EnergyMatching (EM) Tool for optimization of RES harvesting at building and district scale

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Adaptable and adaptive RES envelope solutions to maximise energy harvesting and optimize EU building and district load matching

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Executive summary

This report presents the result of task activities aimed at developing a tool for optimization of RES harvesting at building and district scale.

Chapter 1 contextualizes the EM (EnergyMatching) tool development and provides few basic information about the tool.

Chapter 2 presents the methodology implemented into the tool, the required inputs, the performed calculations, the provided outputs, the application of the tool to three demo buildings.

Chapter 3 presents some comments and touches upon the future exploitation of the tool in the online EM Platform.

1. Introduction

The price of renewable energy technology is dropping amidst ever larger capacities installed, this trend lasted for decades and will likely continue for decades to come. BIPV (Building Integrated PhotoVoltaics), intended as the use of photovoltaic material as cladding for buildings and infrastructures, is participating in this trend. Unfortunately, its installation rate is growing slowly, if at all, and the prices of the products do not drop, condemning this technology to be long confined to the niche of high end new constructions. The diffusion of BIPV constitutes a so-called “chicken or the egg causality dilemma”, because higher installation volumes would help reduce the prices, while at the same time price reductions could kick-start an uptake in installation volumes. The EnergyMatching consortium is betting on the improvement of the techno-economic design of BIPV system to ensure that its installation is profitable, and thus to kick-start a virtuous cycle for BIPV. To do this, a software, called EnergyMatching Tool (EM Tool), has been developed to optimize the positions and capacity of the BIPV system and the capacity of the associated electric storage. The tool will be available online (without need for installation) through the platform developed in a related task. In this way, for example, given the specific price (€/kWp) of the technology chosen, a designer or an investor will immediately know how much capacity should install and also have an indication on the expected self-sufficiency and NPV of the system.

2. EnergyMatching (EM) Tool optimization process

The following section describes in tolerable detail the method that is core of EnergyMatching Tool (see Figure 1). A set of inputs are required for the optimization to take place (section 2.1). After the inputs are processed, a ray-tracing procedure (section 2.2) is used to produce the irradiation matrix (section 2.3). In turn, a sub-set of the irradiation matrix will be chosen by the optimization algorithm and used to simulate a possible PV system (section 2.3), the performance of said PV system will be evaluated (section 2.5) according to one out of a set of reward functions (section 2.6). Once the optimization ends, the tool provides a set of outputs (section 2.7).

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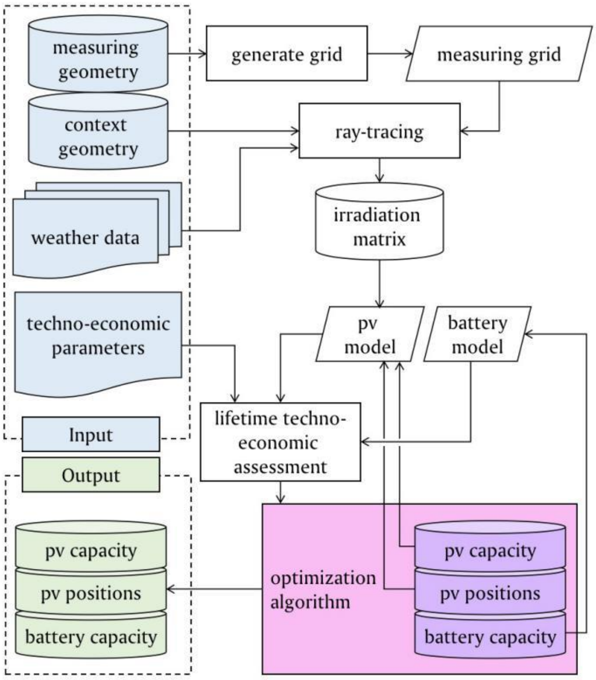

Figure 1: flow diagram of the method described, the main processes are described in the following paragraphs: inputs, ray-tracing, irradiation matrix, PV model, battery model and outputs.

