Multi-objective genetic algorithm for the optimization of a PV system arrangement

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Abstract

Urban landscapes feature complex topographies and many shadow casting elements, which can jeopardize the energy yield of building integrated photovoltaic (BIPV) systems. Phenomena like partial shading have a significant impact in the electric performance of PV modules, mostly when systems are deployed in conventional arrangements regardless of surrounding obstructions. The goal of this assessment is to test a multi-objective genetic algorithm (MOGA) in order to find one optimal string sizing and tiling, considering two different scenarios: a west facing building facade and a south facing rooftop, both located in Lisbon, Portugal. Relevant loss mechanisms are considered, such as hourly solar irradiance changes caused by shadow events, high incidence angles and module temperature. Optimization processes allow a reduction of around 24% and 23% in the cost of energy for the rooftop and the facade, respectively, when compared to a scenario that considers individual modules with micro-inverters.

Keywords: *Photovoltaic, partial shading, genetic algorithm, multi-objective optimization*

1. Introduction

Planning a PV system often relies on software-based approaches that employ averages of solar radiation and ambient temperature for the desired location. When non-obstructed areas are under consideration, such simplistic methodologies might be reliable as a means to estimate energy yields. However, when there is complex dynamic shadow casting (typical in urban environments), the incident solar radiation can vary dramatically throughout the day, requiring a more detailed system sizing procedure: as the connection between solar cells and modules is done in series (PV strings), partial shadow on one of the modules significantly impacts the production of the whole string.

Shadow patterns cast on surfaces make this a non-trivial problem for systems optimization. These problems cannot be fully represented and solved through well-defined mathematical expressions, since they deal with continuously changing and entangled variables. When a problem has neither a unique and obvious solution or the search space is overly large, or even if the problem has more than one objective, Genetic Algorithms (GA) (Goldberg, 1989) are numerical modelling procedures that can be used to reach one possible optimal solution. GA rely on the replication of the behavior of natural evolution of species in nature, and for that purpose populations of individuals are created, which are then subject to selection, recombination and mutation operators.

A different approach would be to avoid numerical optimization and invest in micro inverters as an alternative to conventional string based systems (Kurokawa et al., 1997). Micro inverters are immune to output power drop when a module is partially shaded thus avoid mismatch losses. Nevertheless, their installed power cost is higher and maintenance can be costly and hard to perform in urban environments, such as in vertical mounted systems.

The goal of the present assessment is to address two different surfaces to test a multi-objective GA aiming at maximizing the PV production of the system and minimizing system costs (wiring, module and inverter costs). The relevant losses to the system are considered together with solar radiation changes caused by shadow events. The solutions obtained are compared with micro inverter scenarios.

2. Methodology

In order to estimate the PV production of a system, solar radiation data is mandatory. However, while solar radiation long-term measurements in the horizontal plane are somewhat common, measurements on the tilted plane are rare, which demands the employment of a solar potential algorithm adapted to a 3D environment. The SOL model was used (Redweik et al.,2013) to calculate annual solar irradiance in a 3x6m^2 south facing rooftop

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and a 7x5m^2 west facing building façade (Fig. 1), obtained from a digital surface model (DSM) of the district of Campo Pequeno, in Lisbon, Portugal (38.74N, 9.15W), with 1m^2 resolution. A local typical meteorological year (TMY) data set allows hourly irradiation calculations for any point of the DSM, taking into account mutual shading between buildings and other urban elements.

