Design optimization for large-scale solar photovoltaic power plants in Uruguay

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***Abstract*—This article focuses on maximizing the relative net present value of a photovoltaic power plant by applying optimization techniques to its design. The case study refers to a 50 MW (AC) plant with parameters specific to the northwestern region of Uruguay. Test scenarios are created by exploring variations in energy prices, contract duration, DC cable costs, project discount rate, among others. The control variables include the tilt of the photovoltaic panels, the number of series and parallel connections, the number of rows and columns of photovoltaic blocks in the sub-park, the distance between the rows, and the ratio of the DC power of the photovoltaic panels to the nominal AC power of the plant. According to the experimental results, the optimized relative net present value ranges from 1.37 to 1.39, with optimized capacity factors around 24%.**

***Index Terms*—PV power plant, optimization, NPV, Uruguay.**

I. Introduction

Solar photovoltaic (PV) installed capacity is growing at unprecedented rates around the world every year [1]. This energy source is next in line for grid expansion in Uruguay [2]. Local optimization of the PV plant design is important to make good use of the available solar resource. This optimization has to take into account the local meteorology, the local economic conditions (type of contracts, prices, costs, tariffs) and technological aspects. An optimized PV plant design can provide a better return on investment by leveraging costs and energy production, resulting in higher solar PV capacity factors (the ratio of energy produced to maximum potential production). However, when designing a large-scale solar farm, current industry practice is to explore different configurations from previous experience and run simulations using PVsyst [3] or similar software to refine the design. This exploration is typically done manually and covers only a minimal fraction of the possible alternatives, resulting in sub-optimal design choices.

The design of a large-scale grid-connected PV power plant can be divided into several physical parts: i) the DC design; ii) the choice of inverter architecture responsible for converting DC (direct current) to AC (alternating current) whose output is at low voltage (LV); iii) the LV aggregation network that connects these inverters; iv) a transformation level that raises the AC voltage levels of the LV inverters to medium voltage (MV); v) a MV distribution network to collect the power from the various MV transformation centers; and vi) a station that transforms from MV to high voltage (HV) before connection to the national grid. Depending on the design, some of these conceptual elements may be combined. In particular, the inverter capacity may be high enough to justify a single and dedicated transformation center, eliminating the need for part (iii). There are also different topologies for a PV power plant, depending on the connections between the PV arrays and the inverters, the number and capacity of the inverters, and the hierarchy of the inverters [4]. In particular, the central inverter topology is a modular architecture that can represent either a complete park or a sub-park within a larger PV installation, the latter being the case in this work.

Previous research has explored how to optimize the design of PV plants to maximize economic outcomes. The article by Kerekes et al. [5], [6] is the most similar to this work. The authors proposed a genetic algorithm to optimize the layout and electrical models of PV plants using financial metrics such as net present value (NPV), internal rate of return (IRR), and levelized cost of energy (LCOE). Their method includes geometric variables such as panel tilt and block spacing, and electrical variables such as panel type and interconnections. However, it does not take into account land costs or low and medium voltage wiring geometries. The optimization is based on analytical reference models to continuously track the expected generation, whose parameters are adjusted through simulations with the PVSyst software. Other studies have focused on various aspects of PV farm design, taking into account different locations, project sizes, technologies and market environments [7]–[14]. These studies demonstrate the complexity of PV system optimization and the need to balance multiple variables such as financial metrics, system layout, electrical configuration, and meteorological factors to achieve optimal performance and maximum economic profitability for large-scale PV installations.

This work presents an optimization of PV power plants in Uruguay based on the aggregation of sub-parks and the central inverter topology for each sub-park, using local meteorological data and local contract characteristics, up to the MV-AC level. The optimization is tested against different DC cabling, panel costs, land costs, inverter costs, and financial interest rates. Optimal designs are found for each case and sensitivity analysis is performed. In particular, an optimal design is obtained for the Northwest of Uruguay and its production and profitability results are discussed. The optimization results depend significantly on the meteorological conditions and therefore could not be directly extended to other regions. However, the methodology can be applied elsewhere if the meteorological data, costs and financial conditions are given. In order to extend the work to other regions and countries, the simulations need to be performed with these local data.

This article is organized as follows. Section II describes the meteorological data and the local market constraints. Section III presents the optimization strategy and the models beings used. Section IV provides the results and their discussion. Finally, Section V summarizes the main conclusions.