2.1 Inputs

The method proceeds as shown in Figure 1, as input for the procedure the following data is required:

- Measuring geometry, is the surface under exam for the PV optimization. It is subdivided in arrays of smaller elements that represent single PV modules or more generically a measuring mesh over which the irradiation is calculated in each time-step of the simulation, typically one year with hourly frequency (i.e. 8760 data points). Each element contains 1 measuring point (i.e. its centroid). The irradiation for each time-step, measured with ray tracing (see section 2.2), constitutes one column of the irradiation matrix (see section 2.3) and forms the basis for the simulation of the photovoltaic system.

- Context geometry, constitutes the surroundings of the measuring geometry. It contains information about the geometrical and material properties of the scenery within which the building is located. In other words it can casts shadows over the measuring surface or reflect light over it (thus determining the albedo of the surroundings).

- Weather data, represents the annual weather conditions where the building is located. An epw file format (Energy Plus Weather) is used. The information retrieved from this file contains 3 vectors, each with a number of data points equal to the number of time-steps in the simulation. These are direct normal and diffuse horizontal radiation (used to calculate the irradiation over the measuring surfaces), and the ambient temperature (used to calculate the module temperature).

- Techno-economic parameters, are a list of parameters that are used in the techno-economic assessment to calculate the value of each reward function (see section 2.6). Among these are costs and variables affecting revenues (or savings). The costs include the initial unitary cost of the PV system [€/kWp], the unitary cost of the electric storage [€/kWh], and the maintenance costs for the PV [€/kWp]. The variables affecting the savings include the electric demand every time-step,

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efficiency and PR (Performance Ratio) of the PV system, the degradation of the components due to ageing, the cost of the electricity for the consumer (socket cost), the value of the excess energy sold to the grid, the presence of incentives, the discount rate and the long term variations in price of electricity. Some of the techno-economic inputs, such as the degradation of the components or the long-term trends in electricity costs, are difficult to know in advance, thus the possibility is given to insert minima and maxima so that the simulation will produce stochastic results.

2.2 Ray-tracing

The method of choice to calculate the irradiation over the building geometry is the ray-tracing. This technique employs the computation of a large number of virtual photons (or rays) that are either generated at the source or at a receiver (reverse case). These photons, once generated, are sent in a random set of directions (i.e. according to an instance of Monte Carlo technique) within a given solid angle. Each photon is then computed in its interactions with the object in the scene (reflection, transmission and absorption) providing information about the irradiation at the receiver. As shown in the previous paragraph, the envelope of all the possible positions where the PV system could be installed is provided in the form of a measuring geometry (see input area in Figure 1). The measuring geometry is then subdivided into a grid of smaller surfaces, the centroid of each of these smaller surfaces becomes a node in a measuring grid (i.e. a receiver in the ray-tracing simulation). The irradiation on each node for each time-step of the simulation is calculated on the measuring grid using the Radiance reverse ray-tracing engine [1]. More specifically, given the need to calculate a high number of time-steps, the irradiation is not computed directly from the light sources present in the scene, but using a matrix based method called “daylight coefficients”. For a more detailed information, see the Radiance manual in the relevant section [2]. The output of the ray-tracing procedure is an irradiation matrix as described in section 2.3.

2.3 Irradiation matrix and PV model

The purpose of the irradiation matrix is to simulate the power output of any PV system that is placed on the area under exam. The irradiation matrix, produced by the ray-tracing procedure and saved as a csv file, contains the irradiation for each node (or receiver) of the measuring grid in each time-step of the simulation. As the efficiency of the PV system drops amidst high temperatures, it is corrected according to a temperature coefficient. The irradiation matrix cannot be used in its entirety but one sub-set should be chosen because the PV capacity and the positions of the modules are parameters of the optimization. In other words, the optimization algorithm chooses some of the positions available for the PV system and evaluates the performance of a system located in said points. The electric power output is assumed equal to the simple linear relation:

$$p_{HOY,P} = g_{HOY,P} \cdot \eta \cdot PR \cdot A$$

Equation 1: electric output of each node at specific time-step

where $p_{HOY,P}$ is the power output [W_{el}] of each node P at the time-step HOY (Hour Of the Year), $g_{HOY,P}$ is the irradiation on P, and η , PR and A are efficiency, performance ratio and associated area respectively.