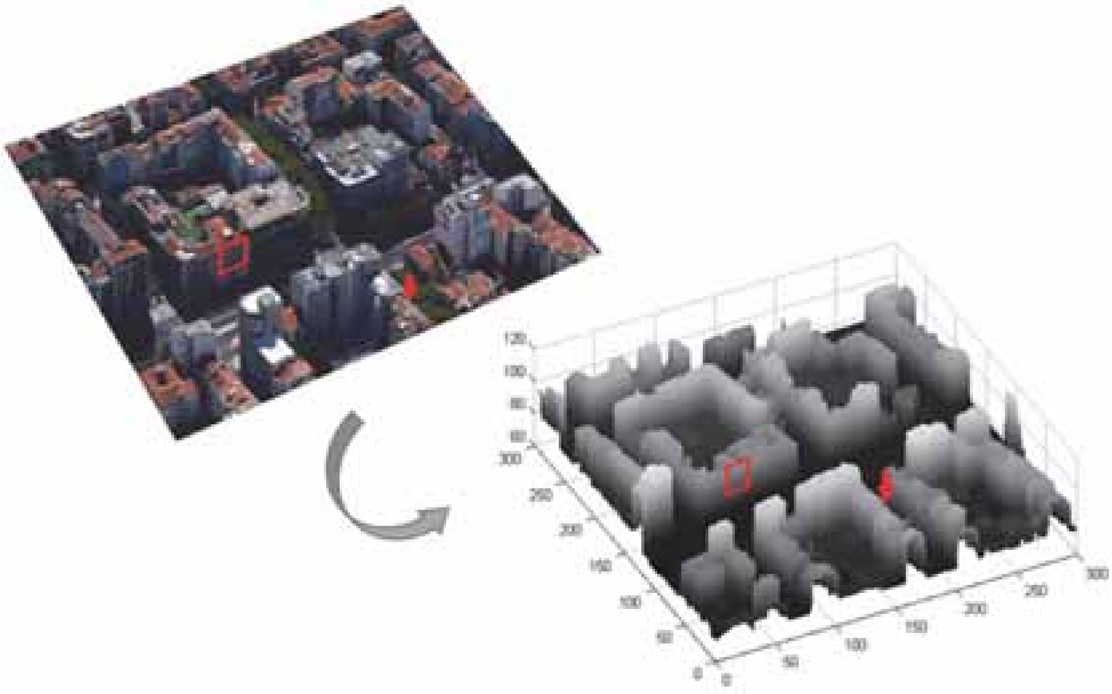

Figure 1 – Bird's eye perspective for the area under analysis and the respective digital surface model (DSM). The rooftop and façade case-studies are indicated in red.

The electricity production estimate considering relevant losses to the PV system typical 1m^2 PV module characteristics were considered and employed in the following equations (Marion, 2002):

$$T_{m,p,t} = T_{a,t} + \frac{T_{NOCT} - 20\ ℃}{800\ Wm^{-2}} G_{p,t} \qquad \text{(eq. 1)}$$

where T_a is the ambient temperature in °C, NOCT is the Nominal Operating Cell Temperature, G is the Global irradiation on the tilted plane in Wh/m^2, the index m identifies one module, the index p identifies a position on the layout and t is the time index.

The effect of the temperature on the efficiency of each PV module can be estimated through (eq. 2) while the expected angular losses due to the angle of incidence in the panels is given by (eq. 3):

$$\eta_{m,p,t} = \eta_{ref}\left[1 + \Delta\eta(T_{m,p,t} - 25)\right] \qquad \text{(eq. 2)}$$

$$AL_{\alpha,t} = \frac{\left(1 - e^{-\cos\alpha_{,t}/\mathrm{a}_r}\right)}{\left(1 - e^{-1/\mathrm{a}_r}\right)} \qquad \text{(eq. 3)}$$

where α is the irradiance angle of incidence and a_r the angular losses coefficient (Martin et al., 2001).

Then, as PV modules are connected in series in a string, by knowing the positions of the modules that belong to each string in the surface, the hourly expected energy yield in Wh of all PV strings can be estimated by:

$$E_{s,t} = min\left(G_{p,t}\eta_{m,p,t}AL_{\alpha,t}\right) n_{m,s} A\eta_{i,s} \qquad \text{(eq. 4)}$$

where the index s identifies a PV string, the index p identifies the positions of the modules belonging to string s, $n_{m,s}$ is the total number of modules in string s, A = 1m^2 is the module area, and $\eta_{i,s}$ = 0.95 denotes an average efficiency of the inverter *i* connected to string *s*. The *min*() function reflects the fact that the current in a string is determined by the lowest module current in that string.