II. Data

A. Meteorological data

The local meteorological dataset used in this study is the Typical Meteorological Year for Solar Energy Applications, known as "AMTUes" [15]. This dataset contains hourly information on global horizontal, diffuse horizontal, and direct normal irradiance (GHI, DHI, and DNI, respectively), ambient temperature, relative humidity, barometric pressure, and wind speed and direction. It is based on 15 years of solar radiation data generated with a low uncertainty satellite estimation model [16], locally adapted to the specific characteristics of the Uruguayan territory [17]. The non-solar quantities were measured on the ground by national measurement networks. The northwestern site of AMTUes was chosen for the analysis (the Salto site, latitude $-31.3°$S and longitude $-57.9°$W). This region has one of the highest levels of solar resource in the country [18].

B. Local market

The case study in this article is the Uruguayan electricity market, where - in most years - more than 90% of annual electricity consumption is supplied by renewable energy, with peak values of up to 98%. The success of integrating non-conventional renewables to such an extent in Uruguay is multi-causal, but largely explained by the business model adopted, which is mainly driven by long-term, fixed-price power purchase agreements (PPAs) between the national electricity company and generators. The existence of a reference price avoids the need to follow the spot price on an hourly basis (as in [5], [6]), but it requires the network operator to carefully design these contracts, especially with regard to the price of the energy supplied. The curtailments due to transmission constraints or oversupply are paid to the generators by estimating the curtailed generation based on the plant's solar measurements. The scheme described above helps to de-risk investments and introduces long-term predictability into the market, as auctions for new plants with a certain installed capacity and contract expiry date are expected on a regular basis. This is the main market organization for centralized generation in Uruguay and is a key element of this work, where the objective is to maximize the relative net present value (NPV) under this framework, disregarding generation variance and volatility. An assumption that has a significant impact on the results is the price of energy. For this study, a range of prices between 30 USD/MWh and 85 USD/MWh was evaluated. The maximum value corresponds to the price of PPAs signed in Uruguay between 2015 and 2017 for solar PV projects. The minimum value corresponds to the expected medium-term evolution of PV energy prices [19].

III. Methodology

The optimization objective in this work is the NPV, i.e. the present value of future economic revenues, given a general PV plant topology (model), its expected degradation, a cost structure and the data of Section II. The result of the optimization is the PV plant model parameters (the PV plant design) for the maximum NPV obtained. The NPV is calculated as

$$\mathrm{NPV} = \sum_{t=1}^{T_m} \frac{E_t \cdot P_t - C_s \cdot C_o}{(1+\lambda)^t} - C_s, \tag{1}$$

where E_t is the energy produced in year t, P_t is the price of energy in year t, C_s is the initial investment, C_o is the OPEX cost as a rate of C_s (note that $C_s \cdot C_o$ is the annual OPEX), λ is a reference interest rate, and T_m is the duration of the contract (20 years for this case study). E_t and C_s depend on the design of the plant, the latter also depending on the different costs. P_t depends on the terms of the contract. C_o is set to 1% according to the NREL report on solar PV cost benchmarks [20]. The parameter λ is varied during the sensitivity analysis, ranging from a base of 2% [21] to 5%. The relative NPV is obtained by normalizing with C_s, so $\mathrm{rNPV} = \mathrm{NPV}/C_s$.

As E_t and C_s depend on the PV plant design, it is not possible to estimate them in detail in advance based on historical generation data or previous PV designs, although these certainly provide a reasonable frame of reference. Therefore, each PV plant design needs to be simulated with local meteorological data in order to estimate its power output and feed it into the optimization. The approach taken in this work is to use PVSyst simulations with different plant designs. Since PVsyst does not have an API and can only be run manually or with predefined settings, it is not possible to integrate it directly into the optimization. In change, several gridded PVSyst simulations were performed (16836 simulations), from which parameterizations were extracted for use with the optimization framework.