If different part of the measuring geometry (see Figure 1) have different properties, different values of η, PR, and A values can be associated the nodes. This condition can occur, for example, if part of a building is glazed and can only host semi-transparent modules whose efficiency differs from the standard ones.

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2.4 Electric storage model

The electric storage is modelled as a simple energy reservoir characterized by a static efficiency, thus for every kWh introduced in the battery only part of it can be extracted, while the rest is dissipated. The battery does not get any time related losses, the energy that is inserted dissipates some energy regardless if it is used in the next time-step or several time-steps later. Furthermore, there are no temperature related effects, thus the capacity and efficiency of the storage are static regarding the ambient temperature. The battery is modelled to suffer a degradation of the capacity due to ageing; such degradation causes the capacity to shrink at every cycle of the battery. The control strategy of the battery is a simple decision tree as shown in Figure 2.

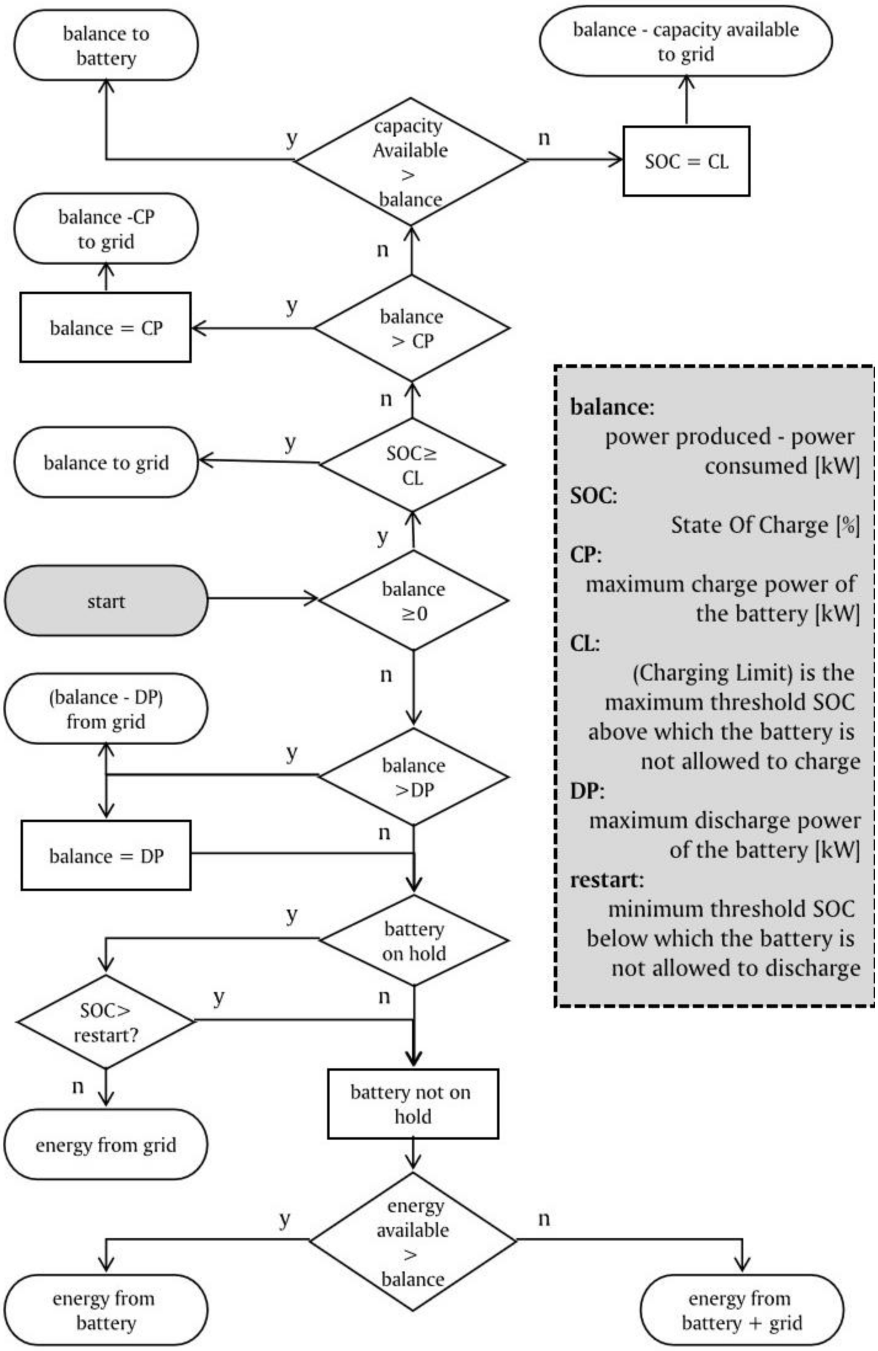

Figure 2: decision tree governing the behaviour of the electric storage.

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2.5 Lifetime techno-economic assessment

The method and the tool presented are meant for optimizing the design of BIPV systems to increase their techno-economic performance according to a specific reward function (see section 2.6). The optimization implies knowing or guessing the electric demand of the building under study, then simulates a large number of different systems to assess their performance. The performance of the BIPV system is determined by the interplay of a handful of dimensions as shown in Figure 3.