The PV production function of a system layout with n_s strings can be defined by adding the hourly PV yield of all strings throughout the year:

$$E_{syst} = \sum_{s=1}^{n_s} \sum_{t=1}^{n_t} E_{s,t} \quad \text{(eq. 5)}$$

The total systems cost of a certain PV layout is assumed to cover three components: the cost of the modules plus the copper wiring required to connect the modules in series and the inverters needed to the conversion of the output current from DC into AC. Since the purpose of the optimization is the selection of the layout but not the full financial project evaluation of the project, no maintenance or operating costs nor discount rates were taken into account in the system costs function[1], which is defined by:

$$C_{syst} = C_m \sum_{s=1}^{n_s} n_{m,s} + \sum_{s=1}^{n_s} L_s C_s + \sum_{i=1}^{n_i} C_i \quad \text{(eq. 6)}$$

where L_s,and C_s are the length and wire costs for string *s*, respectively, and C_i is the cost of each of the chosen inverters for the PV system. A module price C_m= 150€/m^2 was considered. Thus, the first summation refers to the modules' costs, the second summation to the wiring costs and the third one to the inverters' costs.

The typical constraint of 3% for the maximum voltage drop allowed on a PV string was assumed. Regarding the inverters, in order to distribute the PV strings to a set of inverters, two main constraints must be calculated to prevent unfeasible solutions: $N_{m,i}$ the maximum number of modules connected in a string (eq. 7) and $N_{s,i}$ he maximum number of strings connected to a certain inverter *i* (eq. 8).

$$N_{m,i} \leq \frac{min\left(V_{s\_max}, V_{DC\,max,i}\right)}{V_{oc}[1+\beta(-10-25)]} \quad \text{(eq. 7)}$$

$$N_{s,i} \leq \frac{I_{DC\,max,i}}{1.25 I_{sc}} \quad \text{(eq. 8)}$$

The relevant properties of 13 inverter models were considered (Table 1), including the maximum values allowed for the DC input current I_{DCmax}, the DC input voltage V_{DCmax},and the DC input power P_{DCmax}, as well as prices.

Table 1 – List of 12 inverter and 1 micro-inverter models.

Model	Pnom [kW]	Average price [€][2]	Vcc_max [V]	Icc_max [A]	Pcc_max [kW]
SMA micro	0.24	150	45	8.5	0.24
Fronius 1.5-1	1.5	893	420	13.3	1.5
Fronius 2.0-1	2	916	420	17.8	2
Fronius 2.5-1	2.5	938	420	16.6	2.5
Fronius 3.0-1	3	960	550	19.8	3
IG 20	1.8	832	500	14.3	2.70
IG 30	2.5	1220	500	19.0	3.60
IG 40	3.5	1568	500	29.4	5.5
Plus 60-V1	6	1474	600	27.5	6.32
Plus 70-V2	6.5	1579	600	30.0	6.88
Plus 80-V3	7	1678	600	32.0	7.36
Plus 100-V3	8	1693	600	37.1	8.43
Plus 120-V3	10	1885	600	46.2	10.59

[1] Thus assuming that the O&M costs are independent of the layout connection of the strings, which is an optimistic approach regarding the micro-inverter solution.
[2]Prices retrieved between December 2014 and August 2015 from (SMA, 2015), (CCL, 2014), (Energy Matters, 2014), (MG, 2014)

3. Results

The developed GA, fully described in Freitas et al., 2015, has achieved optimal solutions for the case-studies analysed in this paper with 23% and 24% lower costs of energy, and helped finding one possible solution to give the best trade-off between cost and energy yield.

Rooftop

The optimization process encompassed 50 individuals per generation, with 3% mutation rate, 10% elitism reinsertion rate and a maximum of 500 generations. The best individual in each generation has the lowest cost of energy (C_{syst}/E_{syst}) over a lifetime period of 25 years. In Fig. 2 the optimal layout for the partially obstructed rooftop under study shows 0.22€/kWh, with 5 clustered strings in the most sunlit areas and two places that have no modules (string number 0), while 0.29€/kWh corresponds to individual modules with micro-inverters.