E_t is calculated as,

$$E_t = N_v \cdot N_c \cdot N_r \cdot (1 - \gamma_e \cdot (t-1)) \cdot e_t - L_w, \tag{2}$$

where N_v is the number of PV panels per bench, N_c is the number of benches per row (columns), and N_r is the number of rows. γ_e is an annual efficiency degradation rate, which was set to 0.7% in this work. L_w is the energy loss in the DC wiring, an important part of the optimization [22], depending of the wiring length and cable cross sections. e_t is the annual energy per panel produced in the first year of operation, and was parameterized from the PVSyst simulations as

$$e_t = c_1 + c_2 \cdot \beta + c_3 \cdot \xi + c_4 \cdot \beta^2 + c_5 \cdot \xi^2. \quad (3)$$

In this equation, β is the tilt of the PV panels (facing North), ξ is the ratio between the PV panels DC power and the nominal AC power, known as the Inverter to Load Ratio (ILR), and c_i are the adjusted parameters. ξ is also, the panel capacity relative to inverter capacity. β is set here as a pre-optimized tilt angle for PV power generation, which is linked to the local meteorological data and the row spacing (l_r) due to inter-row shading. Given the meteorological data set, the optimized β is a function of l_r [22].

The energy price is calculated for each year as,

$$P_t = P_1 \cdot (1 + \gamma_p \cdot (t - 1)), \quad (4)$$

where P_1 is the first year (initial) price and γ_p is an annual energy price variation rate, both of which are specified in the PPAs.

Finally, the installation cost is calculated as,

$$C_s = C_i + (C_m \cdot N_r + C_t \cdot l_w \cdot (l_h + l_r \cdot (N_r - 1))) \cdot N_c, \quad (5)$$

where C_i is the inverter price, C_t is the land price, and l_w and l_h are the width and length of each PV block. C_m is the cost of the bench, which includes the cost of the PV panels (C_p) and the cost of the structure (C_{bs}), and is therefore calculated as follows:

$$C_m = C_{bs} + N_v \cdot C_p. \quad (6)$$

Fig. 1 shows a single line diagram of the installation of each sub-park, from the low voltage DC level to the medium voltage AC level. Fig. 2 illustrates the main geometric parameters involved in the design of each sub-park.

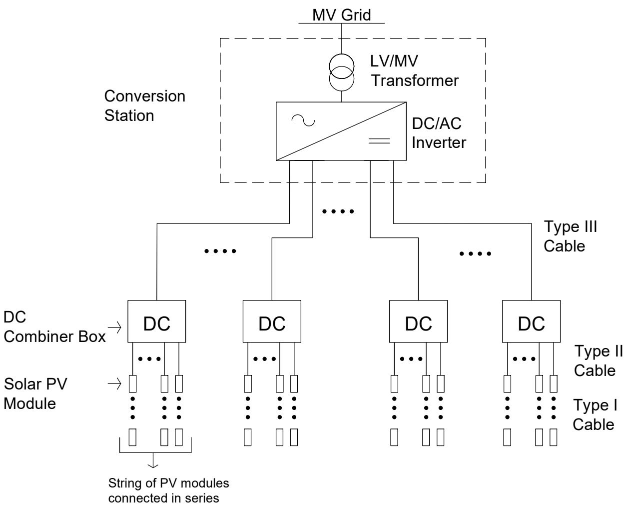

Fig. 1. Reference components in a subpark with *central inverter* architecture.

A fixed tilt panel, 50 MW nominal power plant with 1 MW sub-parks, rectangular layout PV farm topology is adopted. Each sub-park has a central inverter topology grouping N_p PV blocks in parallel. Each PV block consists

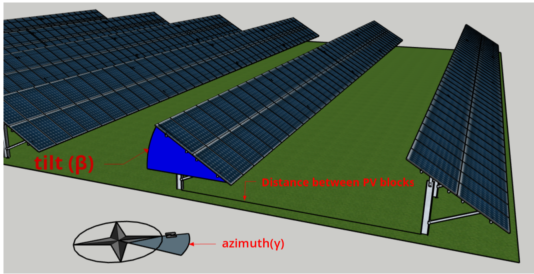

Fig. 2. Geometric variables involved in the design

of N_s PV panels connected in series. Each sub-park layout is arranged in N_c columns and N_r rows, which have N PV panels arranged in $\lfloor N/N_s \rceil$ PV blocks connected in parallel. The rows are separated by a distance l_r (distance between the projection of the row in the ground). Thus, the implemented PV park model has the following variables to optimize:

- Panels tilt and azimuth (β and γ angles, respectively).
- ILR factor (ξ).
- Number of parallel connected blocks (N_p) and series connected PV panels (N_s).
- Number of columns (N_c, benches per row) and rows (N_r) in the sub-park layout.
- Width (l_w) and length (l_h) of each PV block.
- Distance between panels rows (l_r).
- DC cables length and cross-sections.