The PV capacity is the main parameter of the optimization; a large PV capacity generates a higher PV production, which in turn promotes a higher self-sufficiency (i.e. a higher share of the electricity consumed in the building is produced by the BIPV system). Unfortunately, increasing the PV capacity also increases both the investment and the maintenance costs. This fact, thanks to the savings generated by the system, constrains the problem establishing an optimal capacity amidst increasing costs but also savings and revenues. There is an interaction between PV capacity and battery capacity which is shown in [3].

The battery capacity has the peculiarity to increase both self-consumption and self-sufficiency, in fact it acts on self-consumption (i.e. increases the share of the energy output that is consumed on site since it cannot produce electricity) and self-sufficiency comes by consequence. Any increase in battery capacity, as for PV capacity, also increases costs, thus the problem is similarly constrained. A large battery influences the positions where PV modules are placed since it encourages to occupy highly irradiated spots, even when their production profile does not match the demand profile as well as others. The optimal battery capacity is strongly influenced by the shape of the electric demand, if this is in fact already concentrated in the sunny hours (e.g. air conditioners) there is no need for a larger batteries.

The PV positions can influence the self-consumption because their orientation changes the time of production during the year. Vertical or high tilt modules usually produce more than horizontal or low tilt ones in winter, and modules with an East-West direction have a shifted peak production over the day. Most buildings are characterized by a number of façades (including the slopes of the roof) with different tilts and azimuth, thus, moving the modules over different parts of the envelope can generate different production curves.

Some dimensions are not directly influenced by the parameters of the optimization, for example the self-consumption is negatively influenced by the PV production because the highest the latter, the more likely some power will not be used on-site due to lack of demand (unless there is sufficient space in the electric storage). In the same way an elevated electric demand makes it comparatively more difficult to reach high levels of self-sufficiency.