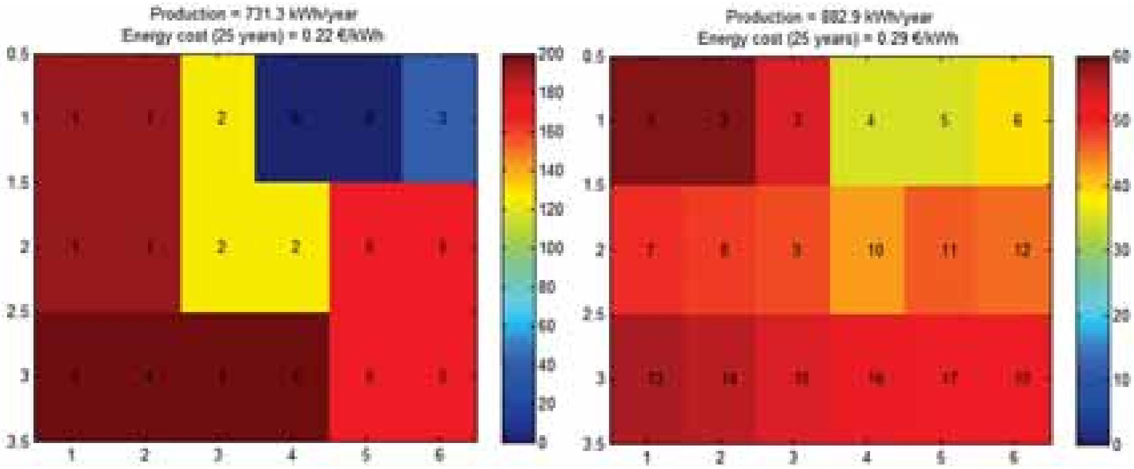

Figure 2 – On the plane perspective of the yearly total and per string PV production [kWh/year] of the optimized distribution of strings (left) and the micro-inverter scenario (right) for the rooftop case-study. Note the differences in the color scale values.

The overview of all individuals throughout the optimization process (Fig.3) reveals that 250 generations could have allowed for a decent optimal layout; however slight improvements were produced after. As all solutions are compared among each other based on their fitness, although some of the individuals with the best cost of energy are eliminated.

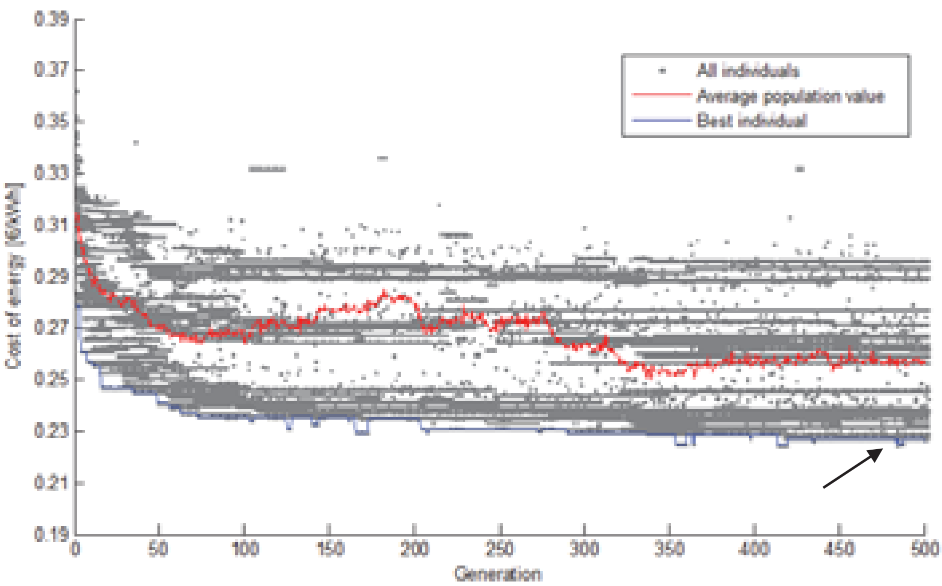

Figure 3 – Chart with the overview of the Cost of Energy in the course of the optimization process for the rooftop case-study.

