policy makers when making their choices.

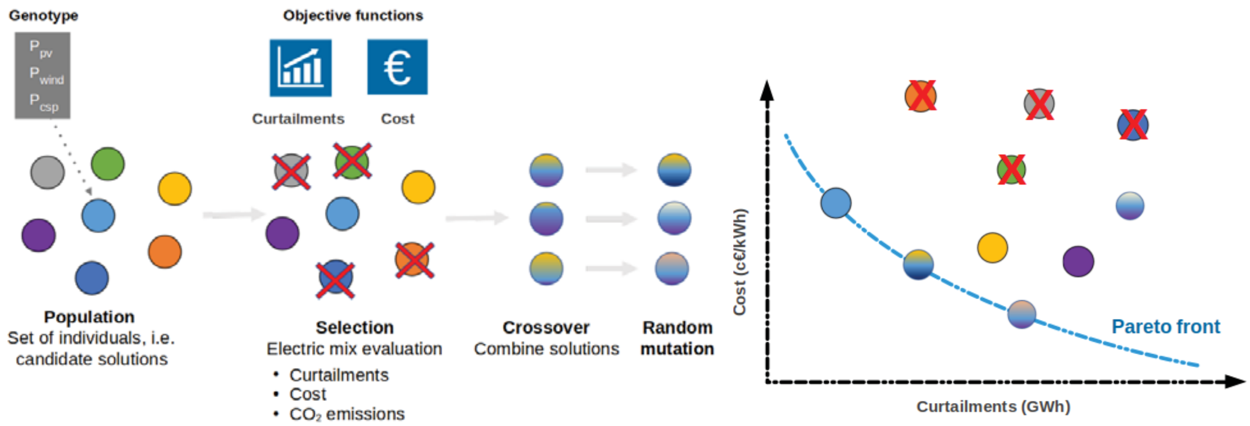
The next three following subsections describe the genetic algorithm, the electric mix evaluation in order to calculate the generated power, curtailments, electricity cost and CO_2 emissions for each evaluated electric mix configuration, and the developed optimization software tool.

Artificial Intelligence: Multi-Objective Genetic Algorithms

A genetic algorithm, that belongs to the larger class of evolutionary algorithms, is used to calculate the optimum solutions. Genetic algorithms are inspired in biological operators such as crossover, selection and mutation based on concepts developed in Darwin's theory of evolution.

In a genetic algorithm, a population of candidate solutions (called individuals) is evolved toward better solutions. Each candidate solution has a set of properties, also called genome, chromosomes or genotype (P_{pv}, P_{wind}, P_{csp}) (see Figure 3(a)). The evolution is an iterative process and usually starts from a population of randomly generated individuals, the population of each iteration is called a generation. The fitness of every individual in the population is evaluated at each generation. The fitness is determined by the objective functions (curtailments and cost). If there is more than one objective function, multi-objective algorithms must be used.

Multi-objective optimization problems deal with conflicting objectives, while one objective increases the other decreases or vice-versa. There is not a unique global solution but a set of solutions. Some individuals may be unfeasible due to restrictions (satisfy demand). A solution dominates another solution when it is better with respect to every objective. The non-dominated set of solutions are those that are not dominated by any member of the population. The non-dominated set of feasible solutions are the optimal set of solutions and they are arranged in the Pareto front (see Figure 3(b)).



(a) One iteration of the genetic algorithm (b) Pareto front

FIGURE 3. Genetic algorithm

The more fit non-dominated individuals are selected from the current population, other individuals can be also selected to keep diversity in the population in order to avoid local optimum solutions. Each selected individual's genome is modified applying crossover and randomly mutated with a certain probability to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. The algorithm commonly finishes when either a maximum number of generations or a satisfactory fitness level is reached for the current population. This works uses the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (4), a popular and fast multi-objective genetic algorithm.

Electric Mix Evaluation

Each individual (P_{pv}, P_{wind}, P_{csp}) in the population represents an electric mix configuration and must be evaluated to determine its feasibility (satisfy demand) and its fitness through the objective functions (curtailments and cost), which will be optimized.

Demand, Generation, Curtailments and CO_2 Emissions

The demand is hourly given for the whole year based on historical data and the predicted increment. The generation of each energy source is also given by historical data and proportional to the installed power. The following three steps are repeated for each hour of the year. As explained before, the new STE fleet should result after auction processes but its dispatch profile must be fixed in the call.