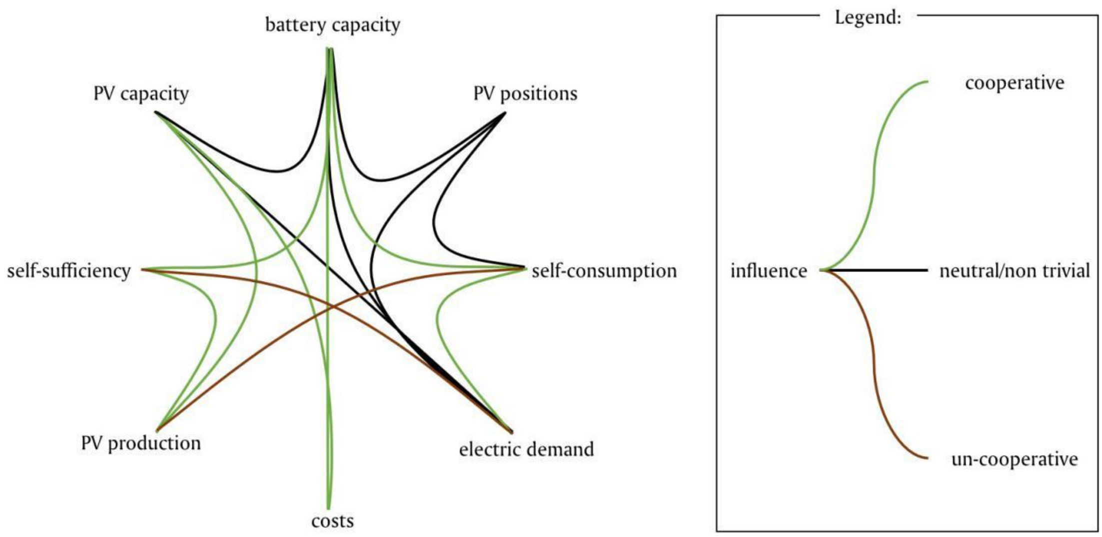

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Figure 3: map of the reciprocal influences among the 8 most relevant dimensions interacting in the techno-economic assessment. PV capacity, battery capacity and PV positions are parameters in the optimization.

2.6 Reward functions

As shown in Figure 1 the optimization algorithm selects the optimal PV capacity, PV positions, and storage capacity according to the result of a techno-economic assessment. The assessment is performed according to one out of a set of reward functions. The standard function consists in the maximization of the NPV defined as in Equation 2.

$$NPV = \sum_{y=0}^{N} \left(\frac{€_u \cdot \sum e_u + €_s \cdot \sum e_s - \omega_{PV} \cdot €_{PV,y} - \omega_B \cdot €_{B,y}}{(1+i)^t} \right)$$

Equation 2: NPV (Net Present Value), this dimension is maximized in the relative reward function

Where:

- €u and €s are the savings obtained thanks to the avoided costs for power used on-site and the revenues received by the sale of excess power respectively.
- eu,year and es,year represent the power used on site and sold to the grid respectively.
- ωPV and ωB represent the capacity of PV system and of electric storage
- €PV,y and €B,y represent the cost for PV and storage at the year y. When y =0 these value represent the investment costs, else they represent the maintenance costs.

Another option for the optimization would be to maximize the self-sufficiency (i.e. the fraction of the overall energy consumed that has been produced with on-site renewables). The cumulative self-consumed energy throughout the whole life-time of the system is simply expressed as:

$$SCE = \sum_{y=0}^{N} \left(\sum e_u \right).$$

Equation 3: SCE (Self-Consumed Energy), this dimension is maximized in the relative reward function

SCE cannot simply be maximized because any increase in installed capacity would eventually lead to an increase in SCE, thus for a maximum SCE the solution is simply to install as much capacity as possible. Nevertheless, if SCE grows quickly for small capacities, it becomes ever more static compared to the capacity increase when the capacity is large. This is because, when the capacity is large, most of the additional PV production cannot be consumed on-site and is therefore lost to the grid. To have a meaningful reward function, SCE should be maximized maintaining a condition, for example that the NPV should not become negative.

Yet another dimension on which the techno-economic performance of the PV system can be measured is the LCOE (Levelized Cost Of Electricity) defined as in Equation 4.

$$LCOE_{self}, LCOE^{*} = \sum_{y=0}^{N} \frac{\omega_{PV} \cdot €_{PV,year} + \omega_B \cdot €_{B,year}}{\sum e_u + \left(\sum e_s \right)^{*}}$$

Equation 4: LCOE (Levelized Cost Of Electricity), it can refer to the self-consumed fraction of the electricity or the whole production (if the sold energy e_s is added *)

As Equation 3, also Equation 4 would result in a meaningless system: the price model of the system is in fact proportional to the capacity (i.e. there is no price reduction associated with larger capacities). To minimize the LCOE and the LCOEself, the algorithm would try to use only the most irradiated spots on the surface and to produce as little as possible to never over-produce. Thus, to provide a condition for the reward function, a minimum self-sufficiency is mandated as in Equation 1.