All solutions in a generation can be organized in Pareto fronts (Fig. 4), i.e. groups of solutions which optimize both objectives (C_{syst} and E_{syst}) and that are compared among each other. The best fitted individuals belong to the highest Pareto front (red dots) and dominate all the other fronts. Looking specifically at the Pareto fronts from the initial population and the last, the convergence of solutions throughout the generations is evident. Higher higher yielding solutions, at higher cost, are located in the right end of the front, while more affordable arrangements, but featuring lower electricity production, can be found in the left. The layout with micro-inverters is placed on the top right, achieving high yields but requiring very high investment, thus being far from the optimal solution (€/kWh).

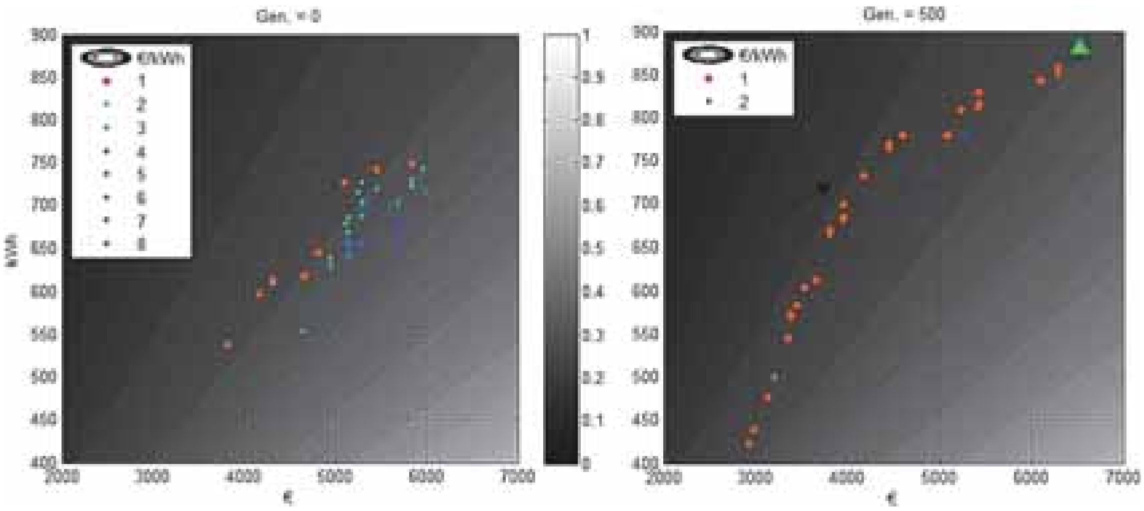

Figure 4 - Comparison between the Pareto fronts from the initial (left) and 500th (right) generations. The arrow points the individual with minimum €/kWh in 25 years of system lifetime (i.e. 0.22 €/kW h and 731 kW h/year) and the green triangle marks the location of the micro-inverter scenario.

Facade

The building facade case-study optimization followed the same procedure. In Figure 5 the optimal layout reveals that a west facing and also partially obstructed facade is able to match PV production of a rooftop in non-optimal conditions (0.30 vs 0.22 €/kWh). It is worth mentioning that this facade layout accounts for blanks that represent prohibited locations for modules, in this case due to windows or balconies.