1. The hourly energy generation of hydraulic, nuclear, cogeneration, residues, PV, wind and current CSP (existing CSP) is summed up. New CSP energy (CSP with 12-hour thermal storage) is stored as much as possible, the remaining new CSP energy is therefore added to the current generated electricity.
2. If the demand is not satisfied, CSP storage is summed up as needed. If the demand cannot be covered, then combined cycles are used up to their maximum power. If there is still demand to cover, electricity is imported up to its maximum power. If the demand is finally not covered the solution is marked as unfeasible and directly discharged without further calculations.
3. If the demand is already covered and there are curtailments, such curtailments are exported up to the maximum power capacity, otherwise they finally produce curtailments.
4. If the solution is valid, curtailments and CO_2 emissions are accumulated, and the process is repeated for the next hour of the year until the last hour of the year is reached.

If the solution is valid, it is ranked according to the accumulated curtailments and the annual average electricity cost, this last calculation is described in the next subsection.

Annual Average Electricity Cost

The annual average electricity cost can be calculated considering the hourly electricity generation in the previous subsection and the electricity cost. For each energy source, if there are not curtailments, electricity cost is given by Table 1. If the energy source generates curtailments, the previous cost is adjusted considering Equation 1, where the nominal cost is given in Table 1.

TABLE 1. Average generation, import and export costs assumed for 2030

Technology	Cost (€/MWh)	Technology	Cost (€/MWh)
Hydraulic	20	Biomass	60
Pumping	25	Cogeneration	70
PV	30	Combined Cycles	74
Wind	40	Residues	80
CSP	55	Import / Export	60 / 40

$$\frac{(electricity + curtailments) \cdot cost}{electricity}$$

EQUATION 1. Adjusted electricity cost as a function of curtailments

Optimization Software Tool

The optimization software tool is programmed in Python (5) and makes used of several libraries (see Figure 4). The tool downloads data from Red Eléctrica de España – Sistema de Información del Operador del Sistema (REE-ESIOS) (6) server, performs the optimization tasks and presents the results in a generated website. The main used Python libraries are briefly described as follows.

- Request (7) is used to download demand and electric generation data from REE-ESIOS through API calls.
- Pandas (8) is used to perform transformations and calculation over time series data.
- NumPy (9) is used for scientific calculations.
- DEAP (10) is a framework for distributed evolutionary algorithms. The genetic algorithm is implemented using this framework.
- Multiprocessing (11) is used together with DEAP to parallelize the calculation of individuals, taking advantage of the CPU available cores.
- Plotly (12) provides a set of different graphs for data science.

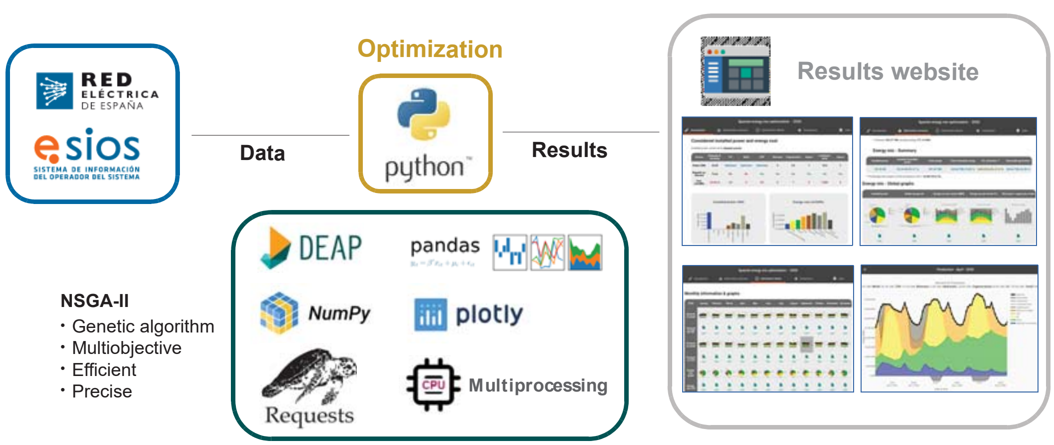


FIGURE 4. Software optimization tool

OPTIMIZATION RESULTS

The set of non-dominated solutions, being chosen as optimal, defines the "Pareto front" where no objective can be improved without further sacrificing the others. For two objectives, the Pareto front can be represented in a two-axis chart where the fleet would have the minimum cost for a given value of the other variable. The cloud of points represents just some samples of all the possible potential generation fleet structures.