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$$\mathrm{Re}\,wardFunction = \begin{cases} \left(LCOE_{self} + LCOE\right)^{-1} & \forall \gamma \geq \gamma_{\min} \\ -\left(LCOE_{self} + LCOE\right)^{-1} & \forall \gamma < \gamma_{\min} \end{cases}$$

Equation 5: condition complementary to Equation 4 to define the reward function

Where:
γ and γ_{min} are the self-sufficiency of the solution under exam and the minimum self-sufficiency mandated respectively.

2.7 Outputs

As shown in Figure 1, after simulating and evaluating different combinations of PV positions, PV capacity, and storage capacity the algorithm selects the optimal combination maximizing the techno-economic performance of the system according to the reward function chosen. Thus, as a result of the procedure, an optimal set of parameters (i.e. a combination of capacities and positions) are chosen. The results of the simulation of said capacity are also an output of the optimization, but as shown in [4] these are way more prone to error than the optimal capacity itself. The main outputs of the tool are the following:

NPV over-time: expected NPV (and other more or less likely scenarios) along the lifetime of the system

Expected payback time: as the NPV also the payback time is affected by the stochastic inputs, the most likely value (i.e. the expected value) is reported for the optimal solution found.

Electricity production and consumption: both hourly and annual cumulative values are provided.

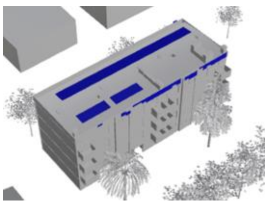
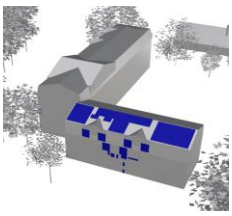
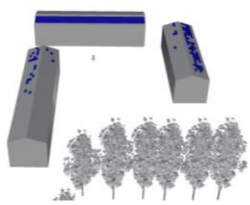
Self-consumption and self-sufficiency: the quantity of produced electricity that is self-consumed (self-consumption) and the quantity of the electricity demand that can be covered are reported for the year 0 (i.e. the stochastic variables are not relevant) for the optimal configuration. Over the life of the building, the self-consumption is likely to increase while the self-sufficiency is likely to decrease.

Expected LCOE ans LCOEself: the cost of the electricity produced (or that of the self-consumed fraction) is reported for the optimal configuration. The real values can vary according to the scenario (because of maintenance costs, discount rate, demand growth and degradation), therefore the value reported is an expected one.

Specific equivalent CO2 emissions for the electricity produced and for its self-consumed fraction: also in this case the value reported is the expected one because the results are affected by degradation levels and growth of the electric demand over the lifetime.

2.8 EM Tool application in demo case studies

The EM Tool was applied within the EnergyMatching project in the retrofit process of three multi-family demo buildings in Italy, France and Sweden. The inputs were set up with regard to the different related contexts and design requirements. The provided BIPV configurations are shown in Table 1, with some optimization outputs.

			
PV capacity [kWp]	13.4	13.2	41.4

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Battery capacity [kWh]	8.8	0	0
Self-consumption [%]	64	79	85
Self-sufficiency [%]	49	18	23
Annual cumulative production [MWh]	13.4	11	34.6

Table 1: optimal BIPV configurations suggested by the EM Tool

3. Conclusion

The EM Tool has proven to be a useful support in individuating preliminary profitable configurations of BIPV systems for BIPV design. It was used to support the three EnergyMatching demo buildings design, later subject to a detailed design phase towards real demo installation. It was an effective instrument as characterized by some important aspects: (i) capacity and positions of a BIPV system are not input but output, (ii) an hourly profile is basis for the calculation, allowing the user to know the expected ratio of energy directly self-consumed by the buildings, (iii) the optimization of BIPV can be performed both at building and district scale.

The EM Tool shows an interesting exploitation potential thanks to its integration within the the EnergyMatching Platform (https://platform.energymatching.eu/index.html), that is a public platform currently under development within the EnergyMatching project (more information will be available in deliverable D2.4, that will be published in October 2021). Interested stakeholders will thus be able to perform simulations and get the tool results through this public platform. This fact will give to the EM Tool the chance to reach the common design practice, becoming a real support for stakeholders out of the project and boosting the spread of BIPV technology.

4. References

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Technical references

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