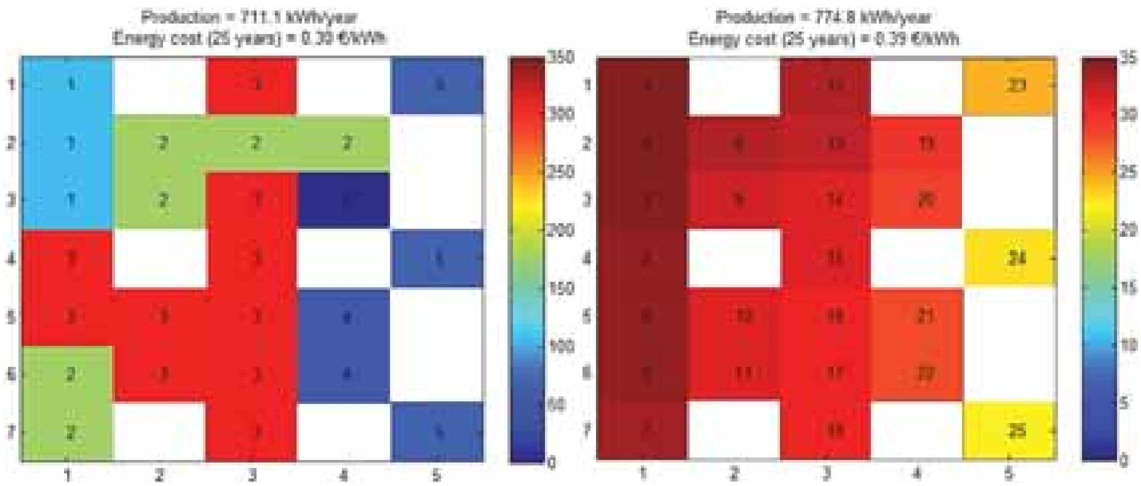

Figure 5 – On the plane perspective of the yearly total and per string PV production [kWh/year] of the optimized distribution of strings (left) and the micro-inverter scenario (right) for the facade case-study. Note the differences in the color scale values.

Again, optimization proves to be more cost-worthy than installing micro-inverters for all individual modules. The Pareto fronts of the initial population and 500th generation (Fig.6) also corroborate conclusions taken from the rooftop assessment.

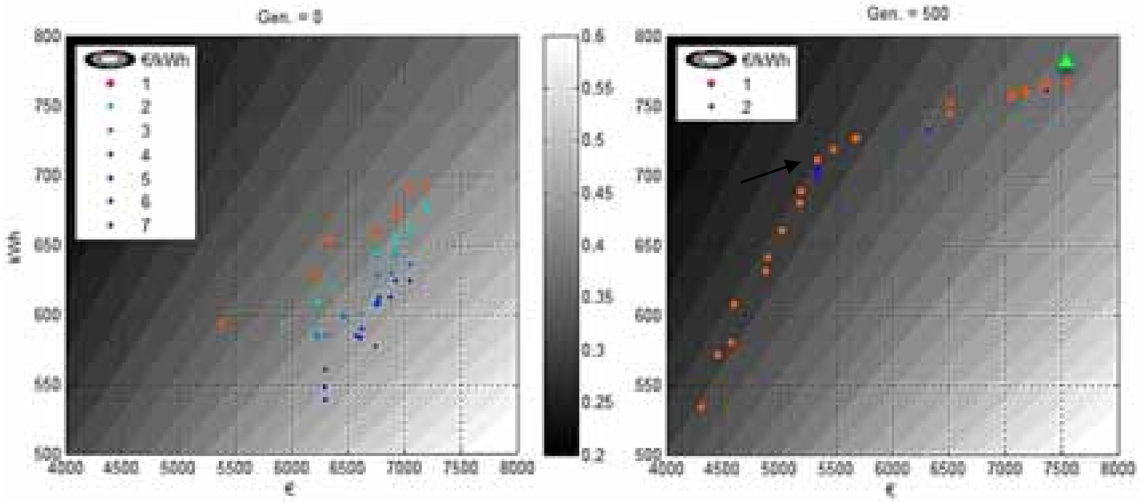

Figure 6 - Comparison between the Pareto fronts from the initial (left) and 500th (right) generations. The arrow points the individual with minimum €/kWh in 25 years of system lifetime (i.e. 0.30 €/kW h and 711 kW h/year) and the green triangle marks the location of the micro-inverter scenario.

4. Conclusions

A partially obstructed south facing rooftop and a west facing building facade were subject to a PV system sizing optimization using a multi-objective genetic algorithm (MOGA). This study aimed at the maximization of yearly energy yield, based on hourly solar radiation profiles obtained from a 3D urban-oriented solar potential model, and the minimization of wiring, modules and inverter costs, and the comparison with a micro-inverter scenario. Results show which PV string tiling strategies are more adequate in case the end-user has financial limitations or aims at the highest possible yield. By examining the arrangements with minimum cost of energy €/kWh, it is suggested that higher number of PV strings formed by individual modules using micro-inverters achieves the highest electricity yields, but the costs double those of the layouts with longer and clustered strings in the more sunlit areas. An improvement of 23% and 24% in the cost of energy is observed from the micro-inverter scenarios to the MOGA solutions.

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