In Figure 5, the starting point of the Protermosolar report can be seen in red. It is close to the Pareto front and has a very low level of curtailments. The optimization already considers the impact of curtailments in the required remuneration of non-dispatchable renewables. That is why the Pareto front has a "U" shape. Fleets with large curtailments will cause technical dysfunctionalities in the system and could require further investments on frequency and voltage control equipment's.

The data corresponding to three specific cases can be seen in the picture. It is important to mention that CSP has a relevant contribution in all cases along the Pareto front. Looking the rather small differences in cost, it would be advisable to select generation fleets, which will prevent from high curtailments in order to avoid technical and market issues that would have further actual impacts on costs. For example, the curtailments happen after the export capacity would have been saturated but, most probably in those cases, the resulting export levels would have been unfeasible and, therefore, the curtailments would have been much higher. The hidden costs regarding grid stability issues, with such high curtailment levels, would have been very important as well. Ancillary services would have been also more demanded, etc. Therefore, the additional costs on top to the ones considered by the program would have been actually higher. In addition, the impact in market prices, in those points of the Pareto front with high curtailment would prevent investors for promoting new plants unless high subsidies were assured. That's why we highly recommend to make the choices in the low curtailment part of the Pareto front.

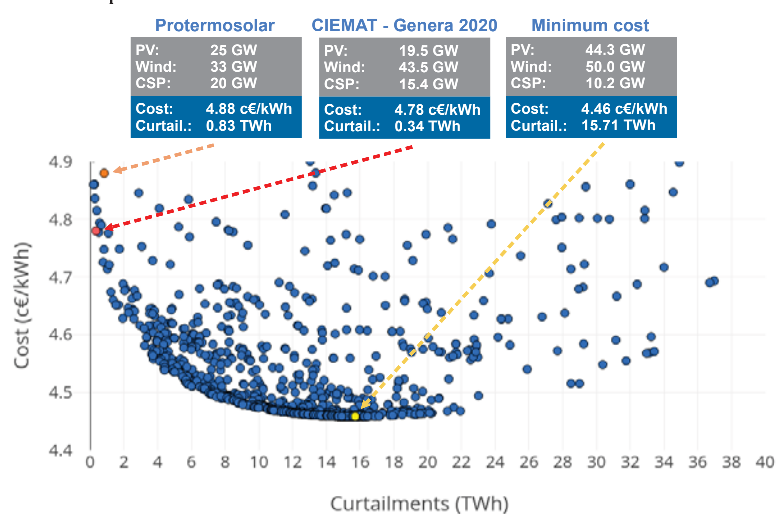


FIGURE 5. Pareto front with optimized renewable fleets: Cost vs Curtailments

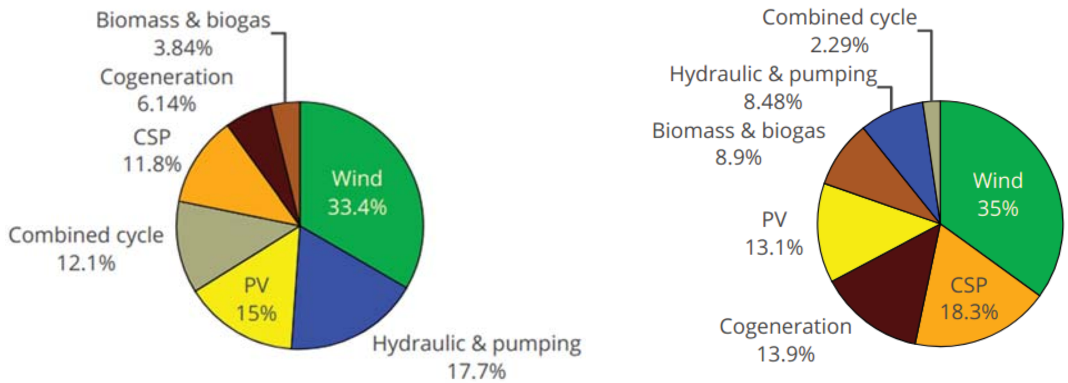
The software tool provides detailed information about the evaluation of any mix configuration. As an example, the CIEMAT electric mix configuration for 2030 is considered in this section. Table 2 and 3 summarize the main results, whereas Figure 6 show the installed power and electricity generation distribution among all electric sources.