Some of these variables depend on others in such a way that one can be expressed in terms of the other within the optimization process. This is the case for N and N_s, β^{opt} and l_r, l_w and l_h with the number of PV modules per block, and DC cable length with other distance variables. Since no east-west asymmetry is considered, the panel azimuth is trivially set to $\gamma = 0$ (North). The NPV optimization also requires the setting of: (i) appropriate local values for PV modules, inverters, structure, cabling, land, O&M, and financial costs; (ii) an energy price rate for each year (γ_p) as specified in the PPAs; and (iii) the PV plant efficiency degradation rate (γ_e). In particular, the inclusion of DC cabling energy losses and costs proved to be an important element to consider in the optimization. The cabling consists of two different types of cables: Type II cabling, which is responsible for connecting the PV blocks to each DC panel, and Type III cabling, which is responsible for connecting the DC panels to the inverters (and therefore requires conductors with a larger cross section, which have a higher price). The detailed relationship between Type II and Type III cabling with costs and losses can be found in Ref. [22].

The optimization is also constrained by valid technical and engineering criteria, to avoid producing results that are not possible. Several voltage and current restrictions are imposed by the inverters and the Maximum Power Point Tracker (MPPT) system, given by the maximum allowed values and the range of tracking convergence, respectively. The inverter capacity also limits the ILR to a maximum of 40%. The distance between the PV rows has a minimum distance of 3 m to allow for vehicle circulation.

Other constraints are imposed by the formulation itself. For example, a homogeneous, symmetrical and modular geometric design has been chosen to ensure that the project avoids any particular complexities during construction. One assumption adopted is that the PV panels are arranged vertically in groups of two, so N_s must be even to avoid interconnecting blocks or PV panels of different rows, ensuring clarity and simplicity in the wiring process.

IV. Problem Instances and Results

The optimization process is conducted in two steps. First, tilt and azimuth are adjusted to maximize annual energy production for a given row spacing. A pre-optimization is performed after running simulations for combinations of these three variables on a discrete grid defined by technical limits. The simulations were done using PVsyst software and local meteorological data for the region. The results of this step not only identify the optimal tilt and azimuth for a given row spacing, but also allow the energy production per panel to be expressed as a function of this spacing (using the optimal β as a proxy). An analytical expression is then fitted to these samples by linear regression (equation (3)). In the second step, the remaining control variables are integrated with the previously optimized production function to create the complete model. This model integrates cost and revenue functions along with financial parameters and metrics to calculate the relative net present value, which serves as the objective function to be maximized for each set of parameters (i.e., each instance). Solutions are found after examining feasible combinations of discrete variables (e.g., the number of series and parallel connections, as well as columns and rows), which are very few. For each combination, the continuous variables are determined using standard nonlinear optimization techniques (i.e., steepest descent).

A. Optimization results

The main general settings for the optimization were: (i) polycrystalline PV panels of 325 Wp with a price of 0.47 USD/Wp [20]; (ii) 1 MW inverters with a cost of 0.05 USD/W[1] [20]; (iii) an annual linear energy price variation of 0.9% based on the estimate of the USD producer price index variation used in the Uruguayan PPAs for this price update; (iv) a maximum land cost of 0.58 USD/m^2 [23]; (v) a fixed financial interest rate of 2%; and (vi) an annual PV plant efficiency depreciation of 0.7%[2]. Several tests were performed with different contract duration, energy prices, and DC cable types. A subset of these tests is shown in Table I and their results are shown in Table II. These tests are based on reasonable and technically feasible possibilities.

In all cases, the optimization resulted in an optimal tilt of 26°, an ILR of 32.6% (close to the maximum capacity of the inverter), and 8 columns and 15 rows in each sub-park layout. The row spacing and the achieved capacity factor vary slightly in these simulations, as can be seen in Table II. However, the relative NPV shows significant variation, with a maximum value of 1.393 found in these tests. The optimal capacity factor obtained in these tests was about 24%. It can be seen that, from an NPV point of view, it is better to have contracts with better energy prices and shorter duration than vice versa. Another observation is that it is not worth investing in DC cables with larger cross-sections, as the reduction in Joule losses does not compensate for their higher price. It is important to mention that if the optimization is not carried out taking into account the DC wiring, the optimal ILR was found to be 40%, the maximum inverter capacity.