TABLE 2. Installed power and average electricity cost

Installed PV power (GW)	Installed Wind power (GW)	Installed CSP power (GW)	Total installed power (GW)	Installed renewable power (GW)	Average electricity cost (c€/kWh)
19.50	43.50	15.36	130.68	106.41 (81%)	4.78

TABLE 3. Electricity generation and emissions

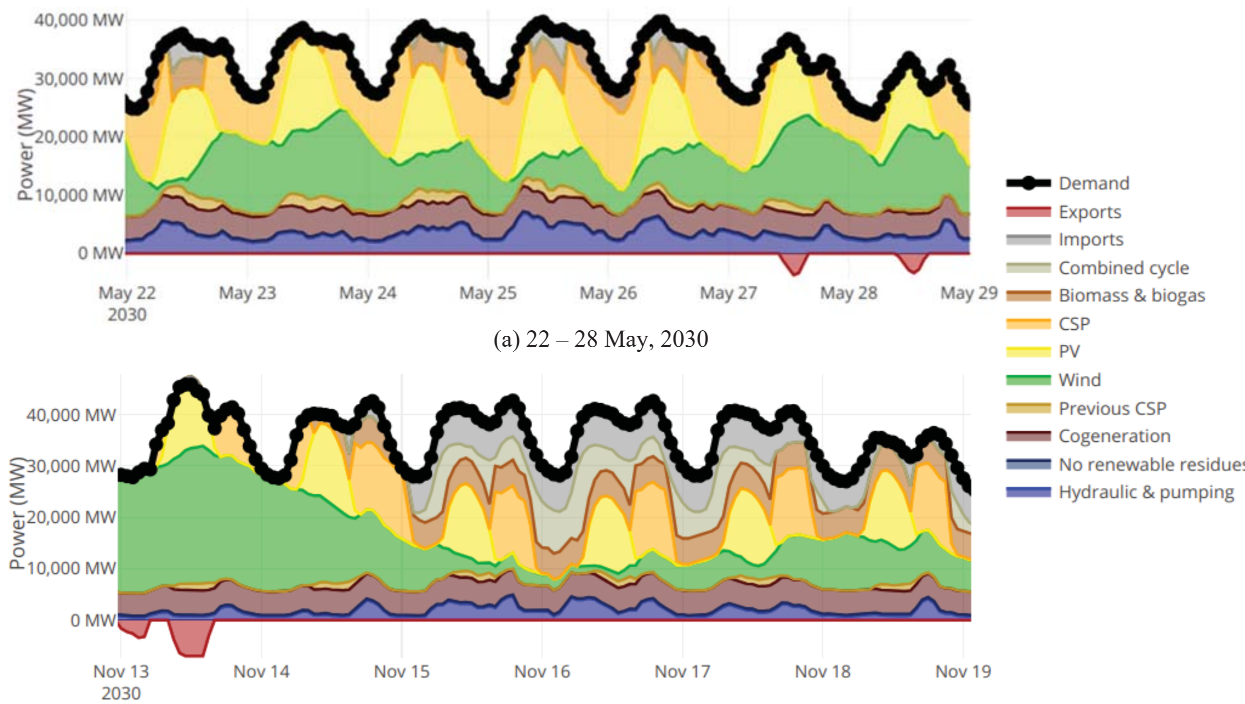
Demand (TWh)	Generated elec. (TWh)	Exported elec. (TWh)	Imported elec. (TWh)	Curtailments (TWh)	CO_2 equivalent emissions (ktons)
296	281.15	4.24	19.43	0.34	2,264.19



(a) Installed power distribution (b) Electricity generation distribution

FIGURE 6. Installed power and electricity generation distribution

Figure 7 shows the results for the CIEMAT's choice in the case of a favorable week for renewable production (on the top) and another less favorably case in the bottom. The complementary between the PV and the STE production can be easily seen. Exports in both cases caused by PV in good sunny days (on the top) or by wind (in the bottom) can be seen as well. Little curtailments can be also observed in the first day of the graph at the bottom.



(a) 22 – 28 May, 2030

(b) 13 – 19 November, 2030

FIGURE 7. Hourly electricity production

CONCLUSION

The summarized results in both cases, Protermosolar and CIEMAT choices, can be seen in Table 4. Both choices are much better than the results from LCCE models (13).

TABLE 4. Protermosolar and CIEMAT electric mix comparison

	Protermosolar	CIEMAT	Expert Committe using LCCE model (13)
Electric demand	296 TWh	296 TWh	296 TWh
Installed power	130 GW	130.4 GW	147 GW
Renewable power	106 GW	106.4 GW	106 GW
PV power	25 GW	19.5 GW	47.2 GW
Wind power	33 GW	43.5 GW	31 GW
CSP power	20 GW	15.4 GW	2.3 GW
Biomass power	5 GW	5 GW	2.6 GW
Emissions (1)	4,991 kt CO_2	4,356 kt CO_2	12,593 kt CO_2
Curtailments	830 GWh	344 GWh	4,600 GWh
Cost	4.88 c€/kWh	4.78 c€/kWh	5.20 c€/kWh

(1) Combined cycles and residues are considered for the calculation of the CO_2 equivalent emissions

The Inductive Projection Planning approach is a robust and sound methodology, which will facilitate achieving more ambitious goals in terms of renewable penetration and emission reduction, mainly thanks to the contribution of STE plants in Sunbelt countries. The contribution of CIEMAT/PSA using artificial intelligence and genetic algorithms represents an outstanding improvement as compared with the initial Protermosolar methodology. It provides an automatized approach to find a wide set of optimum fleets, leaving final decisions to the additional weighting criteria of planners. We want to conclude with a wise advice to policy makers in sunny countries: Try it! The planning would be surely improved and CSP will naturally appear in the picture.

REFERENCES

1. Protermosolar, Informe de Transición del sector eléctrico. Horizonte 2030, https://protermosolar.com.
2. Ministerio para la Transición Ecológica y el Reto Demográfico (MITECO), Plan Nacional Integrado de Energía y Clima (PNIEC) 2021-2030, 2020, https://www.miteco.gob.es/es/prensa/pniec.aspx.
3. J. Bonilla, Herramienta para optimizar el mix eléctrico aplicando técnicas de inteligencia artificial. GENERA 2020, Madrid.
4. K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," in IEEE Transactions on Evolutionary Computation, vol. 6, no. 2, pp. 182-197, April 2002, https://doi.org/10.1109/4235.996017.
5. Python Core Team (2020). Python: A dynamic, open source programming language. Python Software Foundation. https://www.python.org/.
6. Red Eléctrica de España (REE), Sistema de información del operador del sistema (ESIOS) https://www.esios.ree.es/.
7. Request: HTTP for Humans, https://requests.readthedocs.io/en/master/.
8. McKinney, Data structure for statistical computing in Python Proceedings of the 9th Python in Science Conference, Volume 445, 2010, https://conference.scipy.org/proceedings/scipy2010/pdfs/mckinney.pdf.
9. Stéfan van der Walt, S. Chris Colbert and Gaël Varoquaux. The NumPy Array: A Structure for Efficient Numerical Computation, Computing in Science & Engineering, 13, 22-30 (2011), https://doi.org/10.1109/MCSE.2011.37.
10. Félix-Antoine Fortin, François-Michel De Rainville, Marc-André Gardner, Marc Parizeau and Christian Gagné, “DEAP: Evolutionary Algorithms Made Easy”, Journal of Machine Learning Research, pp. 2171-2175, no 13, jul 2012.
11. M.M. McKerns, L. Strand, T. Sullivan, A. Fang, M.A.G. Aivazis, Building a framework for predictive science, Proceedings of the 10th Python in Science Conference, 2011, http://arxiv.org/pdf/1202.1056.
12. Plotly Technologies Inc. Collaborative data science. Montréal, QC, 2015. https://plot.ly.
13. Comisión de Expertos de Transición Energética, Análisis y propuestas para la descarbonización, 2018. http://www6.mityc.es/aplicaciones/transicionenergetica/informe_cexpertos_20180402_veditado.pdf.