[1] 100 kW inverters were also tested with worse optimization results.
[2] https://atb.nrel.gov/electricity/2023/utility-scale_pv

TABLE I
Tests with different DC wiring and contract conditions.

test	USD	contract	type II wiring		type III wiring	
name	per MWh	years	mm^2	USD/m	mm^2	USD/m
C01	50	25	6	0.75	120	16.20
C02	50	25	10	1.25	120	16.20
C03	50	25	6	0.75	150	20.25
C04	50	25	10	1.25	150	20.25
C05	40	30	6	0.75	120	16.20
C06	40	30	10	1.25	120	16.20
C07	40	30	6	0.75	150	20.25
C08	40	30	10	1.25	150	20.25

TABLE II
Optimization results with varying contract and DC cables.

test name	l_r	relative NPV	capacity factor
C01	14.6 m	1.393	24.0%
C02	14.6 m	1.390	24.0%
C03	14.6 m	1.376	24.1%
C04	14.6 m	1.373	24.1%
C05	14.3 m	1.152	24.0%
C06	14.3 m	1.150	24.0%
C07	14.3 m	1.137	24.1%
C08	14.3 m	1.134	24.1%

B. Sensitivity analysis

From the previous analysis, test C01 is the one with the best NPV. This case is used as the basis for the sensitivity analysis. Four parameter variations were analyzed, namely financial interest rate, land cost, PV panel cost and inverter cost. These variations of case C01 are labeled as S02 to S13. The results of this analysis are shown in Table III. It is observed that the financial interest rate has a significant impact on the NPV, and when this rate increases up to 4%, the PV project becomes unprofitable. The price of PV panels also has a significant impact on the economic result of the project, as expected, and panels costing up to 0.60 USD/Wp also result in an unprofitable project. Naturally, the cheaper the PV panels, the more profitable the PV project. Regarding the land price, it is observed that an increase leads to a decrease in the row spacing and almost no change in the NPV. The inverter price has a limited impact on project optimization. All these results are consistent with the cost structure of a PV project and all achieve capacity factors around 24%.

TABLE III
RESULTS OF THE SENSITIVITY ANALYSIS.

test name	variable setting	l_s meters	relative NPV
With varying financial interest rate, λ			
C01	2%	14.6	1.39
S02	3%	14.6	1.14
S03	4%	14.6	0.92
S04	5%	14.6	0.73
With varying land cost			
S05	0.30 USD/m^2	16.4	1.39
C01	0.58 USD/m^2	14.6	1.39
S06	0.70 USD/m^2	14.1	1.40
S07	0.80 USD/m^2	13.8	1.40
With varying PV panel cost			
S08	0.30 USD/Wp	14.6	2.40
S09	0.40 USD/Wp	14.6	1.73
C01	0.47 USD/Wp	14.6	1.39
S10	0.60 USD/Wp	14.6	0.93
With varying inverter cost			
S11	0.030 USD/W	14.6	1.46
S12	0.040 USD/W	14.6	1.42
C01	0.050 USD/W	14.6	1.39
S13	0.060 USD/W	14.6	1.36

V. CONCLUSIONS AND FUTURE WORK

This work presents a computer-assisted approach to address the challenge of designing an optimal PV plant with parameters specific to the northwestern region of Uruguay, where the solar resource is most abundant and the transmission network is readily accessible. Control variables vary across multiple domains: the geometry of the photovoltaic panels (tilt and azimuth), the configuration of the panel arrays (number of rows and columns of photovoltaic blocks within a sub-park and the spacing between these rows), the DC interconnection scheme (number of series and parallel connections and sections for different types of DC cables), and the AC to DC power ratio (inverter to load ratio). The sensitivity analysis revealed that the financial interest rate and the cost of the PV panels have the greatest impact on the NPV. Relatively small variations in these parameters determine whether a project is profitable or not. Future work will include improvements to this framework, including distinguishing the degradation of PV panels and inverters from the overall efficiency degradation of the PV plant, incorporating different PV technologies (such as different cell types, bifacial modules, and tracking systems), and exploring alternative business models, among other improvements. In addition, the optimization of PV plants in other locations will be addressed.

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